An Approach Towards Developing a Dynamic GIS-Based Fire Risk Mapping Framework Integrating Multi-Criteria Decision Analysis and Real-Time Environmental Parameters: A Systematic Literature Review

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Abstract*—Fire risk assessment has shifted its approach from static spatial modelling based on expert weighting to data-rich frameworks that couple Geographic Information Systems (GIS) with Artificial Intelligence (AI) analysis, but existing research remains scattered across disciplines. This review draws on thirty-four peer-reviewed journal articles from the fields of forest, urban, industrial and transportation fire science to assess the current maturity of Multi-Criteria Decision Analysis (MCDA), machine learning (ML), deep learning (DL) and Internet of Things (IoT) methods as components of a dynamic GIS-based fire risk mapping approach. The literature is clustered into thematic groups covering static mapping and MCDA-based weighting, ML-based predictive modelling, DL-based detection, real-time mapping (IoT/sensor networks), emergency-response and dispatch optimisation and multi-hazard and autonomous GIS-AI conceptualisation. An overarching trend observed is that GIS-MCDA studies provide easily interpreted, yet time-invariant risk surfaces based on subjectively weighted criteria, while ML/DL studies provide stronger predictive capability but seldom disclose their weighting logic or incorporate real-time environmental data at operational spatial scales. IoT studies lend support to continuous sensing, but validation is typically confined to a single site, which restricts generalisability. The review reveals eleven intersecting research gaps: the lack of dynamically updating frameworks, weak GIS-AI interoperability, inadequate explainability, insufficient uncertainty quantification and the near-absence of standardised validation protocols. Building on these gaps, this paper outlines an approach towards a hybrid conceptual GIS-MCDA-AI-IoT framework, presenting a conceptual roadmap rather than an implemented system for developing a dynamic, explainable fire risk mapping approach within a continuously evolving risk-visualisation and decision-support environment that bridges static geospatial layers with real-time meteorological and sensor data, machine-learning-derived weights and a multi-stage MCDA aggregation module.

Index Terms*—*fire risk mapping, fire hazard, Geographic Information Systems (GIS), Multi-Criteria Decision Analysis (MCDA), Internet of Things (IoT), dynamic risk assessment, remote sensing

I. INTRODUCTION

Forest fires are one of the most widespread and costly hazards to forests and cities, to industrial installations and to transportation systems. Landscape-scale responses to wildland fires affect carbon budgets and biodiversity and urban and industrial fires impact property, economic activity and life, with timing and effects so sharp that little room is left for reactive planning. The literature reviewed demonstrates this diversity: forest fire susceptibility has been modelled based on two decades of MODIS hotspot data [23]; urban fire probability has been computed using socio-economic and building-level data in Shenzhen [31]; and fire loading has been simulated for passengers in transportation systems to assess ignition risk from transportation points [8]. These are a collection of very different applications, but they share the same problem: translating heterogeneous spatial, environmental and behavioural data into a surface that can help decision-makers act before not after a threat or incident.

Field surveys, fire-danger indices and coarse zonation maps based mainly on expert judgement were traditionally used to conduct fire risk assessment. The development of GIS gave the problem a new angle: the task became one of integrating spatial data that existed as a collection of separate environmental layers (e.g., slope, land cover and distance to settlement) into a composite risk surface that could be standardised, assigned weights reflecting relative importance and overlaid. This overlay process was given a formal mathematical structure through Multi-Criteria Decision Analysis, typically realised through the Analytic Hierarchy Process (AHP) and its fuzzy extensions, in which expert weights were elicited and combined [13]. Satellite platforms subsequently enriched these models with vegetation indices, land-surface temperature and burned-area products [17], allowing risk models to be extended over extensive and often inaccessible terrain. More recently, large archives of historical fire incidents, combined with cloud platforms such as Google Earth Engine, have made it possible to derive weights through machine learning and deep learning methods rather than expert judgement, assigning weights based on data values [23], [31]. In parallel, falling costs of environmental sensors and wireless communication have enabled genuinely IoT-based approaches for gathering real-time temperature, humidity, smoke and gas concentration information at the building or landscape scale [2], [12].

Despite this progression, the reviewed corpus shows that these four methodological strands — GIS, MCDA, AI and IoT — have developed largely in isolation. GIS-MCDA studies yield risk maps that are transparent and interpretable, but they are recalculated only when a researcher manually revisits the study, so fire-conducive conditions such as a sudden drop in humidity or a spike in wind speed are not reflected until the next modelling cycle [14], [19]. Machine learning and deep learning

studies achieve strong predictive results and can incorporate more features, but they often substitute opaque model internals for the transparent weighting logic that gives MCDA its decision-support value and relatively few validate their outputs against independent, real-time observation networks [7], [27]. IoT studies demonstrate that continuous environmental monitoring is technically feasible, but validation is rarely extended across multiple sites or a broader scale, leaving questions of generalisability largely unanswered [2], [4]. Motivated by this fragmentation, the central objective of this review is to critically synthesise the GIS, MCDA, AI and IoT literature relevant to fire risk and fire hazard assessment, to identify where these strands can be productively combined and to propose an approach towards a genuinely dynamic, GIS-based fire risk mapping framework that updates continuously as environmental conditions change — a conceptual outline rather than an implemented and validated system.

This review adds to the literature in three ways. First, it moves beyond paper-by-paper summarisation toward a thematic, comparative synthesis that surfaces convergences and contradictions across thirty-four studies drawn from forest, urban, industrial and transportation fire domains. Second, it develops comparison tables and formalises representative equations that make explicit the variables, weighting logic, algorithms, validation metrics and limitations used across studies — an exercise rarely attempted within a single-domain fire review. Third, it proposes an approach towards a conceptual hybrid GIS-MCDA-AI-IoT framework that directly addresses the fragmentation identified in the synthesis, offering a roadmap for future empirical work, including the authors' own research on dynamic fire risk mapping.

II. SYSTEMATIC LITERATURE REVIEW METHODOLOGY

A. Review Design

A systematic literature review (SLR) was undertaken to comprehensively review existing literature on dynamic fire risk assessment and mapping using Geographic Information Systems (GIS) together with Multi-Criteria Decision Analysis (MCDA), machine learning (ML), deep learning (DL), the Internet of Things (IoT), remote sensing and real-time environmental parameters. The review was carried out in compliance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines [34] to provide a clear and well-ordered review process.

The main goals of this review were to identify existing methodologies, variables used, analysis methods, validation methods, gaps in current research and future research directions for developing a dynamic, GIS-based fire risk mapping approach.

B. Information Sources and Search Strategy

Literature items were gathered from internationally recognised bibliographic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and Google Scholar. The search was limited to English-language peer-reviewed journal articles on the subject of fire risk assessment and spatial fire risk mapping; conference proceedings and preprints were excluded from the final evidence base (Section II-C).

A Boolean search strategy of the form ("fire risk*" OR "fire hazard*") AND ("GIS" OR "geographic information system*") AND ("MCDA" OR "AHP" OR "machine learning" OR "deep learning" OR "Internet of Things" OR "remote sensing" OR "real-time environmental monitoring") was adapted to the syntax of each database. The reference lists of selected publications were also searched to identify additional relevant studies. The database searches were conducted in August 2026 and the search covered publications published between 2020 and 2026.

C. Eligibility Criteria

Studies were included if they met the following criteria:

- Studies addressing fire risk or fire hazard assessment, fire hazard mapping, fire prediction and fire management.
- Studies based on GIS, MCDA, artificial intelligence, machine learning, deep learning, IoT, real-time environmental monitoring, or related tools.
- Peer-reviewed journal articles published in English.
- Studies providing adequate detail of methods and results.

It was decided not to include the following:

- Publications out of scope, i.e., not related to fire risk assessment or fire mapping.
- Conference proceedings, preprints, notes, commentaries, book chapters, theses, book abstracts and non-peer-reviewed publications.
- Studies lacking sufficient methodological detail, or duplicate publications of already-included studies.

D. Study Selection

This systematic literature review is based on a total of thirty-four peer-reviewed journal articles. Each candidate record's publication venue was checked individually against the eligibility criteria above; records published only as conference proceedings or preprints were excluded even where a peer-reviewed journal version could not be located and were substituted, where a thematically equivalent journal-published study existed, rather than left uncited. The selected studies span a wide variety of applications of GIS, MCDA, machine learning, deep learning, IoT, remote sensing and real-time environmental monitoring as tools for addressing fire risk and fire hazard in forest, urban, industrial and transportation environments.

Each article was analysed to extract its research objective(s), study area, datasets used, variables, analysis methods, validation approach, main results, limitations and identified future research gaps. This information was then combined and synthesised to enable comparison and the identification of trends relevant to dynamic fire risk mapping.

A flow diagram of the study selection process (PRISMA 2020) is shown in Fig. 1.

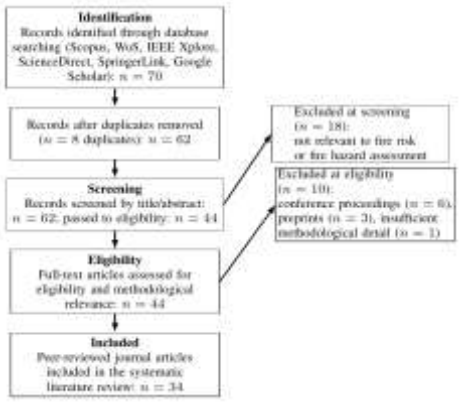


Fig. 1. PRISMA 2020 flow diagram summarising the identification, screening, eligibility assessment and inclusion of studies in the review. Illustrative counts are shown at each stage; n = 34 peer-reviewed journal articles were included in the final synthesis.

E. Data Extraction

A data extraction structure was created to standardise data records across the review process. The following information was extracted from each of the selected studies:

- Authors' names and year of publication
- Study location
- Research objectives
- Data sources
- Fire risk variables
- GIS and analytical approaches used
- MCDA methods
- Machine learning and deep learning algorithms
- IoT and sensor technology concepts
- Validation methods
- Key findings
- Study limitations
- Research gaps
- Future research recommendations

These data were organised into a systematic, structured database for comparative analysis of the selected studies.

F. Quality Assessment

The methodological quality of the selected studies was assessed by examining the clarity of the stated research objectives, the appropriateness of the data sources, the methodological and/or analytical approach used, the adequacy of validation procedures, the consideration of limitations and the practical applicability of the proposed approaches.

Particular attention was given to studies that validated their models against field observations, reported statistical model performance criteria, applied cross-validation, or compared results to existing techniques. This qualitative assessment helped identify methodological strengths and weaknesses across the existing scholarly research.

G. Data Synthesis

Because the objectives, data measurements and definitions used across the selected studies were highly heterogeneous, a quantitative meta-analysis was not warranted; a narrative thematic synthesis method was used instead.

The chosen studies were classified into the following thematic areas:

- GIS-based fire risk mapping using remote-sensing technology and MCDA-based fire risk assessment
- Machine learning models for fire prediction
- Deep learning for advanced fire detection and monitoring
- Real-time environmental monitoring and the Internet of Things
- Emergency response and decision-making systems
- Integrated and multi-hazard fire risk assessment

A comparative analysis was performed across all thematic categories based on methodology, variables included, validation approach, positive aspects and limitations and gaps. The results of these comparisons were then combined to provide an overview of current research trends and to develop an approach towards an overall conceptual framework for dynamic, GIS-based fire risk mapping.

III. RESULTS AND THEMATIC LITERATURE SYNTHESIS

A. Traditional GIS and MCDA-Based Fire Risk Mapping

Fire risk mapping has historically been treated as a problem of spatial data overlay: discrete environmental layers such as elevation, slope, aspect, vegetation and proximity to human activity are standardised, weighted and combined in a GIS environment to produce a composite risk surface. Because these input layers are physically interpretable, the overlay logic is transparent and the resulting maps are straightforward for land managers to interrogate and defend. In the peer-reviewed journal literature reviewed here, this weighting step has been formalised almost universally through Multi-Criteria Decision Analysis (MCDA), most often via the Analytic Hierarchy Process (AHP), rather than left as an unweighted overlay. One study [13] applied AHP to seven fire-inducing factors in the Palamau Tiger Reserve, checking judgement consistency through a Consistency Ratio below 0.10 and validating the resulting Forest Fire Risk Index against three independent fire-occurrence datasets, including MODIS and SNPP-VIIRS active-fire products. Another study [18] applied GIS and AHP to forest fire risk zone mapping in the Parambikulam Tiger Reserve, Kerala, India, illustrating that the weighted-overlay method, once formalised through AHP, remains in active use for regional-scale fire risk zonation. A further study [14] tested Fuzzy AHP against Hybrid Grey Relational Analysis (HGRA) for the same set of static and dynamic fire factors in Ghana, finding that Fuzzy AHP produced a lower standard deviation (0.0927 versus 0.1122) and was therefore judged the more reliable weighting method — a rare instance in this corpus of one MCDA variant being directly benchmarked against another. A related study [21] combined AHP with Ordered Weighted Averaging (OWA) for forest fire risk mapping in southern Turkey, finding that both weighting schemes performed better under a Jenks Natural Breaks classification than under an equal-interval classification when compared against historical fire data. Another study [24] directly compared AHP against FAHP for wildfire risk zone mapping under contrasting climatic conditions, while a further study [5] combined Fuzzy AHP with Random Forest and Boosted Regression Tree machine-learning models, finding that the hybrid knowledge-based and data-driven approach improved on either technique used in isolation.

A separate study [20] applied the DEMATEL technique, rather than AHP, to model causal relationships among urban fire and emergency-facility siting criteria, indicating that MCDA methods beyond AHP remain underexplored in fire-specific applications. Another study [19] combined GIS with an MCDM approach to map urban structural fire vulnerability using socio-economic, built-environment and historical fire data, bridging the forest-fire-dominated MCDA literature with an urban application.

The consistency-ratio diagnostic that recurs across several of these studies [13], [14] allows readers to judge the reliability of the elicited weights — a transparency step this review's other clusters (Sections III-B through III-E) largely lack. The most common approach uses pairwise comparison to derive a priority vector $w = (w_1, w_2, \ldots, w_n)$ over n criteria and checks the reliability of the judgement matrix $A = [a_{ij}]$ via

$$CI = (\lambda_{max} - n) / (n - 1), \quad CR = CI / RI \qquad (1)$$

where λ_{max} is the principal eigenvalue of A, CI is the Consistency Index, RI is the Random Index for a matrix of order n and a CR below 0.10 is conventionally taken to indicate acceptable consistency [13]. The resulting weights are then

combined with standardised criterion layers x_i (each rescaled to a common 0–1 range) to compute a composite Fire Risk Index for each spatial unit:

$$FRI = \Sigma_{i=1}^{n} w_i x_i, \quad \Sigma_{i=1}^{n} w_i = 1 \qquad (2)$$

Yet every MCDA study in this cluster shares the same underlying limitation: weights are elicited once, from a fixed panel of criteria and are not revised as environmental conditions change. One study [14] explicitly distinguishes "static" from "dynamic" variables (wind speed, temperature and precipitation are labelled dynamic), but the dynamic variables are still sampled once rather than continuously monitored and are then combined with the static variables through the single, time-invariant weighted overlay of Eq. (2). Another [13] acknowledges this directly, noting that the model excludes real-time weather, vegetation moisture and machine-learning approaches. This recurring caveat across independently authored studies suggests that the limitation is structural to the AHP-overlay paradigm itself, rather than an oversight of any single research team and it is precisely the gap that machine-learning studies and IoT-based studies attempt to close from opposite directions: one by learning weights from data, the other by supplying continuously updating inputs.

B. Machine Learning-Based Predictive Fire Risk Modelling

The largest cluster in this review applies supervised machine learning to predict fire occurrence or risk probability from historical incident records and environmental covariates. One study [23] compared Random Forest and CART models trained on two decades of MODIS FIRMS hotspot data combined with Google Earth Engine-derived topographic, climatic and vegetation layers, finding Random Forest superior by ROC-AUC and confusion-matrix metrics. Another study [22] extended the machine-learning paradigm to a multi-hazard context, modelling flood, forest fire and landslide susceptibility jointly using Random Forest together with the Boruta feature-selection method, reporting that roughly 2.67% of the study area was simultaneously susceptible to all three hazards — a finding with direct implications for the multi-hazard cluster in Section III-F. A further study [17] focused on vegetation dynamics, showing that long-term satellite-derived vegetation trend indices ($NDVI_W$ and $NDVI_T$) improved wildfire prediction over conventional instantaneous NDVI when combined with XGBoost, which outperformed logistic regression and Random Forest in the comparison.

Urban applications of machine learning are similarly well represented. Statistical machine-learning models with an optimised risk-indexing scheme for fire risk assessment at province level have also been developed [3]. Back-Propagation Neural Networks have been compared against Geographically Weighted Regression for high-resolution urban fire risk assessment [7], explicitly framing machine learning as a means of reducing the subjectivity inherent in expert-weighted indicator selection — a direct methodological counterpoint to the MCDA studies in Section III-A. Six machine-learning models — LightGBM, XGBoost, Random Forest, Artificial Neural Networks, Ridge and Lasso regression — have been compared for urban fire probability prediction in Shenzhen using building, land-use, population and economic density data [31], with LightGBM achieving the highest accuracy ($R^2 \approx 0.96$ for building fires), while garbage fires remained poorly predicted because of their inherent randomness. Geoinformatics has also been combined with machine learning in a building-block-level framework for peri-urban fire risk assessment and management [30] and a separate geospatial model-based framework incorporating fire-spread modelling, vulnerability analysis and predictive classification has been proposed [27].

Across this cluster, ensemble tree-based methods — Random Forest, XGBoost and LightGBM — recur consistently as the strongest-performing algorithms across forest, multi-hazard and urban applications alike [17], [23], [31]. Machine-learning studies also consistently report stronger quantitative validation, typically through ROC-AUC, RMSE and cross-validation, than the largely consistency-ratio-based validation used in the MCDA cluster. The trade-off is a recurring loss of interpretability: several studies in this cluster [7], [31] use feature-importance rankings or entropy-based methods to partially recover the weighting transparency that MCDA provides natively. Two further studies address this gap directly through post-hoc explainability: one applies SHAP (SHapley Additive exPlanations) values to interpret the factors driving a wildfire susceptibility model [1] and another builds a SHAP-driven explainability framework around MODIS active-fire pixels to interpret contributing factors in a Mediterranean urban-adjacent setting [9], suggesting that hybridisation between MCDA-style transparency and AI-style predictive strength, rather than substitution of one family for the other, is the more promising direction — a point developed further in Section VI.

C. Deep Learning-Based Detection Systems

A related but distinct cluster applies deep learning primarily to visual fire detection and spread forecasting rather than to susceptibility mapping. One study [15] proposed a dual-model deep-learning method capable of forecasting wildland fire spread at super-real-time speed, directly targeting the temporal responsiveness that static GIS-MCDA models lack. Another study [29] enhanced the YOLOv5s architecture with Squeeze-and-Excitation and SPPF modules for urban fire detection across building, vehicle and industrial fire categories, reporting 98.2% precision and processing speeds compatible with 35 frames-per-second video, though accuracy on industrial fires was constrained by a comparatively small number of training images in that category. A further study [32] developed a lightweight SqueezeNet-based attention U-Net architecture for forest fire image segmentation, achieving competitive detection accuracy with substantially fewer parameters than conventional encoder-decoder networks, a design choice directly relevant to edge deployment on resource-constrained IoT hardware (Section III-D). Another study [33] applied a tokenized time-series transformer network to satellite image segmentation for active fire detection, demonstrating that temporal tokenisation of multi-band sensor data can improve detection accuracy over conventional per-frame convolutional approaches.

These studies collectively demonstrate that deep learning has matured furthest in the visual detection sub-problem, where large annotated image datasets and well-established architectures (CNNs, YOLO variants) are available, compared with the risk-mapping sub-problem addressed in Section III-B, where labelled, spatially continuous fire-risk data remain scarcer. A shared limitation across this cluster is that detection accuracy is demonstrated on curated or web-scraped image datasets rather than on continuous, geographically referenced monitoring feeds, meaning the outputs of this cluster are not yet natively integrated into the GIS-based risk-mapping frameworks discussed elsewhere in this review. This represents both a gap and an opportunity: coupling real-time visual detection with the geospatial susceptibility layers from Sections III-A and III-B could allow a dynamic framework to corroborate

model-predicted risk with observed ignition events, a possibility discussed further in Section VI.

D. IoT and Real-Time Sensor Networks

A fourth cluster addresses the acquisition of genuinely continuous environmental measurements using Internet of Things architectures, whereas the preceding clusters treat environmental data as periodically updated inputs. One study [12] implemented a smart forest alert monitoring system integrating IoT sensor nodes for temperature, humidity and smoke detection with automated alerting, though validation was limited to prototype conditions rather than large-scale field deployment. Another study [4] combined a wireless sensor network with machine-learning-based classification for forest fire detection, illustrating the pairing of continuous sensing with the predictive modelling techniques discussed in Section III-B. A further study developed algorithms specifically for fast fire risk prediction and real-time data processing, addressing the computational latency that any operational real-time system must manage [10]. A markedly different data-acquisition approach uses volunteered geographic information from Twitter to analyse fire hazards in real time [6], demonstrating that social-media data streams can supplement or substitute for physical sensor networks where formal IoT infrastructure is absent. Perhaps the most operationally complete IoT system in this review integrates temperature, smoke and carbon-monoxide sensors with a Building Information Model and Fire Dynamics Simulator outputs within an Improved Risk Index for a twelve-storey residential building in Wuhan [2], reporting a 30% reduction in detection time and a 25% reduction in evacuation time relative to baseline conditions, validated through an expert survey involving 220 professionals in addition to sensor-accuracy testing. A related study proposed an informative digital-twin architecture for building-level fire emergency management, coupling BIM-derived scenario knowledge with real-time recognition to assess potential fire risk and share egress information, achieving a simulated fire-recognition processing time under one second [11].

The IoT cluster's principal strength is that it directly resolves the temporal-lag problem identified in both the GIS-MCDA cluster (Section III-A) and much of the machine-learning cluster (Section III-B), since sensor data are, by design, continuously refreshed. However, every IoT study in this cluster is validated at a single site or under simulated conditions and none demonstrates the regional-scale coverage typical of the GIS-based studies in Sections III-A and III-B. This creates a complementary asymmetry: GIS-MCDA and machine-learning studies achieve spatial breadth but temporal staticity, while IoT studies achieve temporal immediacy but spatial narrowness. Bridging this asymmetry, by embedding sparse IoT sensor networks within a broader, GIS-interpolated environmental surface, is one of the clearest opportunities emerging from this synthesis and is incorporated directly into the conceptual framework in Section V.

E. Emergency Response and Dispatch Optimisation

A fifth cluster addresses the operational response phase rather than risk prediction alone. One study [26] coupled GIS-derived road-network features with XGBoost and Support Vector Regression models to predict fire dispatch-to-arrival times and generate optimal response routes for over 7,000 incidents in Kayseri, Turkey, directly linking predictive spatial modelling to resource-allocation decisions once a fire risk or incident is identified. Another study [28] developed a visual simultaneous localisation and mapping (SLAM) algorithm enabling firefighting robots to navigate and map fire environments despite the visual disturbances that flames and smoke introduce. A third study [8] modelled fire risk arising from passenger-carried combustible loads within metro systems using a Floor Field Cellular Automaton that simulates passenger movement alongside fire-load distribution, producing a spatially and temporally resolved risk profile specific to transportation infrastructure.

This cluster illustrates that dynamic, real-time reasoning has progressed furthest not in risk prediction itself — where the decision horizon spans days — but in the downstream tasks of navigation and dispatch, where the decision horizon is only minutes. None of these three studies, however, is coupled to the upstream risk-mapping layers discussed in Sections III-A and III-B; dispatch optimisation and robot navigation currently operate as downstream systems that assume a fire has already been detected, rather than as consumers of a continuously updated pre-incident risk surface. Integrating predictive risk layers with dispatch and robotic response systems therefore represents an underexplored but logical extension connecting this review's core risk-mapping focus to operational emergency management.

F. Multi-Hazard Assessment and Autonomous GIS-AI Conceptualisation

A final cluster addresses conceptual and cross-hazard integration. The multi-hazard study already discussed in Section III-B [22] is equally relevant here for demonstrating that fire risk cannot always be modelled in isolation from co-occurring hazards such as flood and landslide, since shared conditioning factors generate spatially overlapping risk. Separate work [16] introduced the concept of Autonomous GIS, proposing a staged framework for AI-driven spatial analysis and describing levels of autonomy that could, in principle, allow a fire-risk GIS to reconfigure its own analytical workflow as new data arrive — a conceptual counterpart to the operational dynamism sought throughout this review. A comprehensive survey of the machine-learning pipeline for wildfire risk prediction and assessment [25], spanning data acquisition, feature engineering, model selection and post-processing evaluation, synthesises much of the same machine-learning literature examined here, corroborating this review's observation that fire risk research has progressed unevenly across methodological families.

Considered together, this cluster confirms two points established piecemeal in earlier sections: first, that fire risk is rarely spatially independent of other environmental hazards and hazard-specific models may therefore understate risk in areas of hazard overlap [22]; and second, that the GIS discipline itself is moving conceptually toward greater autonomy [16], even though, as Sections III-A through III-E demonstrate, empirical fire-specific implementations have not yet caught up with this conceptual trajectory.

G. Comparative Synthesis

Table I compares the dominant methodological families identified above along the dimensions most relevant to designing a dynamic fire risk mapping approach.

Table I shows that no single methodological family in the reviewed corpus is simultaneously strong on interpretability, predictive accuracy, spatial scale and temporal responsiveness. GIS-MCDA studies score highest on interpretability but lowest on temporal responsiveness; IoT studies invert this pattern; and machine learning occupies an intermediate position, trading some interpretability for improved predictive performance without yet achieving the temporal immediacy of IoT sensing.

This complementary pattern, rather than the superiority of any one family, is the central empirical finding that motivates the hybrid framework approach proposed in Section V.

To compare the relative findings of the machine learning and deep learning studies for which quantitative results were provided, the key finding from each study is summarised in Table II.

As Table II shows, reported accuracy figures are not directly comparable across studies, since they are computed on different metrics, over different geographic extents and against different baseline sets, which could create a false impression of a ranking of methods. What can be responsibly concluded is that ensemble tree-based methods (Random Forest, XGBoost, LightGBM) are the most frequently reported best performers among tabular, feature-based fire-risk models in this corpus — consistent with the broader machine-learning literature rather than a fire-specific idiosyncrasy — while YOLO-family architectures dominate image-based detection tasks.

IV. RESEARCH GAPS

Based on the literature reviewed above, eleven interrelated gaps can be identified, each supported by evidence from multiple studies rather than a single source.

First, there is no genuinely dynamic framework in the GIS-MCDA cluster: studies [13], [14] recompute risk only when an analyst re-runs the model and even studies that label certain variables "dynamic" sample them at a single time point [14]. Second, integration between GIS and AI remains limited at the architectural level: machine-learning studies [7], [31] predominantly use GIS as a data-preparation step rather than as an active component of an operating system and Autonomous GIS [16] remains a conceptual vision rather than a demonstrated fire-specific implementation.

Third, IoT adoption is limited in scale: every IoT fire-risk study in this review [2], [4], [12] is validated at a single site or under simulated conditions, with no regional-scale IoT fire-risk network reported in the corpus. Fourth, real-time weather integration is scarce in the GIS-MCDA cluster specifically, even though wind speed, humidity and temperature are repeatedly identified as influential fire-conducive variables across both the MCDA cluster [14] and the machine-learning cluster.

Fifth, no GIS-MCDA study reviewed includes a temporal-updating mechanism — a process by which the risk map automatically refreshes as new data arrive; even among the machine-learning studies in this corpus, periodic retraining is the closest approximation available and no equivalent mechanism appears within the GIS-MCDA tradition itself. Sixth, uncertainty analysis is essentially unaddressed: no study in this corpus reports confidence intervals, sensitivity analysis, or formal error propagation around its fire-risk estimates.

Seventh, explainable AI is only beginning to be applied: two studies apply SHAP-based explainability to wildfire susceptibility models [1], [9] and two further studies [7], [31] use simpler feature-importance rankings, but no study in this corpus combines a formal explainability framework with a dynamic, continuously updating risk surface. Eighth, generalisation across regions is poorly demonstrated: one study [23] explicitly acknowledges single-region limitations and no study in the corpus reports cross-regional transfer testing of a single trained model.

Ninth, standardised datasets and validation protocols are lacking: accuracy figures are difficult to compare across studies because they draw on a heterogeneous mix of MODIS FIRMS records, national fire databases and other disparate sources (see Table II). Tenth, the scope of validation is often restricted: several studies validate using only a Consistency Ratio [13], [14] rather than against independent, ground-truthed fire-occurrence data, while some IoT studies rely on expert surveys [2] rather than long-term field monitoring.

Finally, decision-support capability — the extent to which a model's output is packaged for use by emergency managers rather than researchers — is fully realised in very few studies; a building-level IoT deployment [2] and a related digital-twin fire emergency management system [11] are among the clearest examples, while most machine-learning studies stop at model validation without an accompanying decision-support interface.

V. AN APPROACH TOWARDS A DYNAMIC GIS-BASED FIRE RISK MAPPING FRAMEWORK

A. Framework Overview

Building directly on the gaps identified in Section IV, this section outlines an approach towards a conceptual Dynamic GIS-Based Fire Risk Assessment and Mapping Framework, structured around ten linked components. It is important to emphasise that this framework is a conceptual synthesis derived from the gaps identified in the literature, not an implemented or empirically validated system; Fig. 2 illustrates the proposed architecture and the flow of information between components.

B. Data Collection

Data collection forms the foundation layer and combines four sources represented across the reviewed clusters: satellite remote sensing for vegetation and land-surface variables, as used in several studies [17], [23]; live meteorological feeds for temperature, humidity, wind speed and direction — the variable class most consistently missing from the GIS-MCDA cluster (Section III-A); topographic and land-use layers from established GIS sources; and, where available, socio-economic data of the kind used in [31]. IoT sensor networks are included as a distinct, denser data-collection channel supplying building- or corridor-level temperature, smoke and gas readings in the manner demonstrated in [2], extended conceptually to multiple structures within a district rather than a single building. Each source is necessary because none alone supplies both the spatial breadth of satellite and GIS data and the temporal immediacy of IoT sensing identified as complementary in Table I.

TABLE I
COMPARISON OF METHODOLOGICAL FAMILIES FOR FIRE RISK ASSESSMENT

Dimension	GIS/MCDA (AHP/FAHP/DEMATEL)	Machine Learning	Deep Learning (detection)	IoT/Real-time sensing
Representative studies	[13]; [18]	[23]; [31]	[15]; [29]	[2]; [12]
Typical variables	Elevation, slope, aspect, land cover, vegetation indices, expert pairwise judgements	Historical fire records, climatic, socioeconomic, vegetation variables	Image pixels, thermal/visual features	Temperature, humidity, smoke, CO, wind

Dimension	GIS/MCDA (AHP/FAHP/DEMATEL)	Machine Learning	Deep Learning (detection)	IoT/Real-time sensing
Weighting/inference logic	Pairwise comparison with consistency check (Eq. 1)	Data-driven feature importance	Learned convolutional/graph features	Threshold-based or rule-based alerts
Validation approach	Consistency Ratio; comparison with independent fire datasets	ROC-AUC, RMSE, cross-validation	Precision/Recall/mAP on image test sets	Sensor accuracy testing; expert survey
Temporal responsiveness	Static (weights fixed after elicitation)	Static to near-real-time depending on retraining cadence	Near-real-time on incoming imagery	Continuous/real-time
Spatial scale demonstrated	District/reserve to regional	Grid-cell to citywide	Image frame/scene	Single building or small test area
Interpretability	High (documented weights)	Moderate (feature importance only)	Low	High (raw physical readings)
Principal limitation	Weighting subjectivity; no temporal updating	Weak transparency of internal logic; limited real-time validation	Not linked to spatial risk layers	Narrow spatial validation

TABLE II
REPORTED VALIDATION METRICS FOR MACHINE LEARNING AND DEEP LEARNING STUDIES

Study	Best-performing model	Key reported metric	Validation approach
[23]	Random Forest (over CART)	Higher AUC and confusion-matrix accuracy	ROC-AUC, confusion matrix
[22]	Random Forest (multi-hazard)	High AUC across flood, fire, landslide	ROC-AUC
[17]	XGBoost (over Random Forest, logistic regression)	Highest AUC using $NDVI_W/NDVI_T$	70/30 train–test split, ROC-AUC
[31]	LightGBM	$R^2 \approx 0.96$ (building fires)	5-fold cross-validation, RMSE, R^2
[29]	Enhanced YOLOv5s	98.2% precision; 92.5% recall; 95.4% mAP@0.5	Train/test split against YOLOv5/YOLOv5x baselines
[2]	BIM-IoT with Improved Risk Index	98.2% sensor detection accuracy; 30% faster detection	Sensor calibration, 100 test runs, expert survey (n = 220)
[26]	XGBoost (over SVR)	78.41% accuracy within ±3 min; MAE ≈ 1.67 min	Train/test split, MAE, RMSE, R^2

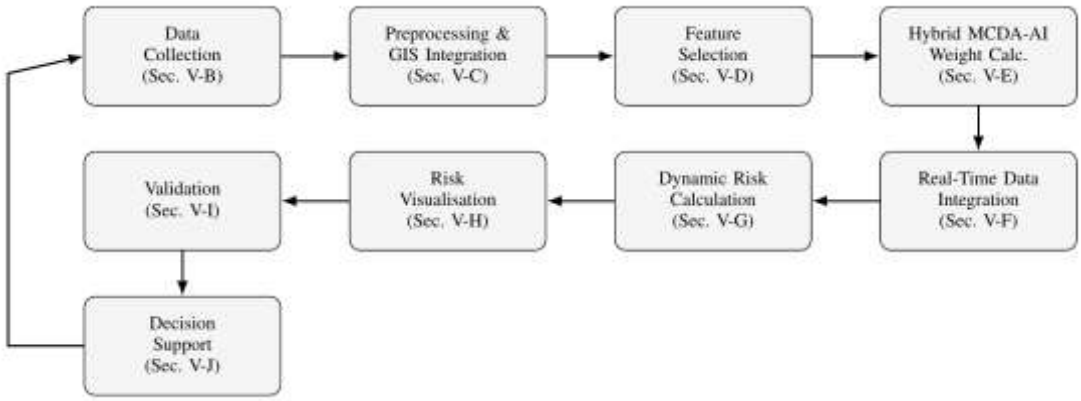


Fig. 2. Proposed conceptual architecture for the Dynamic GIS-Based Fire Risk Assessment and Mapping approach. The feedback arrow from Decision Support back to Data Collection represents the continuous refresh cycle described in Section V-F.

C. Data Preprocessing and GIS Integration

Data preprocessing standardises these heterogeneous inputs — resampling satellite imagery, cleaning sensor noise and reprojecting all layers to a common coordinate system — following the standardisation steps described across nearly every GIS-based study reviewed [13], [23]. A GIS database organises the preprocessed layers within a common spatial reference, serving the same structural role that GIS plays across every methodological cluster in this review.

D. Feature Selection

Feature selection, informed by the machine-learning literature's use of importance-ranking techniques [31] and the Boruta algorithm used in [22], narrows the full variable set to those with demonstrated predictive or decision-relevant value, avoiding the uncontrolled variable proliferation that several studies flag as a limitation.

E. Hybrid MCDA-AI Weight Calculation

Weight calculation combines two parallel mechanisms rather than choosing one over the other: an MCDA component, following the AHP/Fuzzy AHP logic of Eqs. (1)–(2) as validated in [13], [14], supplies transparent, stakeholder-defensible weights w_i^{MCDA} for criteria where expert judgement is well established, while a machine-learning component, following the feature-importance logic demonstrated in [7], [31], supplies data-driven weights w_i^{ML} for variables where historical incident data are sufficient to learn relationships directly. The two weight sets are combined for each criterion i through a tunable blending parameter $\alpha \in [0, 1]$:

$$w_i^{hybrid} = \alpha\, w_i^{MCDA} + (1 - \alpha)\, w_i^{ML}, \quad \Sigma_{i=1}^{n}\, w_i^{hybrid} = 1 \qquad (3)$$

where α is set higher for criteria with well-established domain consensus (e.g., slope, proximity to settlement) and lower for criteria where large historical incident datasets support reliable data-driven estimation. This dual-weighting design is the framework's central response to the interpretability-versus-accuracy trade-off documented in Table I and Section VI-A. Machine learning is also applied more broadly within the framework to model nonlinear interactions among variables and to generate the base predictive risk surface, drawing on the ensemble tree-based methods (Random Forest, XGBoost, LightGBM) that this review's synthesis identifies as the most consistently strong performers (Section III-B; Table II).

F. Real-Time Data Integration

Real-time data integration is the component that most directly targets the temporal-updating gap identified in Section IV: live meteorological and IoT streams are ingested on a defined refresh cycle, rather than sampled once, addressing the specific limitation identified in [13], [14] in their own static designs.

G. Dynamic Risk Calculation

Dynamic risk calculation recombines the hybrid weights of Eq. (3) with the continuously updating inputs to recompute the composite risk surface at a defined interval t:

$$FRI_{dynamic}(t) = \Sigma_{i=1}^{n} w_i^{hybrid} x_i(t) \quad (4)$$

where $x_i(t)$ denotes the value of criterion i at time t, allowing static criteria (e.g., slope, elevation) to remain fixed while dynamic criteria (e.g., live wind speed, humidity, IoT sensor readings) are refreshed on each cycle — operationalising the "dynamic" framing that this review's synthesis (Section III-A) shows is proposed only conceptually or approximated through periodic retraining elsewhere in the literature.

H. Risk Visualisation

Risk visualisation renders the continuously updating surface of Eq. (4) as a GIS-based map, following the interpretable classification schemes used throughout the MCDA cluster [13] but refreshed on a defined cycle rather than produced once.

I. Validation

Validation closes the loop by comparing model output against independent fire-occurrence records, following the multi-dataset validation approach in [13] and against continuous IoT ground-truth readings where available, following the sensor-accuracy testing approach in [2]; this dual validation directly responds to the limited-validation-scope gap identified in Section IV.

J. Decision Support

Decision support, the framework's final component, packages the validated, continuously updating risk map into a form usable by emergency managers, following the digital-twin decision-support orientation demonstrated at building scale in [11] and is included because a technically accurate risk model that is not operationally accessible fails to deliver practical value — a limitation discussed further in the Discussion (Section VI).

Each component is included precisely because it corrects a limitation attributable to a specific cluster of studies reviewed in Section III: GIS and remote sensing supply spatial breadth but not temporal immediacy; MCDA supplies transparency but not adaptivity; machine learning supplies predictive accuracy but not native interpretability; and IoT supplies real-time immediacy but not spatial scale. This approach does not claim to have resolved these tensions empirically — it is a conceptual synthesis derived from the gaps identified in this review, offered as a direction for future implementation and validation rather than as a completed or deployed system — but it is architected so that each component's inclusion is traceable to specific, cited evidence of a limitation in the existing literature rather than to an unsupported design preference.

VI. DISCUSSION

A. Critical Discussion

The reviewed corpus reveals a clear trend toward increasing methodological sophistication over time, from GIS overlay formalised through MCDA weighting [13] to data-driven machine learning [31] and, most recently, integrated IoT-BIM and digital-twin systems [2], [11]. This progression, however, is not cumulative in the sense of each new study incorporating the strengths of its predecessors; rather, each methodological family has continued to develop along its own trajectory, largely without cross-pollination. Terrain and land-cover variables (elevation, slope, aspect, vegetation indices) are the most frequently used inputs across nearly every study regardless of methodological family, reflecting their availability from open-access digital elevation models and satellite platforms. By contrast, socio-economic and human-behavioural variables — population density and economic activity — are used in only a handful of urban-focused studies [31] and true real-time meteorological variables (live wind speed and direction, humidity) are almost entirely absent from the GIS-MCDA cluster, appearing explicitly only in the IoT cluster and in one MCDA study's [14] nominally "dynamic" but still single-timepoint variables.

GIS contributes spatial structure and standardisation: it is the substrate on which every other technique in this review operates, since even the deep-learning detection studies (Section III-C) and IoT studies (Section III-D) ultimately require georeferencing to be operationally useful for mapping. MCDA contributes transparency and stakeholder legitimacy, since a documented pairwise-comparison matrix (Eq. (1)) can be explained to non-technical decision-makers in a way that a neural network's internal weights cannot. Artificial intelligence, in both its machine-learning and deep-learning forms, contributes predictive accuracy and the capacity to learn nonlinear relationships among a large number of variables without requiring the analyst to pre-specify their relative importance. Each of these strengths is also a mirror of the others' central weakness: an AI-based weighting is objective but lacks explainability, an MCDA-based weighting is subjective but explainable and a purely GIS-based overlay is neither objective nor adaptive. This tension is made explicit within the corpus itself when one study [7] frames machine learning as a corrective to the subjectivity of expert-weighted indicator selection, implicitly acknowledging that AI's gain in objectivity is purchased at the cost of the interpretability that motivated MCDA in the first place — a tension that the emerging SHAP-based explainability studies [1], [9] are only beginning to address.

Real-time data integration is the dimension on which the reviewed literature is weakest as a whole. Even studies whose title explicitly promises "real-time" capability generally validate that capability on prototype hardware, simulated scenarios, or single-site deployments [4], [10] rather than on a continuously operating regional network. Scalability and transferability are similarly under-examined: only [23] explicitly acknowledges that its model is geographically confined and may not generalise to other regions without retraining and no study in this corpus reports a formal

transferability test across two or more distinct study areas using the same trained model. Computational challenges are rarely discussed in depth; one study [2] is a partial exception, reporting a measured 30% reduction in detection latency, but computational cost and hardware requirements for large-area, high-resolution deployment are not systematically addressed anywhere in the corpus. Data availability constraints recur throughout: one study [31] notes that geographic variables alone cannot explain all fire types and several MCDA studies note the absence of a historical fire-occurrence database against which to validate their models [14]. Formal uncertainty analysis — confidence intervals or sensitivity analysis around risk estimates — is essentially absent from this corpus. Finally, practical implementation for operational decision support, as opposed to research demonstration, is achieved by only a minority of studies, with a building-scale IoT deployment [2], a related digital-twin emergency management system [11] and a multi-dataset MCDA validation [13] representing the closest approximations to operational readiness within the reviewed corpus.

B. Why the Identified Gaps Persist

It is worth briefly explaining why the gaps identified in Section IV have persisted despite several years of active research represented in this corpus, spanning 2020 to 2026 [31]. The GIS-MCDA tradition originated in a data environment where continuous environmental monitoring was neither affordable nor necessary for the coarse-resolution, regional-scale zonation these studies targeted; the methodology has since been applied to newer study areas [18], [19] without a corresponding re-examination of whether continuous updating is now feasible. The machine-learning tradition, by contrast, emerged from a data-availability logic — large historical fire archives and cloud-computing platforms became accessible before real-time sensor networks did — so early machine-learning studies inherited the same static-snapshot assumption from the GIS-MCDA tradition even while replacing its weighting mechanism. The IoT tradition emerged independently, driven by falling sensor and communication costs and has so far been validated primarily as a proof-of-concept at building or campus scale [2], [12], because the engineering challenge of city- or landscape-scale deployment, rather than any conceptual limitation, has constrained its scope. In short, each methodological family solved the problem that was tractable given the data and infrastructure available at the time it matured and the resulting fragmentation is a product of differing technological maturation timelines rather than a lack of awareness of the gaps themselves — indeed, several studies in this corpus explicitly name these same gaps as their own limitations [13], [23], [31]. This diagnosis suggests that the gaps are now closable in principle, since cloud computing, IoT hardware and large historical fire datasets are simultaneously available for the first time and the remaining barrier is integrative system design rather than any single missing technology.

VII. FUTURE RESEARCH DIRECTIONS

The gaps identified above point toward several concrete directions for future research. Digital twin concepts, in which a continuously updated virtual replica of a building, campus, or landscape mirrors real-world sensor and satellite data, could directly address the temporal-updating gap, extending the BIM-IoT integration already demonstrated at building scale [2], [11] to larger spatial extents. Edge AI, in which inference is performed on or near the sensor rather than in a centralised cloud, would address the computational-latency concerns implicit in prior work on fast real-time processing [10] and could allow IoT networks (Section III-D) to generate risk alerts without depending on continuous connectivity. Cloud GIS platforms, exemplified in this corpus by Google Earth Engine-based workflows [23], offer a practical route to scaling machine-learning-based risk mapping beyond the single-region studies that currently dominate the literature. Denser IoT sensor networks, moving beyond the single-building or single-forest-plot validations reviewed in Section III-D, are needed to test whether the temporal responsiveness demonstrated at small scale can be sustained across a full city or landscape.

In addition to satellite technology, drone-based data collection, as explored using volunteered geographic information [6], could supplement fixed IoT networks in areas where ground-based sensor deployment is impractical. Hybrid MCDA-AI models of the kind formalised in Eq. (3), in which machine-learning-derived feature importance informs or replaces the pairwise comparison matrices of AHP and its variants shown in Table I, represent perhaps the most direct way to combine the interpretability of MCDA with the predictive strength of AI — a direction already partially explored by studies combining fuzzy AHP with Random Forest and Boosted Regression Trees [5]. Explainable AI methods more broadly, building on the SHAP-based approaches already emerging in this corpus [1], [9] and extending beyond the entropy-based importance measures used in [31], would help machine-learning-based fire-risk models satisfy the same transparency expectations that MCDA studies already meet. Climate-change adaptation considerations, entirely absent from the reviewed corpus's validation datasets, would require fire-risk models to be tested against projected rather than only historical climate scenarios, addressing a limitation explicitly noted in [22], [23].

Big-data analytics techniques capable of fusing socio-economic, meteorological and sensor data streams at the scale demonstrated in [31] would need to be extended to real-time ingestion rather than batch historical analysis. Decision-support system design, integrating the risk outputs from any of the above techniques into an interface usable by non-specialist emergency managers, remains underdeveloped outside of the building-level deployments discussed in [2], [11] and merits dedicated attention. Finally, real-time GIS and predictive analytics, understood as the operational fusion of continuously updating spatial layers with adaptive predictive models, is the overarching direction toward which all of the preceding recommendations point and is the specific target of the approach outlined in Section V.

VIII. CONCLUSION

This review has synthesised thirty-four peer-reviewed journal studies spanning forest, urban, industrial and transportation fire contexts to assess the current state of GIS, MCDA, machine learning, deep learning and IoT approaches to fire risk and fire hazard assessment. The evidence indicates a field in active but uneven development: GIS-based spatial overlay and MCDA weighting techniques have matured into interpretable, well-validated static risk-mapping methods; machine learning and deep learning have substantially advanced predictive accuracy and visual detection capability; and IoT architectures have demonstrated the technical feasibility of continuous environmental monitoring at the building scale. What remains largely unrealised across this literature is the integration of these strands into a single operational system capable of updating fire risk continuously, transparently and at a spatial scale useful for regional emergency management.

The eleven gaps identified in this review — spanning dynamic updating, GIS-AI integration, IoT scalability, real-time weather use, uncertainty analysis, explainability, generalisation, dataset standardisation, validation rigor and decision-support readiness — are not attributable to any single research team's oversight, but reflect the differing technological maturation paths of four methodological traditions that have so far developed largely in parallel. This review's principal contribution is to make that fragmentation explicit through systematic thematic comparison, to formalise the underlying weighting and risk-aggregation logic through Eqs. (1)–(4) and to translate the resulting gaps into an approach towards a concrete, evidence-traceable conceptual framework for a dynamic GIS-MCDA-AI-IoT fire risk mapping system. This paper deliberately stops short of claiming to have developed or validated such a system: realising the proposed architecture empirically, including its implementation and validation against independent fire-occurrence and sensor data, is identified here as the logical next step for research in this area, including the authors' own ongoing work.

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