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A Comprehensive Review of Geographic Information Systems (GIS)-Based Methodologies for Urban Fire Risk Assessment

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Abstract

Urban fire risk assessment is essential for enhancing safety and planning in cities facing rapid urbanization and climate change. The complex nature of urban environments, with dense populations and diverse infrastructure, necessitates sophisticated approaches to fire risk management. Geographic Information Systems (GIS) have emerged as a vital tool, enabling the integration of various spatial data layers to create comprehensive fire risk profiles. This review explores GIS-based methodologies, including Multi-Criteria Decision-Making (MCDM) techniques, index-based approaches, spatial diffusion models, Kernel Density Estimation (KDE), and Euclidean Distance Analysis, which enhance the understanding and management of urban fire risks. MCDM methods, such as the Analytic Hierarchy Process and Fuzzy-VIKOR, help prioritize risk factors, while index-based methods offer a straightforward evaluation of fire risk levels. Spatial diffusion models provide insights into the potential spread of fires, and KDE and Euclidean Distance Analysis identify hotspots and assess proximity risks. The integration of these methodologies within GIS frameworks supports more effective resource allocation, emergency response planning, and risk mitigation. This review highlights the diversity of GIS-based approaches and their applications, providing valuable insights into their effectiveness and the challenges associated with their use in urban fire risk assessments.

Categories: Process Safety and Risk Management, Urban Planning and Development, Sustainable Technologies
Keywords: urban fire risk assessment, geographic information systems (gis), multi-criteria decision-making (mcdm), spatial diffusion models, kernel density estimation (kde)

Introduction And Background

Urban fire risk assessment is increasingly recognized as a vital component of urban safety and planning, especially as cities worldwide face the dual challenges of rapid urbanization and climate change. The complexity of urban environments, characterized by dense populations and diverse infrastructure, necessitates sophisticated approaches to fire risk management. Fires in urban areas can lead to significant loss of life, property damage, and economic disruption, underscoring the need for effective risk assessment and mitigation strategies [1,2].

This assessment is crucial for identifying potential vulnerabilities within urban settings, enabling authorities to prioritize resources and implement targeted fire prevention and response measures. As urban areas expand, the concentration of combustible materials and the complexity of infrastructure increase, elevating the risk of fire incidents [3,4]. Therefore, a comprehensive understanding of fire dynamics and contributing factors is essential.

Geographic Information Systems (GIS) have emerged as a transformative tool in fire risk management. By integrating spatial data from various sources, GIS facilitates the development of detailed fire risk maps that visually represent high-risk areas. These maps guide urban planners and emergency services in resource allocation and the development of effective fire management plans [5,6]. GIS technology enhances spatial analyses, assesses the effectiveness of existing fire safety measures, and supports evidence-based decision-making [7].

Overall, GIS provides a comprehensive framework for spatial analysis, data integration, and risk modeling, enabling urban planners and emergency services to develop targeted strategies for fire prevention and response, thereby enhancing urban safety and resilience [8,9].

In GIS-based urban fire risk assessment, methodologies can be categorized into several major types, including Multi-Criteria Decision-Making (MCDM), index-based approaches, spatial diffusion models, and Kernel Density Estimation (KDE). Each methodology employs distinct strategies for evaluating fire risk. MCDM techniques, such as the Analytic Hierarchy Process (AHP), facilitate the prioritization of various

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factors influencing fire risk through structured decision-making frameworks [10-12]. Index-based approaches utilize composite indices that aggregate multiple risk factors into a single score, allowing for straightforward comparisons across different urban areas [13]. Spatial diffusion models focus on the patterns and spread of fire incidents over time, often incorporating spatial correlations and environmental variables to predict future occurrences [14]. Lastly, KDE provides a statistical method for estimating the probability density function of fire incidents, highlighting areas of high risk based on historical data [15,16]. These methodologies differ fundamentally in their analytical frameworks and the types of data they prioritize, influencing the outcomes and applicability of urban fire risk assessments.

The objective of this study is to provide a comprehensive review of the various GIS-based methodologies employed in urban fire risk assessment. By examining approaches such as MCDM techniques, index-based methods, spatial diffusion models, KDE, and Euclidean Distance Analysis, this study aims to evaluate their effectiveness, applications, and limitations in different urban contexts. The study seeks to highlight the strengths and challenges of these methodologies, providing insights to enhance decision-making, resource allocation, and fire risk management strategies for urban planners and emergency services.

Review

GIS technology is a powerful tool that integrates spatial data management and analysis, enabling the visualization and interpretation of geographic information [17,18]. In the context of urban fire risk assessment, GIS functions as a critical resource for identifying fire-prone areas, optimizing emergency response strategies, and enhancing urban planning efforts [18,19]. The application of GIS in urban fire risk assessment involves the integration of various data layers, including demographic information, land use patterns, infrastructure locations, and historical fire incident data, to create comprehensive risk profiles for urban areas [17,19,20]. One of the primary functions of GIS in urban fire risk assessment is its ability to analyze spatial relationships and patterns. For instance, studies have demonstrated that GIS-based methods can effectively quantify fire risks by comparing different urban settlements and identifying vulnerable zones [3,21]. By employing MCDM techniques, such as the AHP, researchers can prioritize risk factors and assign weights to various parameters, facilitating a more nuanced understanding of fire vulnerabilities [7,22]. This approach allows urban planners and emergency responders to pinpoint high-risk areas and allocate resources more effectively. Moreover, GIS enables the visualization of fire risk data through geo-visualization techniques, which can enhance communication among stakeholders involved in fire risk management [18,23]. For example, mapping fire incidents and evaluating the service areas of fire stations can help local governments optimize their fire response strategies [18,24,25]. By analyzing accessibility to fire hydrants and other critical infrastructure, GIS can inform decisions on where to establish new fire stations or improve existing facilities to minimize response times [24,25]. Additionally, GIS technology supports the development of community fire risk monitoring systems, which can provide real-time data and alerts to residents and emergency services [26]. This proactive approach to fire risk management is essential in urban environments where rapid population growth and infrastructure development can exacerbate fire hazards [26]. By integrating GIS with remote sensing data, urban planners can better understand the dynamics of urban fire risks and implement effective mitigation strategies [26].

Spatial analysis utilized in GIS for assessing fire risk in urban areas

GIS enables the integration and analysis of various spatial and non-spatial data to identify fire-prone zones, optimize emergency response, and inform urban planning. The utilization of spatial analysis in GIS for fire risk assessment involves several methodologies and techniques that enhance the understanding of fire dynamics and vulnerabilities in urban settings [3,7]. One of the primary methods employed in spatial analysis for fire risk assessment is KDE, which allows for the visualization of fire incident distributions and the identification of hotspots [26]. For instance, studies have shown that KDE can effectively illustrate areas with high concentrations of fire incidents, thereby pinpointing regions that require targeted fire prevention strategies [17,26]. This technique is particularly useful in urban environments where the spatial distribution of fires can be influenced by various factors, including population density, building types, and proximity to fire services [17,26]. Moreover, GIS facilitates the integration of multi-criteria decision analysis (MCDA) methods, such as the AHP, to evaluate and prioritize fire risk factors. This approach enables the assessment of multiple variables, including environmental conditions, infrastructure, and socio-economic factors, to create comprehensive fire risk maps [21,27]. By combining these diverse data sources, urban planners can identify high-risk areas and allocate resources more effectively, thereby enhancing fire management strategies. Another significant aspect of spatial analysis in GIS is the ability to model the spatial relationships between different fire risk factors. For example, the Geographically Weighted Regression (GWR) model has been utilized to capture the nonlinear relationships among various factors contributing to fire occurrences, providing a more nuanced understanding of fire risk distribution in urban areas [10,28]. This modeling capability allows for the identification of specific vulnerabilities within neighborhoods, which can inform tailored fire prevention measures [10,28]. Additionally, GIS-based spatial analysis can assess the accessibility of fire services, which is crucial for effective emergency response. By analyzing the spatial distribution of fire stations and their service areas, researchers can evaluate response times and identify gaps in coverage [25]. This information is vital for optimizing the placement of fire stations and ensuring that emergency services can respond promptly to incidents, ultimately reducing the impact of fires in urban settings [25,29]. Furthermore, the integration of remote sensing data with GIS enhances the ability to monitor and assess fire risks dynamically. For instance, the use of unmanned aerial vehicles to gather spatial data allows for real-time analysis of fire hazards, enabling timely interventions and resource allocation [30]. This capability is particularly important in rapidly changing urban environments where fire risks can fluctuate due to various factors, including weather conditions and urban development [31].

Data integration plays in GIS-based fire risk modeling

Data integration plays a crucial role in GIS-based fire risk modeling by enabling the amalgamation of diverse datasets to create comprehensive risk assessments. This integration allows for the incorporation of various factors influencing fire risk, including socio-economic variables, environmental conditions, and infrastructure data, which are essential for accurate modeling and analysis [7,8,29]. For instance, GIS facilitates the integration of spatial data from multiple sources, such as remote sensing, demographic information, and historical fire incident records, to identify patterns and correlations that inform fire risk assessments [7,31,32]. By employing techniques like MCDA, researchers can evaluate and prioritize these integrated datasets to generate detailed fire risk maps, which highlight areas susceptible to fire hazards [1,33]. Moreover, the use of data visualization techniques within GIS enhances the understanding of spatial relationships among various fire risk factors. For example, studies have shown that integrating geographic information with socio-economic indicators can reveal critical insights into the dynamics of fire incidents in urban environments [31,34,35]. This approach not only aids in identifying high-risk zones but also supports the development of targeted fire prevention strategies and resource allocation plans. Additionally, data integration allows the simulation of different fire risk scenarios, enabling urban planners and emergency responders to evaluate potential outcomes and optimize response strategies [36,37]. By analyzing the spatial distribution of fire incidents alongside accessibility to fire services, decision-makers can enhance their planning and operational effectiveness in mitigating fire risks [37].

Risk modeling and prediction of fire incidents

GIS technology significantly enhances risk modeling and prediction of fire incidents by integrating diverse data sources, facilitating spatial analysis, and enabling predictive modeling techniques. This integration allows for a comprehensive understanding of fire dynamics in urban environments [8,10,29]. One of the primary benefits of GIS is its ability to combine various datasets, including historical fire incident records, demographic information, land use patterns, and environmental factors [38,39]. For example, studies have shown that integrating socio-economic data with fire incident histories can reveal critical patterns that inform fire risk assessments [39]. This multifaceted approach enables urban planners and emergency responders to identify vulnerable areas and allocate resources more effectively [38,40,41]. Moreover, GIS facilitates advanced spatial analysis techniques, such as KDE and GWR, which help visualize and analyze the spatial distribution of fire incidents. These techniques allow for the identification of fire hotspots and the assessment of factors contributing to fire risks, thereby enhancing the accuracy of risk predictions [10]. Additionally, GIS supports the implementation of predictive modeling techniques, such as machine learning algorithms, which can analyze historical data to forecast future fire incidents. The integration of GIS with artificial intelligence techniques has been shown to improve the accuracy of fire risk prediction models by analyzing various environmental and socio-economic factors. This predictive capability is crucial for proactive fire management strategies, enabling timely interventions and resource allocation [42-44]. Furthermore, GIS technology aids in simulating different fire scenarios, allowing for the evaluation of potential outcomes based on varying conditions. This capability is essential for emergency planning and response, as it helps identify optimal locations for fire stations and hydrants, ensuring rapid response times during fire incidents [18,29,32,45].

Advantages of using GIS technology in fire risk management

GIS technology offers several key benefits in fire risk management, significantly enhancing the effectiveness of prevention, response, and recovery efforts. Firstly, GIS facilitates the integration of diverse datasets, including topographical, meteorological, and socio-economic information, which are essential for comprehensive fire risk assessments. This integration allows for the identification of high-risk areas by analyzing factors such as vegetation types, proximity to human settlements, and historical fire incidents [46,47]. For instance, the ability to overlay different data layers enables fire managers to visualize and understand the spatial relationships that contribute to fire risks, leading to more informed decision-making [23,48]. Secondly, GIS enhances predictive modeling capabilities. By employing advanced analytical techniques, such as machine learning and simulation models, GIS can forecast potential fire behavior under various scenarios. This predictive power is crucial for planning effective mitigation strategies and resource allocation [49,50]. For example, simulations can evaluate the impact of fuel treatments on fire behavior, helping to prioritize areas for intervention [50,51]. Additionally, GIS supports real-time monitoring and response coordination during fire incidents. By providing up-to-date spatial information, GIS enables emergency responders to assess the situation quickly and optimize their response strategies, such as determining the best routes for fire trucks and identifying safe evacuation paths for residents [45,52]. This capability is particularly vital in urban-wildland interface areas where rapid decision-making can save lives and property [53]. Moreover, GIS technology aids in post-fire recovery planning by analyzing the extent of damage and guiding rehabilitation efforts. By mapping affected areas and assessing ecological impacts, GIS can inform restoration strategies and help allocate resources effectively for recovery [53-56].

Categories of methodologies

Multi-Criteria Decision-Making (MCDM) Approaches

MCDM approaches play a vital role in GIS-based urban fire risk assessment by enabling the evaluation and prioritization of various factors influencing fire risk, such as socioeconomic conditions, infrastructure quality, and environmental elements. These methods integrate both qualitative and quantitative criteria, allowing for the systematic analysis of complex scenarios with potentially conflicting objectives [1,10]. Techniques like the AHP are used to assign weights to criteria, facilitating a structured decision-making process that reflects the relative importance of each factor (Figure *1*) [57,58]. Combining GIS with MCDM supports a comprehensive assessment of land suitability and risk, leading to more effective urban fire management strategies. This integration is increasingly crucial in optimizing resource allocation and enhancing public safety as urban environments grow more complex [59-61].

However, MCDM approaches have limitations, particularly concerning the subjectivity in criteria weighting, which can result in biased outcomes if not properly managed. The use of expert judgment to assign weights can introduce variability and inconsistency, potentially compromising the assessment's robustness [62,63]. Furthermore, the complexity of handling multiple criteria may overwhelm decision-makers, especially in high-stakes situations requiring timely decisions [64].

FIGURE 1: GIS-Based Urban Fire Risk Assessment Using MCDM

GIS, Geographic Information Systems; MCDM, Multi-Criteria Decision-Making

Analytic Hierarchy Process (AHP): The AHP is a popular MCDM technique that organizes complex decision problems into a hierarchical structure, enabling systematic analysis of different criteria and alternatives by breaking down the problem into smaller, manageable components [65,66]. In scenarios like urban fire risk assessment, the AHP follows several structured steps. Initially, decision-makers define the problem, set the goal, and identify relevant criteria and sub-criteria. These criteria are arranged hierarchically to facilitate evaluation by dividing the problem into simpler parts [65-67]. Pairwise comparisons are then conducted using a scale of 1 to 9 to determine the relative importance of each criterion [68]. This process quantifies subjective judgments, allowing a systematic evaluation of the significance of each criterion concerning the overall goal [68,69]. The AHP algorithm subsequently calculates weights for each criterion based on these comparisons, reflecting their relative importance in influencing fire risk and guiding resource allocation (Figure *2*). This method ultimately improves clarity and consistency in decision-making for fire risk management [68,70].

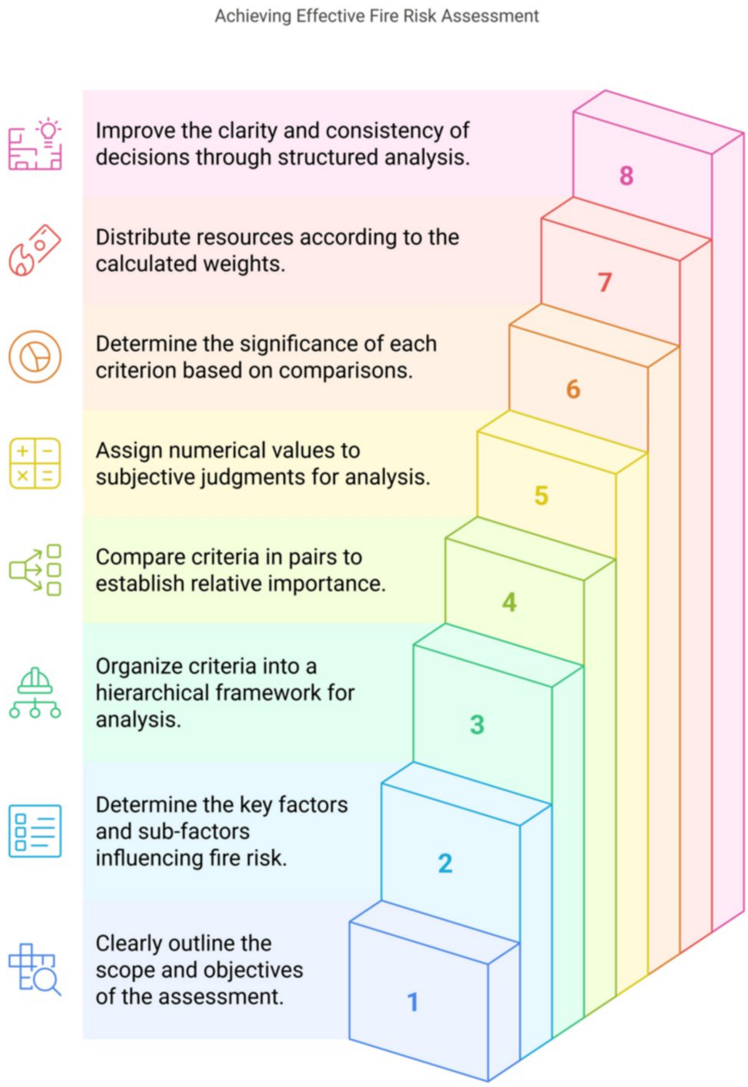

FIGURE 2: AHP Process Flow for Urban Fire Risk Assessment

AHP, Analytic Hierarchy Process

Fuzzy-VIKOR: The VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method is an MCDM technique aimed at finding the best compromise solution among conflicting criteria by maximizing group utility and minimizing individual regret, making it suitable for scenarios involving trade-offs among alternatives [71,72]. Key steps in the method include defining the decision matrix, normalizing the data, identifying the ideal and anti-ideal solutions, and calculating the VIKOR index for each alternative, which ranks them based on their proximity to the ideal solution to support informed decision-making (Figure 3) [73,74].

Fuzzy-VIKOR builds on this by incorporating fuzzy logic to handle imprecise data, enabling decision-makers to express preferences flexibly through linguistic terms and fuzzy sets [75,76]. This integration addresses uncertainties in qualitative assessments, leading to a more accurate evaluation of alternatives [77]. Fuzzy-VIKOR enhances the standard VIKOR framework by allowing a more robust analysis in situations where data may be incomplete or ambiguous [78]. In urban fire risk assessments, this method effectively models fire risks by prioritizing control measures in uncertain environments, thereby supporting better decision-making [10].

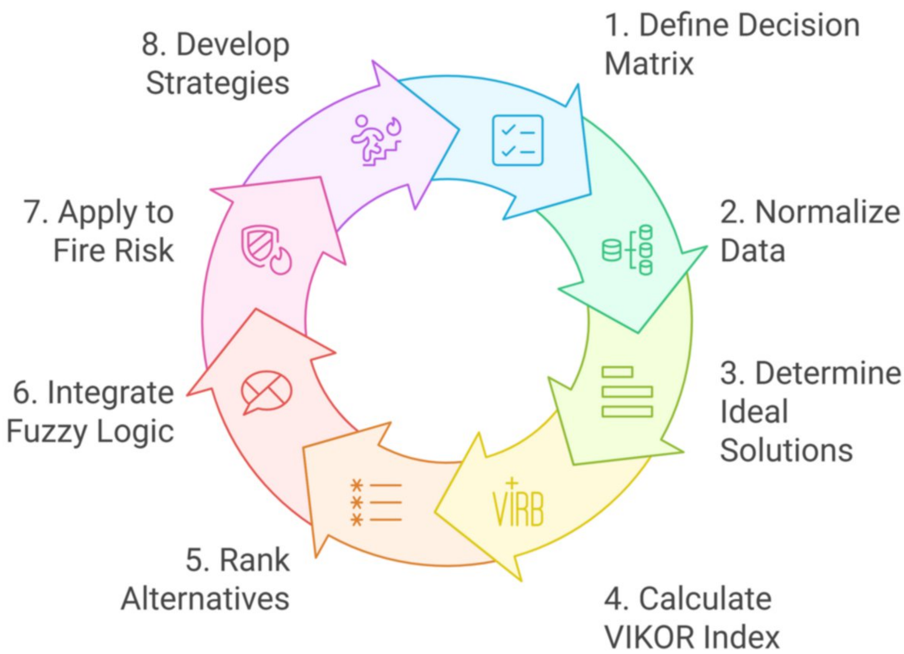

FIGURE 3: Fuzzy-VIKOR Process Flow for Urban Fire Risk Assessment

Index-Based Approaches

Index-based methodologies in GIS-based urban fire risk assessment use predefined criteria and scoring systems to create comprehensive risk indices like the Fire Risk Index (FRI) [8,79]. The FRI is developed by evaluating multiple factors, such as building materials, fire load, proximity to fire services, and population density (8,26,36,79]. This index combines various attributes into a single score, enabling rapid fire safety assessment [8,79]. The methodology involves systematically scoring each risk factor, where higher scores indicate greater risk; for example, buildings made of flammable materials or far from fire services receive higher risk scores (Figure *4*) [8,26,36,79]. Integrating GIS technology enhances the spatial analysis of these factors, helping urban planners and fire safety officials identify high-risk areas and prioritize interventions [8,26,36]. This approach not only aids in risk assessment but also supports strategic planning for fire prevention and response [8,79].

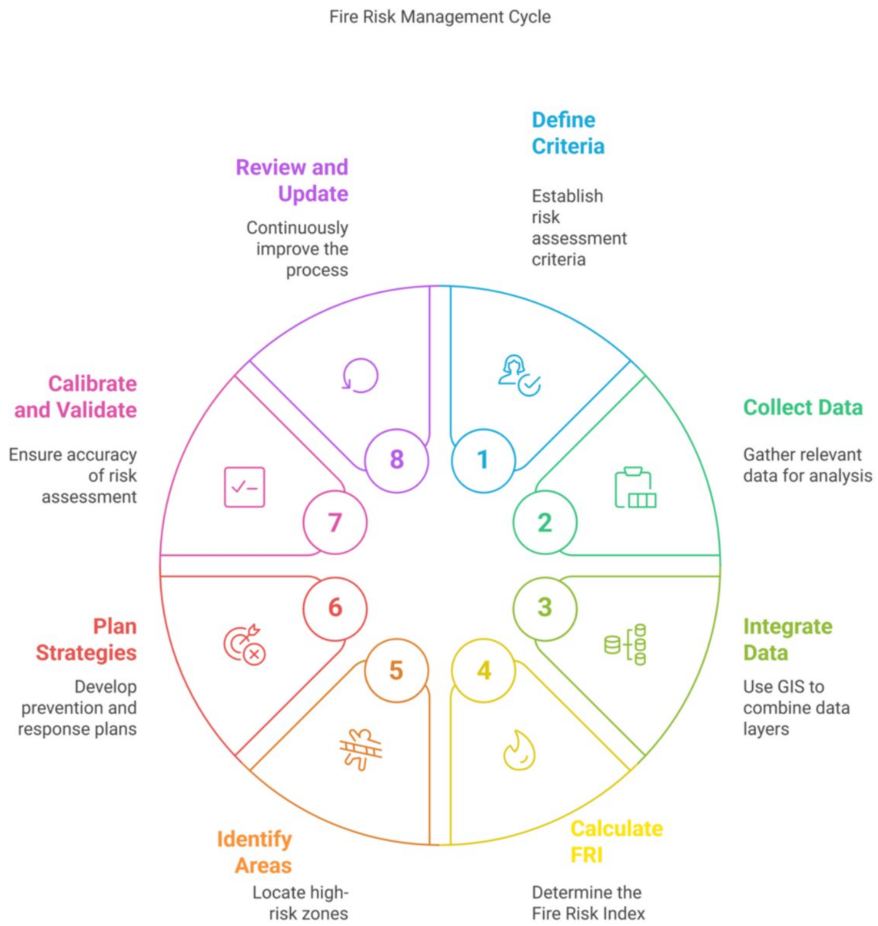

FIGURE 4: Index-Based Methodology Flow for Urban Fire Risk Assessment

GIS, Geographic Information Systems; FRI, Fire Risk Index

However, index-based approaches face challenges related to data sensitivity and interpretation [80]. The accuracy and availability of data are critical, as discrepancies in data quality can result in invalid risk assessments [80]. Reliable input data are essential for effective fire risk modeling, as highlighted in studies emphasizing this need [80,81]. Variations in meteorological data or vegetation characteristics, for instance, can skew results, affecting fire management decisions [80,81]. Additionally, interpreting results can be difficult when different data sources or criteria are used, as inconsistent methodologies across studies may lead to varied conclusions about fire risk, complicating efforts to establish a unified understanding of fire vulnerability [80]. Therefore, integrating diverse datasets requires careful calibration and validation to ensure that the derived indices accurately represent the underlying fire risk dynamics [80].

Spatial Diffusion Models

Spatial diffusion models are crucial in GIS-based fire risk assessments, allowing for the simulation of fire spread and the distribution of risks across urban areas (Figure *5*). These models predict fire behavior and assess vulnerability by incorporating geographic, environmental, and infrastructural factors. For example, the Fire Area Simulator (FARSITE) combines surface fire spread models with crown fire transition models using Huygens' Principle to simulate fire perimeter growth [81]. GIS enhances this modeling by integrating spatial data layers representing fire risk factors like vegetation, topography, and climate [81,82]. The use of stochastic models and cellular automata further refines simulations, capturing complex interactions between fire dynamics and environmental variables [83,84]. Analyzing factors like fuel moisture and wind direction provides a comprehensive view of fire risk, aiding in decision-making for fire management [85,86].

These models are particularly effective in visualizing potential fire spread within urban environments by considering factors such as topography, vegetation, and urban development, thereby enabling a detailed understanding of how fire risks propagate [87,88]. Incorporating spatially explicit data helps identify high-risk zones, essential for strategic planning in fire prevention and response [89,90]. Leveraging historical fire incident data allows for the analysis of spatial and temporal patterns, improving the accuracy of risk assessments [89,90]. Geovisualization techniques also facilitate effective communication of fire risk information, supporting resource allocation and emergency response strategies [91-93]. Ultimately, applying these models in GIS helps identify vulnerable areas and develop targeted fire management policies [91,93].

However, spatial diffusion models face significant limitations, particularly in terms of computational challenges [94,95]. Modeling multiple variables, such as wind speed, humidity, and urban infrastructure, can greatly increase computational requirements [10,96]. The need for high-quality data is critical, but inconsistencies in data availability can lead to inaccuracies [2,97]. Additionally, these models often require substantial computational resources, which may limit their use in real-time applications or resource-constrained environments [95,98]. To remain computationally feasible, models may oversimplify real-world scenarios by reducing variables or assumptions [94]. Thus, while spatial diffusion models provide valuable insights, their limitations must be considered in practical applications [94].

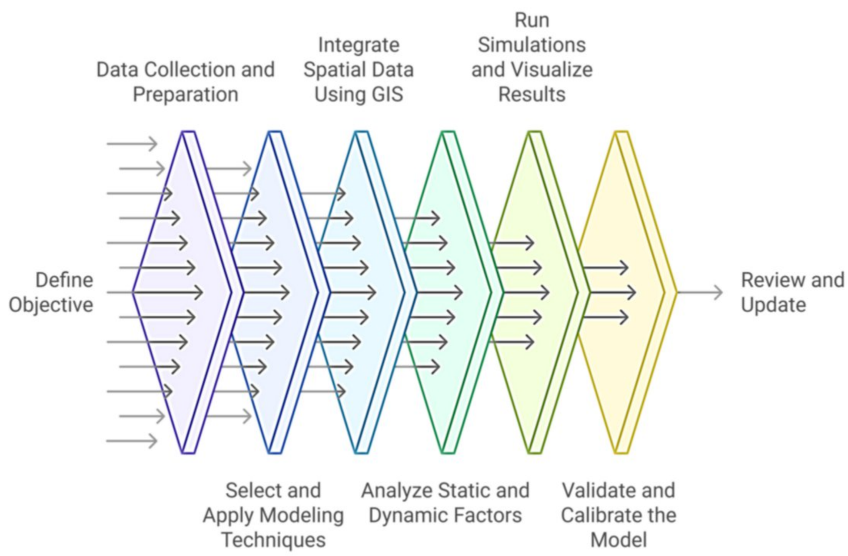

FIGURE 5: Spatial Diffusion Models in GIS-Based Fire Risk Assessment

GIS, Geographic Information Systems

Kernel Density Estimation (KDE) and Euclidean Distance Analysis

KDE is a non-parametric statistical method used to estimate the probability density function of a random variable, which is crucial for fire risk mapping by visualizing hotspots of fire incidents in geographic areas (Figure *6*) [16,26]. This technique analyzes spatial patterns of fire occurrences, allowing researchers and policymakers to identify areas with a higher likelihood of fire incidents based on historical data [16,26]. To create a density surface, KDE is applied to fire incident data, where each incident contributes to the overall density estimate according to a specified kernel function and bandwidth [99,100]. The resulting surface highlights regions with elevated fire risk, aiding targeted risk management and resource allocation [16,26]. KDE enables stakeholders to prioritize areas for intervention, thereby improving fire prevention strategies [16,26].

Euclidean Distance Analysis is a GIS technique that measures straight-line distances between points, such as fire incidents and critical infrastructure [3]. It is particularly valuable for assessing fire risk by evaluating the proximity of fire occurrences to vulnerable locations, like residential areas or essential services [3,26]. By quantifying these distances, analysts can identify infrastructure at greater risk from nearby fires, supporting risk mitigation efforts [3,26]. Euclidean Distance Analysis complements other GIS methods, such as KDE, by providing insights into spatial relationships and potential risk exposure [16,26]. While KDE identifies fire incident hotspots, Euclidean Distance Analysis assesses how close these hotspots are to critical assets, enhancing overall fire risk understanding and resource allocation [10,16,26].

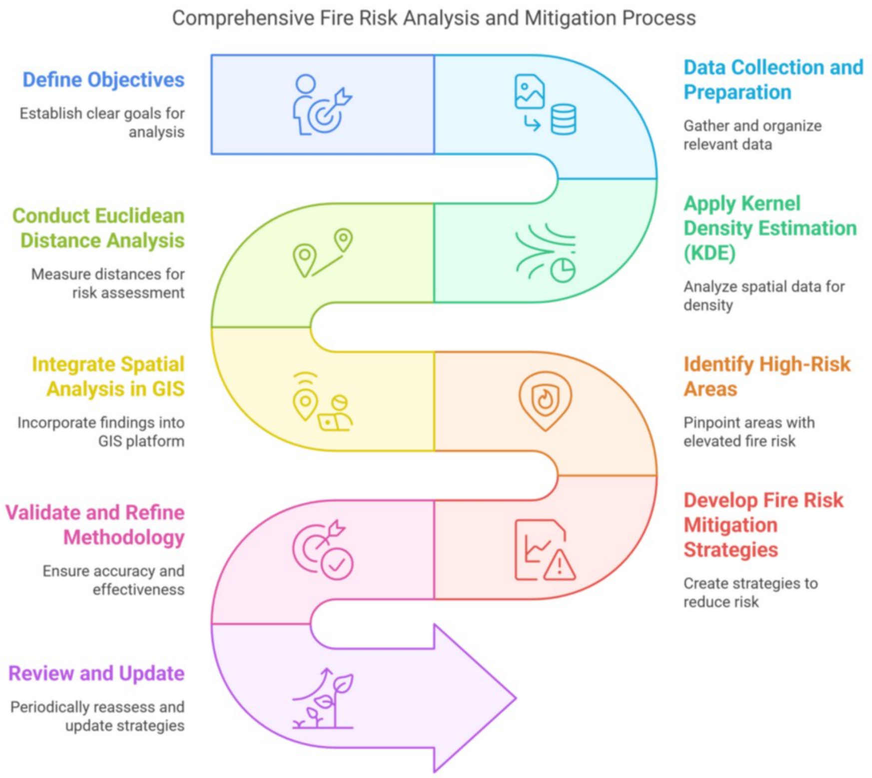

FIGURE 6: Methodological Workflow of KDE and Euclidean Distance Analysis in Urban Fire Risk Assessment

GIS, Geographic Information Systems

Both KDE and Euclidean Distance Analysis face challenges in urban fire risk assessment, primarily due to data quality and computational demands [15,101]. The accuracy of KDE depends on the granularity and quality of input data; poor data can result in misleading density estimates, which are crucial for identifying fire risk hotspots [15]. The choice of kernel function and bandwidth can also significantly affect results, requiring careful selection to avoid bias [15]. Both methods face scalability issues in complex urban environments with large datasets, where increased data dimensionality and volume make real-time analysis challenging [101,102]. For example, traditional KDE methods may become inefficient for extensive urban datasets, necessitating more efficient algorithms to handle large-scale computations without sacrificing accuracy [101,102].

Summary of studies on GIS-based urban fire risk assessment

In recent years, GIS have become integral to urban fire risk assessment, enabling more precise identification, analysis, and management of fire hazards in diverse urban environments. Various methodologies, including MCDM approaches, index-based methods, spatial diffusion models, and spatial analysis techniques like KDE and Euclidean Distance Analysis, have been employed to enhance the accuracy and effectiveness of fire risk assessments. Table *1* provides a comparative overview of key studies that have utilized these GIS-based methodologies to address urban fire risk, highlighting their objectives, methodologies, data sources, evaluation techniques, and key findings. This summary aims to illustrate the diversity of approaches and their applications in different urban contexts, offering valuable insights into the effectiveness and challenges of GIS-based fire risk assessment.

Author (Year)	City and Country	Research Objective	Methodology	Software Used	Data Source	Evaluation	Key Findings
MCDM Approaches							

Noori et al. (2023) [103]	Ardabil, Iran	The study aims to identify urban areas at risk of fire using 19 evaluation factors across economic, social, built environment-infrastructure, and prior fire rates dimensions. The objective is to model and map the urban vulnerability index against potential structural fire-related risks in Ardabil city.	The study employs a MCDM approach, including the AHP for determining the criteria's importance and the Fuzzy-VIKOR approach within a GIS to create an urban vulnerability index map. The study involves spatial analysis and integrates various socioeconomic and built environment factors to assess urban vulnerability.	QGIS, ArcGIS Desktop 10.8, ArcGIS Pro 3.0.2, Expert Choice-11, GeoDa v. 1.20.0.10, and TerrSet	Socio-economic data from the Statistics Centre of Iran, spatial data from Ardabil Municipality, and fire incidents data from the Ardabil City Fire Department. The study analyzed data from 2015-2020 and included about 250,000 building units within Ardabil city.	The study validated the GIS-MCDM model by comparing the urban vulnerability index values with the spatial distribution of actual fire incidents using Spatial Linear Regression (SLR). The model's accuracy was confirmed by a high correlation coefficient (r^2 = 100%) between the predicted and actual fire incidents.	Approximately 31% of Ardabil city, involving roughly 179,000 people, is at high or very high risk of fire. High-risk areas include the city center and neighborhoods with low socio-economic and environmental conditions. The findings highlight the importance of socioeconomic factors and built environment variables, such as building quality and age, in determining urban fire risk. The study provides valuable insights for decision-makers to implement effective fire risk mitigation strategies.
Dong et al. (2018) [104]	Lanshan District, Linyi City, Shandong Province, China	The research focuses on addressing deficiencies in the fire protection planning in Lanshan District and the new problems brought by the rapid development of the city. The study aims to identify and evaluate the fire risk of city buildings in Lanshan District and use GIS technology to solve the problem of site selection for new fire stations and the layout of existing fire stations.	The study used AHP and fuzzy comprehensive evaluation methods to classify fire safety grades, identify high fire risk demand points, and preliminarily determine fire station candidates. The optimization process involved reverse checking and simplifying the candidate sets based on emergency response time and shortest path constraints.	ArcGIS 9.3 platform	The data for the study were obtained from the fire brigade of Lanshan district, including map images, description data, and the locations of existing fire stations.	The evaluation included the creation of a network topology map of the fire passage in Lanshan district, the generation of 67 candidate fire stations using GIS, and the optimization of these candidates based on constraints such as shortest average distance and maximum coverage of high fire risk demand points.	The research suggested adding four new fire stations close to high fire risk places and main roads. The optimized layout provided a balanced distribution of fire stations, ensuring rapid response to high fire risk areas and saving construction costs.
Srivanit (2011) [105]	Chiang Mai Municipality, Chiang Mai Province, Thailand	To develop a GIS-based approach for fire risk assessment to identify sites for disaster mitigation planning and management within Chiang Mai	Selection of risk factors based on stakeholder analysis involving four groups: urban planners, fire wardens, local residents, and local government officials. Integration of data into raster-based GIS software. Spatial analysis using an overlay technique to generate fire risk maps. Use	Raster-based GIS software.	Data gathered from stakeholder analysis involving urban planners, fire wardens, local residents, and local	Generation of a fire risk map showing varying levels of fire risk across Chiang Mai Municipality. The use of GIS technology and AHP provided a systematic approach to	The study produced a map indicating varying levels of fire risk across Chiang Mai Municipality. GIS-based fire risk assessment is effective for disaster management and can help in minimizing fire hazards by identifying high-risk areas. The model integrates both

		Municipality.	of AHP to determine the weight of each factor.		government officials.	assess and map fire risk areas.	vulnerability and mitigation capacity, offering a comprehensive view of fire risk.
Index-Based Approaches							
Urbina et al. (2023) [3]	Guimarães, Portugal	To develop correlation maps that define the vulnerability to fire risk of critical infrastructure and its zone of influence within the historic city center of Guimarães, Portugal.	The study employs an index-based approach for vulnerability assessment using GIS mapping techniques. It integrates multiple levels of assessment to identify vulnerable elements and optimize decision-making processes before and after extreme events.	QGIS (Geographic Information System software).	Data from the municipality's online services, open-source project from Lisbon's university, previous studies, Fire Risk Index (FRI) obtained through the simplified Arica methodology, QuickOSM plugin for querying specific information, and Quick Map services from Bing.	The study evaluates essential components crucial to the normal functioning of the city, such as critical infrastructure, population needs, economic aspects, and city governance. It uses a vulnerability assessment framework integrating spatial, sociodemographic, and crisis management vulnerability.	The historic city center of Guimarães has significant fire risk due to its medieval infrastructure. Zones 2 and 3 exhibit high vulnerability due to the concentration of critical infrastructure. Emergency plans should prioritize these high-risk zones to enhance resilience and ensure safety.
Granda and Ferreira (2019) [106]	Guimarães, Portugal	The study aims to assess the fire risk in the Historical Centre of Guimarães, a UNESCO World Heritage Site, using an index-based fire risk assessment method to identify the most vulnerable buildings and provide data for risk mitigation strategies.	Application of the FRI method: evaluates fire risk based on factors such as fire ignition, propagation, evacuation, and combat. The method integrates various sub-factors and partial factors to determine the overall fire risk index of buildings.	QGIS (an open-source Geographic Information System software) and Visual Basic for data layering and editing within a spreadsheet environment.	The study involved in situ inspections of 436 buildings in the Historical Centre of Guimarães, complemented by personal interviews and historical data from municipal records.	Buildings were assessed based on their conservation state, electrical and gas installations, fire load, evacuation routes, and fire combat capabilities. Data were organized into a comprehensive database connected to the GIS tool for spatial analysis.	67% of the assessed buildings have a moderate to high fire risk. Major risk factors include non-refurbished electrical installations, insufficient fire detection systems, and constrained evacuation routes. Historical buildings often lack proper fire compartmentalization and have significant fire loads.
Ferreira et al. (2016) [107]	Seixal, Portugal	To develop and apply a new urban fire risk assessment methodology to the old city center of Seixal, integrating risk results into a GIS platform for enhanced emergency planning and risk mitigation.	The research involves field inspections and data collection for over 500 buildings using the ARICA method, adapted for urban scale fire risk assessment. The methodology includes calculating the FRI based on the Global Risk Factor (FGR) and Global Efficiency Factor (FGE). Buildings are categorized based on their conservation state, electrical and gas installations, fire load, and other safety factors.	ArcGIS® 10.2	Field inspections and data collection from over 500 buildings in the old city center of Seixal. The data includes building features, fire safety measures, and infrastructure details.	The evaluation involves mapping the normalized FRI values using GIS, identifying buildings with varying levels of fire risk. The results are validated by comparing with the original ARICA method for a sample of buildings, showing non-expressive deviations.	The majority of buildings have moderate ignition risk and low propagation risk, but commercial and service buildings show higher risk levels. Fire risk index values help identify critical buildings requiring intervention. The GIS-based approach enhances the visualization and management of fire risk, supporting emergency planning.

Spatial Diffusion Models							
Ji et al. (2010) [108]	Xuzhou, China	The study aims to evaluate urban fire risk in Xuzhou City using a GIS-based spatial diffusion model to improve the distribution of firefighting resources and enhance the operability and feasibility of fire risk assessments.	The methodology involves using a spatial diffusion model based on geographic grid combined with GIS technology. The city is gridded, and diffusion analysis of single fire factors and overlay analysis of multiple fire factors are conducted. The evaluation considers geographic features, land use classification, meteorological factors, and the type, nature, and distribution of fire risk sources.	ArcGIS 9.2	Geographic information, land use data, population density, building density, key fire protection units, and fire stations' protection capabilities. "Manual for Fire Special Plan of Xuzhou City (2005-2020)"	Gridding the city into 250 m × 250 m units, calculating the diffusion of influential factors, and conducting overlay analysis to determine the fire risk index of each grid. The evaluation considers the rationality of urban layout, population density, building density, major risk sources, electrical and gas safety, traffic situation, and the rescue ability and distribution of fire stations.	The overall fire risk in Xuzhou City is at a medium level, with higher risk in the old urban area and shantytowns compared to the new urban area. The intersection of old and new urban areas and poorly laid firefighting resources are identified as key areas for optimization. The spatial diffusion model based on geographic grid is shown to improve traditional fire risk assessment methods by making abstract problems more visual and concrete.
KDE and Euclidean Distance Analysis							
Gai et al. (2008) [109]	Kunshan City, China	To develop an urban fire risk assessment model in order to identify, classify, and map fire hazard areas in Yushan Town, Kunshan City. The aim is to help fire department officials prevent and minimize urban fire activities and plan city fire protection construction.	The study employs a spatially weighted index model utilizing GIS technology. This involves considering multiple influence factors such as building density, building fire resistance rating, population density, land use, distance from hazardous buildings, water sources, and fire stations. The GIS spatial analytical procedure is used to combine these factors to derive the fire risk ranging from high to low.	ArcGIS software, specifically the Spatial Analyst extension	The study area is Yushan Town, Kunshan City. Data are collected on building density, building fire resistance rating, population density, land use, distance from hazardous buildings, water sources, and fire stations.	The evaluation involves the use of KDE methods and Euclidean distance analysis in ArcGIS to create a fire risk map. The final fire risk map is validated by comparing it with actual fire occurrence data.	The study finds that high-risk zones mainly distribute in the center of the city, which aligns with actual observations. Areas near fire stations are identified as safer. The model suggests that risk mapping is helpful for urban fire management and can be used to minimize urban fire hazards.
Other GIS-Based Methods							
Tomar et al. (2018) [110]	Delhi, India	The study aims to analyze the spatial pattern of fire incidents in the South-West Division of Delhi Fire Service using geospatial technologies to assess fire risk and create fire hazard zonation maps for effective	Study Area: South-West Division of Delhi Fire Service, covering specific sub-divisions and fire stations. Data Collection: Data were collected from multiple sources, including municipal ward boundaries, population data, location of fire stations, jurisdiction boundaries, number and types of fire incidents, and land use-land cover maps. Analysis: The data was analyzed using GIS to prepare thematic maps depicting fire incidents, population density, and fire	GIS	Geo-spatial Delhi Limited (GSDL), Delhi Fire Service, Delhi Jal Board, and population data from the Census of India 2011.	Fire risk categories were assigned based on a scoring system that considered the likelihood, consequences, and severity of fire incidents. The thematic maps were used to identify high, moderate, and low	The study found that 70.01% of the study area falls under low fire risk potential zone, 26.39% falls under moderate fire risk potential zone, and 3.59% falls under high fire risk potential zone. It was observed that fire incidents and risks differ significantly across various fire stations within the division,

		fire management.	risk zones. The risk levels were categorized based on the number of fire incidents, deaths, injuries, and severity levels.			fire risk zones in the study area.	with residential areas involving low-rise buildings being the most affected.
Yagoub and Jalil (2014) [111]	Sharjah, United Arab Emirates	To understand the spatial and temporal distribution of fire incidents in Sharjah and propose suitable locations for new fire stations using GIS technology.	Data Collection: Fire incidents data were gathered from six local newspapers for the period 2002-2012. Data Processing: Digitization of transport layers from high-resolution satellite images (IKONOS 2010), and fire stations, hospitals, and police stations from Google Earth, Wikimapia, and Sharjah Explorer. GIS Analysis: Geo-coding fire incidents, network analysis to measure emergency response times, and weighted overlay analysis to propose new fire station locations.	ArcGIS	Local newspapers (Gulf News, Al Khaleej, Al Emarat Elyoum, Al Bayan, Al Ittihad, and Al Khaleej Times) Google Earth, Wikimapia, Sharjah Explorer Sharjah Water and Electricity Authority Sharjah Directorate of Town Planning and Survey.	Analysis of spatial and temporal patterns of fire incidents. Measurement of coverage areas and driving times for existing fire stations. Identification of suitable new fire station locations using multi-criteria analysis and network analysis tools.	Majority (60%) of fire incidents occurred in warehouses and structures. In all, 25% of incidents were in industrial and commercial areas, 10% were vehicle fires, and 5% were in scrap yards and landfills. High incidence of fires during the summer months due to increased use of air conditioning and melting of electric wires. Existing fire stations in Sharjah are inadequate to cover the urban expansion, with large portions of the city beyond the eight-minute response time. Six new fire stations were proposed to improve coverage, increasing the area covered within an 8-minute response time from 36% to 75%.
Thakare and Tajne (2024) [112]	Nagpur, India	To analyze the relationship between urban structures, fire risk hotspots, and green spaces in Nagpur city, and assess how urban greenery contributes to fire hazard mitigation.	GIS and satellite remote sensing analysis of five zones in Nagpur; fire incident hotspot identification; mapping of green spaces; correlation analysis using Pearson's coefficient between urban property types and greenery percentages.	ArcGIS	Fire incident data (2011–2020) from Nagpur Municipal Corporation (NMC) Fire Service Department, High-resolution satellite imagery & Ground-level urban structure and greenery surveys.	Calculation of Pearson's correlation coefficient to measure the relationship between urban property types and green space distribution; hotspot mapping of fire-prone areas using GIS overlays.	Positive correlation ($r \approx 0.771$) between urban property development and green space presence. Zones with higher greenery percentages showed fewer fire incidents. Green spaces function as natural firebreaks, enhancing urban fire resilience. The study advocates integrating green spaces into urban planning to mitigate fire risk and improve sustainable urban development.

TABLE 1: Key Studies and Methodologies in GIS-Based Urban Fire Risk Assessment

MCDM, Multi-Criteria Decision-Making; AHP, Analytic Hierarchy Process; GIS, Geographic Information Systems; KDE, Kernel Density Estimation

Critical evaluation of GIS-based methodologies

MCDM Approaches

MCDM techniques, particularly AHP and Fuzzy-VIKOR, have been widely used in GIS-based fire risk assessments due to their ability to integrate diverse spatial and non-spatial factors. However, the reviewed applications reveal significant variation in their methodological rigor, data requirements, and operational feasibility.

Among the reviewed studies, validation strategies differed considerably. One study applied spatial linear regression to assess the correlation between predicted fire vulnerability indices and observed fire incident densities, reporting a high coefficient of determination ($R^2 = 1.0$), thereby supporting the model's predictive validity [103]. In contrast, other applications relied on internal logic-based evaluations, such as spatial overlays and buffer analysis, without comparing model outputs against historical fire data [104,105]. While such methods can provide internally consistent prioritizations, the absence of predictive or statistical validation limits the ability to assess their external reliability.

Data availability and software requirements also influence the adaptability of these models in different urban contexts. Approaches that utilized open-source platforms like QGIS and accessible census-level data demonstrated greater potential for replication in data-scarce or resource-limited settings [103]. In contrast, methodologies that depended on custom datasets or required complex preprocessing steps, such as CAD-to-GIS conversions or topological network modeling, pose practical challenges for cities lacking advanced spatial infrastructure [104]. Some models employed building footprint maps derived from national agencies, which may not be universally available, but could be substituted by simplified land use or zoning data in comparable applications [105].

The ease of operationalizing these methods also varies across studies. Approaches using grid-based overlays and additive scoring models are relatively straightforward to implement with basic GIS training, making them suitable for adoption by local authorities and urban planners [105]. Others involved more sophisticated decision rules, site selection algorithms, and constraint-based optimization, requiring professional expertise and dedicated technical resources [104]. Where methods were designed around standardized spatial units and routinely collected municipal data, their integration into existing planning workflows appeared more feasible [103].

A recurring concern in MCDM applications is the subjectivity introduced through the weighting process. In AHP, the reliance on expert judgment can lead to inconsistencies or biases, particularly when the expert panel is small or lacks diverse representation. Studies that reported consistency ratios ($CR < 0.1$) added credibility to their pairwise comparison processes and demonstrated methodological transparency [103,105]. However, others did not provide such validation, nor did they disclose the criteria for expert selection or the number of participants involved [104]. Furthermore, sensitivity analyses, which could help assess the robustness of the model to changes in weights, were absent across all reviewed cases.

Interpretability and generalizability are also influenced by the structure of these models. While MCDM techniques offer a systematic framework for integrating diverse factors, their outputs are inherently dependent on the contextual relevance of input variables and expert assumptions. Some studies acknowledged the location-specific nature of their models, emphasizing the need for recalibration when applied to different urban or environmental conditions [103,105]. Nevertheless, the lack of uncertainty quantification, probabilistic modeling, or scenario testing suggests that additional measures are needed to improve confidence in the derived fire risk zones [103-105].

Index-Based Approaches

Index-based methods have emerged as a practical alternative to complex MCDM frameworks, offering simplified structures for evaluating urban fire risk using fixed scoring schemes. However, a closer review of recent implementations highlights key limitations and considerations in terms of methodological rigor, adaptability, and operational scalability.

While index-based models benefit from intuitive scoring systems, most lack rigorous validation protocols. In the reviewed studies, the FRI was computed through structured sub-factors such as ignition risk, propagation potential, evacuation challenges, and fire combat readiness. These sub-factors were further broken down into partial indicators scored using predefined thresholds. However, none of the models employed statistical methods such as regression analysis or Receiver Operating Characteristic curves to test predictive performance. Validation efforts were largely visual or comparative in nature-for instance, one study matched FRI-derived maps to historic fire incident zones, while another compared modified FRI scores to those from an earlier ARICA application, reporting a deviation of less than 6% across sample buildings [3,106,107].

The adaptability of these models to data-scarce or low-income urban environments is mixed. On one hand, their reliance on deterministic scoring, open-source platforms like QGIS, and municipal or observational data provides a foundation for transferability. For example, data inputs in some studies were derived from publicly available cadastral records, infrastructure maps, and manual observations using simplified checklists. On the other hand, implementation still required extensive field data collection-one study inspected over 500 buildings, and another relied on interpolated building-level information not easily available in informal settlements or unstructured urban areas. Furthermore, some models integrated elements such as proximity to hydrants or electrical installation quality, which may not be readily accessible without technical surveys [3,106,107].

Despite their relative simplicity, these approaches do not inherently guarantee practical ease of use for municipal authorities. None of the reviewed cases provided turnkey operational guidelines for implementation by low-capacity planning departments. However, the structure of these indices-often based on a limited number of criteria and visual risk maps-offers a feasible starting point for localized adaptation. In certain cases, the index outputs directly informed zone-based recommendations, including inspection targeting, prioritization of retrofitting, and short-term fire service planning. With basic training or collaboration with academic institutions, these models could be partially implemented in cities with limited resources [3,106,107].

A critical methodological issue lies in the subjectivity embedded within scoring and weighting mechanisms. Unlike MCDM methods that formalize expert input through AHP, index-based models typically apply fixed multipliers or deterministic coefficients. For example, ignition-related risks might receive a constant multiplier of 1.2, and evacuation deficiencies might be scored with simple binary thresholds. These values, while operationally convenient, are often derived from internal experience or fire code interpretations rather than statistical optimization. None of the reviewed studies conducted sensitivity analyses to explore how changes in these parameters could affect final risk classifications, and justification for specific weightings was either implicit or absent [3,106,107].

Finally, the interpretability and generalizability of index-based models remain constrained by the localized nature of the indicators and scoring schemes. All three studies acknowledged that their models were tailored to specific urban contexts-such as historical centers, aging infrastructure, or mixed-use zones-and noted that results could not be directly transferred without recalibration. Additionally, none of the models incorporated uncertainty quantification, probabilistic risk ranges, or socio-economic modifiers, all of which could significantly influence fire vulnerability. The deterministic structure of these indices, while transparent, limits their capacity to fully reflect complex interactions in diverse urban environments [3,106,107].

KDE and Euclidean Distance Methods

KDE and Euclidean Distance Analysis represent foundational spatial techniques in GIS-based fire risk modeling. The reviewed application of these methods in Yushan Town, China, demonstrates their capacity to generate visually interpretable and continuous fire risk surfaces. The model calculated a weighted fire risk index using seven variables: building density, building fire resistance, population density, land use, and distances from hazardous buildings, water sources, and fire stations. KDE was applied to map building density distributions, while Euclidean distances were calculated from multiple risk-relevant features [109].

The effectiveness of the model was primarily assessed through visual agreement between high-risk zones and known hazard-prone areas. However, the study did not conduct predictive validation using historical fire incident data, regression analysis, or statistical performance metrics. Although the authors suggest future work will include validation using observed fire occurrence maps, this remains a gap in the current model's assessment [109].

In terms of adaptability, the model's reliance on basic spatial inputs-land use, infrastructure location, and population density-indicates high potential for replication, especially in semi-structured or data-scarce urban environments. However, the requirement for raster-based KDE and distance surfaces, as well as subjective weighting for each variable class, introduces moderate technical complexity. The method assumes access to spatially accurate point data for buildings and infrastructure, which may not be available in low-income or informally developed areas [109].

Practical implementation is facilitated by the model's simple overlay structure and use of the GIS Spatial Analyst toolset. The entire process was executed using ArcGIS, including raster classification, density mapping, and weighted overlay via the Raster Calculator. These operations are well-supported in modern open-source GIS software, suggesting potential for adoption by local planning authorities with moderate technical capacity. Nevertheless, the lack of predefined automation or decision support tools may limit adoption where trained GIS personnel are unavailable [109].

Subjectivity in this approach arises in two areas: class definition for each variable (e.g., population density thresholds) and the assignment of weights to the seven fire risk components. These weights were determined “based on local conditions” without transparency in the decision process or consistency testing. For example, building density and population density were both weighted at 9, while distance from water was weighted at 3-without statistical justification or expert panel documentation. No sensitivity analysis was performed to test the influence of weight variability on fire risk outcomes [109].

Interpretational limitations stem from the deterministic nature of the model. Although the continuous raster outputs and gradient maps produced by KDE and Euclidean distance functions improve spatial visualization, the lack of uncertainty estimation, interactive variable effects, or temporal dynamics limits the model's predictive strength. The authors acknowledge that the model's utility could be improved through calibration with actual fire occurrence data and adjustments for regional differences, but such refinements were not implemented in the current version [109].

Spatial Diffusion Models

The spatial diffusion model developed by Ji et al. for urban fire risk assessment in Xuzhou city presents a significant methodological advancement by integrating geographic grid analysis with weighted overlay procedures. Unlike traditional methods relying on fuzzy AHP or comprehensive evaluation models, this approach enables spatial differentiation of fire risk at a finer resolution by simulating the spread of multiple risk factors across a uniform grid structure [108].

In terms of model evaluation, the study employed diffusion and overlay analysis across 250×250m grids using a GIS-based environment, generating a continuous fire risk surface across urban zones. While the model's structure allowed for nuanced spatial representation, it lacked quantitative validation techniques such as regression, correlation with historical fire incident data, or ROC-based performance metrics. The risk outputs were visualized through gradient-based classifications, but their statistical reliability remains unverified [108].

Regarding adaptability to data-scarce contexts, the model's flexibility is both a strength and a limitation. The grid-based framework and reliance on general urban features such as building density, population data, and fire station coverage allow for replication in cities with minimal spatial datasets. However, its application also requires detailed thematic data including fire hydrant networks, gas pipelines, road classifications, and land use codes. While these may be sourced in structured municipalities, they are often absent in informal urban environments, potentially restricting the model's usability in low-income settings [108].

From an implementation standpoint, the model integrates a clear workflow-comprising grid creation, factor diffusion (distance and resistance-based), and weighted overlay analysis-which is compatible with standard GIS tools. The use of ArcGIS 9.2 and custom VBA scripts for spatial operations makes the method accessible to technically equipped urban planning departments. However, adoption by low-capacity authorities would require simplification or tool automation due to the need for custom programming and intermediate GIS skills [108].

The model involves predefined weights assigned to 22 influential factors grouped under regional characteristics, fire danger, and protection capacity. These weights-such as 0.376 for electrical safety or 0.736 for fire station coverage-were derived from expert ratings and fire safety regulations, yet lack sensitivity analysis or statistical justification for threshold setting. While consistent within the study, these deterministic weights introduce subjectivity and may not reflect risk dynamics in differing urban contexts [108].

The approach also demonstrates interpretational limitations inherent in deterministic grid models. Although the geographic spread of risk is realistically mapped, the interaction effects among variables, uncertainty margins, and temporal dynamics are not captured. The authors acknowledge that fire risk is influenced by land use-resistance patterns and service gaps but stop short of embedding stochastic or probabilistic features in the model. As a result, while the visualization of spatial fire risk is enhanced, the model's predictive capacity and generalizability to other cities remain limited without recalibration [108].

Other GIS-Based Methods

Other GIS-based approaches-such as composite risk scoring, response time mapping, and green space analysis-offer flexible alternatives to MCDM and index-based frameworks. While their methodologies are often practical and locally grounded, important differences exist in terms of data intensity, adaptability, and analytical depth.

In terms of evaluation methodology, each study utilized different techniques to assess fire risk, but none employed predictive statistical validation. Tomar et al. generated fire risk scores using the formula A×B+CA \times B + CA×B+C, where A denoted fire incident frequency, B referred to consequences (casualties), and C represented severity (tender categories), resulting in risk scores ranging from 0 to 21 [110]. Yagoub and Jalil conducted network-based service area analysis, showing an increase in fire station coverage from 36% to 75% using the proposed station locations, based on 220 geo-coded fire incidents

[111]. Thakare and Tajne employed spatial overlay and Pearson's correlation to identify a strong positive relationship ($r \approx 0.771$) between greenery coverage and reduced fire risk zones, using 570 classified incidents across five urban zones [112]. However, none of the models included regression, error quantification, or cross-validation to verify predictive reliability.

Adaptability in data-scarce contexts was notably higher in studies that creatively substituted conventional datasets. Yagoub and Jalil used local newspaper reports as proxies for fire incident data and relied on public imagery sources such as Google Earth, Wikimapia, and IKONOS satellite imagery, enabling model construction without formal fire department records [111]. Similarly, Thakare and Tajne used publicly accessible satellite imagery and basic field surveys to map urban structures and greenery [112]. In contrast, Tomar et al.'s model depended on Delhi Fire Service records and municipal ward boundaries, requiring structured administrative datasets that may not be available in unregulated urban settlements [110].

Regarding practical implementation, these methods generally support low-barrier adoption. All three utilized ArcGIS software with basic tools such as Raster Calculator, Network Analyst, and overlay analysis. Yagoub and Jalil incorporated user-friendly buffer and route planning techniques, and their GIS model offered fire station site suitability based on demographic and infrastructure proximity criteria [111]. Thakare and Tajne's integration of vegetation mapping and hotspot overlay provides a replicable template for urban planning departments to identify dual-purpose zones-both ecologically valuable and fire-resilient [112]. Tomar et al.'s scoring logic, while straightforward, depends on local fire classification norms and may require data normalization for replication outside the Delhi context [110].

Subjectivity in weighting and scoring remains a common limitation. Tomar et al. relied on domain-based logic to assign scores to incident frequency, severity, and casualty counts, but offered no justification for specific threshold values [110]. Yagoub and Jalil assigned raster weights to features such as road hierarchy and distance buffers based on expert-informed but non-statistically justified priorities [111]. Thakare and Tajne used correlation coefficients to interpret urban-green relationships, but did not weight structural risk factors relative to fire incidence, relying instead on visual and spatial association [112]. Across all studies, no sensitivity analyses were conducted to test the stability of outputs against scoring adjustments.

The interpretational limitations of these GIS methods are primarily rooted in their static and deterministic nature. None of the studies incorporated temporal dynamics, probabilistic fire modeling, or uncertainty ranges. While their outputs-risk scores, coverage gaps, or vegetation overlays-are visually compelling and often actionable, they do not reflect interactive or non-linear influences among variables. The authors in each case acknowledge the need for future enhancements: Tomar et al. highlight data standardization issues across wards [110], Yagoub and Jalil recommend replacing manual incident geocoding with official data feeds [111], and Thakare and Tajne call for expanded studies across climate regions to generalize greenery-risk relationships [112].

Future direction

Recent advancements in GIS technology have significantly enhanced urban fire risk assessment methodologies, particularly through the integration of AI and ML [53,113]. These technologies facilitate the analysis of vast datasets, enabling more accurate predictions of fire susceptibility and spread [53,113]. For instance, machine learning models have been employed to analyze remote sensing data, allowing for real-time monitoring and assessment of fire risks across extensive areas [114-116]. Furthermore, AI-driven approaches, such as dynamic Bayesian networks, provide insights into wildfire behavior, helping urban planners and emergency responders optimize risk management strategies [117]. The combination of GIS with ML techniques, including fuzzy logic and ensemble models, has proven effective in mapping fire susceptibility by considering various environmental and infrastructural factors [113,114]. This integration not only enhances predictive accuracy but also supports decision-making processes in urban fire management, ultimately contributing to improved safety and resource allocation in fire-prone areas [53,118].

AI and ML significantly enhance the accuracy and efficiency of fire risk prediction by analyzing large datasets, identifying patterns, and learning from historical data [119]. These technologies enable the integration of diverse data sources, including satellite imagery, weather patterns, and topographical features, to improve fire susceptibility assessments [119]. For instance, ML algorithms like Random Forest and Gradient Boosting have been successfully applied to predict fire risks in urban and rural interfaces, demonstrating superior performance compared to traditional statistical methods [119]. Specific applications of AI and ML in fire risk management include real-time monitoring, predictive modeling, and risk mapping [120]. Real-time monitoring systems utilize sensor data and AI algorithms to detect potential fire outbreaks, allowing for rapid response [120]. Predictive modeling leverages historical fire data to forecast future incidents, enhancing preparedness and resource allocation [120]. Additionally, risk mapping integrates social and environmental variables to create comprehensive fire susceptibility maps, aiding in emergency planning and resource management [120]. These advancements underscore the transformative potential of AI and ML in urban fire risk assessment and management.

Conclusions

In conclusion, GIS have emerged as a pivotal tool in urban fire risk assessment, enabling more comprehensive, accurate, and dynamic evaluations of fire hazards across diverse urban environments. The integration of various methodologies, such as MCDM approaches, index-based methods, spatial diffusion models, KDE, and Euclidean Distance Analysis, has significantly enhanced the ability to identify high-risk areas, optimize emergency response strategies, and inform urban planning decisions.

MCDM approaches, particularly the AHP and Fuzzy-VIKOR, facilitate structured decision-making by evaluating and prioritizing multiple factors that contribute to fire risk. Index-based methods, like the FRI, provide a straightforward approach to aggregate various risk factors into a single score, enabling rapid assessment and comparison across different areas. Spatial diffusion models offer valuable insights into the patterns and spread of fire incidents, while KDE and Euclidean Distance Analysis help in identifying fire hotspots and assessing proximity risks to critical infrastructure.

Despite the strengths of these methodologies, they also face challenges such as data sensitivity, computational demands, and potential biases in criteria weighting. Advances in GIS technology, including the integration of AI and machine learning, present new opportunities to overcome these limitations by enhancing predictive capabilities, improving real-time monitoring, and supporting more dynamic risk management strategies.

Moving forward, the continuous development and adoption of innovative GIS tools and techniques, along with the integration of emerging technologies, will be critical to advancing urban fire risk assessment. These innovations will not only improve the accuracy and efficiency of fire risk modeling but also support proactive fire management, ultimately contributing to safer and more resilient urban environments.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Kirti V. Thakare, Kiran M. Tajne

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