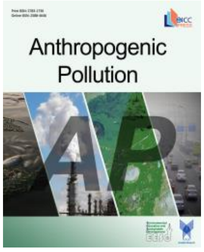

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Research Article

Modeling Anthropogenic Urban Fire Risk and Its Environmental Pollution Implications Using LR–WLC Approaches: A Case Study of Kashan, Iran

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Abstract

Urban fires represent one of the most significant human-induced hazards in modern cities, often linked to increased pollution emissions and environmental degradation. This study aims to evaluate fire risk in Kashan using a multi-criteria evaluation (MCE) method based on fuzzy logic, logistic regression, and the analytic hierarchy process (AHP). Initially, criteria and indicators were identified using the Delphi method and normalized using fuzzy logic as capacity and vulnerability factors. The weight of these factors was determined using the AHP method. Subsequently, all layers were combined using the weighted linear combination (WLC) technique. To evaluate the effectiveness of the methods, the outcomes were contrasted with the fire risk map produced via logistic regression. The ROC index was also used to validate the WLC model and logistic regression results. The results reveal that 0.820% of the total studied area (788.96 hectares) and 5% of the area identified by the WLC method (30,483 hectares) are at high risk of urban fires. The ROC index validation results, with values of 0.95 and 0.74 for the logistic regression and WLC methods, respectively, confirmed the superior predictive performance of the LR model. The validated fire risk maps not only support emergency response planning but also highlight spatial correlations between high-risk zones and areas of potential pollutant release or poor air dispersion. These findings demonstrate that mapping human-induced fire risk can provide a valuable spatial framework for air quality management, the mitigation of anthropogenic pollution risk and for advancing sustainable urban environmental management toward cleaner and safer cities.

Keywords: Risk Assessment; Fuzzy Logic; Multi-criteria Assessment; Logistic Regression; Anthropogenic Pollution

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1. Introduction

Urban fires represent a critical threat to global sustainable development, resulting in significant economic losses, fatalities, and environmental degradation (Zhang et al. 2018). Beyond direct destruction, urban fires act as major anthropogenic pollution sources, emitting particulates and hazardous gases that deteriorate local air quality and ecological health (Jakhar et al. 2023 and Aaleagha et al. 2022). With rapid urbanization worldwide, effective fire risk management is essential for public safety, necessitating advanced predictive modeling and robust spatial analysis (Chisty and Rahman 2020). Enhancing the effectiveness and efficiency of fire safety management requires understanding the spatio-temporal dynamics of fire events. This understanding can provide valuable insights into potential contributing factors of urban fires and enable more accurate predictions for resource allocation and strategic planning for future prevention and mitigation programs (Kumar et al. 2022 and Bispo et al. 2023).

Identifying high-risk areas requires integrating diverse spatial factors such as infrastructure, population density, the increased use of combustible materials and building vulnerability (Aaleagha et al. 2022). Researchers have extensively addressed the relationship between urban fires and contextual factors, highlighting that socio-economic factors like population density, the state of buildings, and the size of households frequently influence fire occurrence more than just the physical characteristics of the environment (Bispo et al. 2023; Taridala et al. 2017; Špatenková and Virrantaus 2013). Also, recent studies have established a strong correlation between urban industrial fire incidents and the release of hazardous organic and inorganic pollutants, significantly impacting human health and environmental integrity (Jakhar et al. 2023; Griffiths et al. 2022 and Aaleagha et al. 2022). Consequently, a robust urban fire risk management plan must utilize spatial analysis tools to integrate and accurately model the complex interplay of these socio-economic and infrastructural parameters for effective hazard zoning. Spatial modeling of fire risk can assist in anticipating pollution hotspots and planning mitigation strategies too.

The use of Geographic Information Systems (GIS) combined with predictive models for risk assessment can provide valuable insights into the patterns and trends of urban fires (Tomaszewski 2020; Li et al. 2019). Among the predictive models, Logistic Regression (LR) stands out as a robust, statistically sound, and highly

interpretable method for binary event modeling in spatial risk analysis (Yalcin et al. 2011 ; Dey et al. 2025). Concurrently, Multi-Criteria Evaluation (MCE) methods, particularly the Weighted Linear Combination (WLC) approach driven by the Analytic Hierarchy Process (AHP), offer a powerful framework to integrate expert knowledge and subjective criteria (Nyimbili and Erden, 2020). While LR relies on historical data, MCE provides a structured approach for complex, data-limited environments (Wang and Wang 2022).

So far, GIS has been used in many studies to analyze the spatial distribution of urban fires, identify hot spots, and identify high risk areas (Thakare et al. 2025). Tomar et al. (2017) carried out a study to assess and map fire risk using GIS by examining the spatial distribution of fire incidents within the South West Division of the Delhi Fire Service. Geospatial technologies served as the core tool for urban fire risk assessment and management. Based on data related to fire occurrences, land use, locations of fire stations, population density, and fire related casualties, the researchers created fire hazard zoning maps. Their analysis revealed that about 70.01% of the region fell under a low fire risk zone, 26.39% under a medium risk zone, and 3.59% under a high fire risk zone. Masoumi et al. (2019) performed an in-depth fire risk assessment specifically for densely populated urban areas. Their method involved fusing various data sources and applying spatial analysis to generate detailed fire risk maps. The study focused on two key areas in Zanjan: the existing urban infrastructure and the specific characteristics of its high-rise buildings. They created a vulnerability map that factored in high-risk urban elements like the placement of oil/gas pipelines and power lines, while also evaluating the fire safety of taller buildings. A sensitivity analysis concluded that social education was the single most influential factor impacting fire risk in the area. Jaman and Pantha (2023) investigated the performance and capability of fire stations with location awareness and past fire incidents. The main objectives were based entirely on the probability of fire hazards in Dhaka South City Agency (DSCC). Data on all fire incidents from 2016 to 2021 were collected from the Fire and Civil Protection Department. The distribution of fire incidents was systematically analyzed using unique land use classes and structure types. The assessment was based on population density and land use type. The lack of a permanent water source for firefighting was identified by fire officials as a major challenge for firefighting activities. Regina Bispo et al. (2023) developed a model to predict where urban fires are likely to occur and compared various methods for measuring spatial correlation. This model successfully allowed them to map the probability of fire incidents across Portugal. After comparing different approaches, they found Dorbin's spatial error model to be the most effective, incorporating variables like population density, the density of destroyed buildings, and local purchasing power. Furthermore, by examining the connection between where fires actually happened and the existing number of fire stations in each municipality, their analysis provides a crucial basis for strategically planning the optimal number and placement of fire stations on a regional scale.

Despite the utility of both LR and MCE, comparative studies that rigorously evaluate their predictive performance across different urban contexts remain scarce. Specifically, Kashan City, characterized by rapid urbanization, significant industrial activity, and a large proportion of old and dilapidated urban textures, presents a high risk environment. Alarmingly, an increasing frequency of fire incidents in the region (documented by the Kashan Fire Organization data) highlights an urgent need for a comprehensive, scientifically validated risk map. Crucially, no similar research has been conducted for the entire urban area of Kashan that not only zones the fire risk but also directly compares the efficiency and accuracy of a data driven model (LR) against an expert-knowledge driven model (WLC/AHP) using validation metrics like the Receiver Operating Characteristic (ROC) index. This index graphically represents a binary classifier's performance across various thresholds by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) (Muschelli 2020).

Against this background, the principal objectives of this study are twofold: first, to develop and apply both the LR and WLC models to create detailed urban fire risk zoning maps for Kashan City; second, and most importantly, to rigorously evaluate and compare the predictive performance of these two distinct modeling approaches using the Area Under the Curve (AUC) from ROC curve analysis. This study's key novelty lies in providing a methodological benchmark for urban risk assessment by demonstrating which framework data-driven statistical modeling or multi- criteria decision analysis offers a more reliable and robust result in the specific spatiotemporal dynamics of the Kashan urban environment. This research illustrates that modeling human induced urban fire risk provides essential, validated insights for urban authorities and planners. It supports strategic resource allocation and mitigation programs while also enhancing the management of anthropogenic pollution.

2. Materials and Models

2.1. Study area

Kashan city, located approximately 240 km south of Tehran, in central Iran, covers an area of 9,647 km^2 and has a population of about 335,878 people, making it the second most populated city in Isfahan province. The city is located between latitudes 51° and 52° N and longitudes 33° and 34° E. Kashan is a significant urban center in the region with rich cultural heritage and historical architecture. The city consists of five districts and 16 urban service areas. District 2 is the most populated with a population of 117,000 people and an area of 8.15 km^2, while District 1 with a surface area of 14.5 km^2 contains the most extensive zone of historical, old and degraded urban fabric.

The industrial sector of the city is well-developed and holds high potential for tourism due to its historical attractions and strategic location along the main transportation route. However, the presence of old and dilapidated buildings, coupled with a high number of industrial units, elevates the risk of fire. According to data from the "Mahar" software of the Kashan Fire organization, 1590 fire cases have been reported in the study area over 10 years, predominantly in residential, commercial, and industrial areas, highlighting the urgent need for a comprehensive fire risk assessment study in the area (Figure1).

2.2. Methodology

The main goal was creating a comprehensive planning tool for emergencies, with a focus on the county's central region, since it is characterized by high population density, several high-risk buildings, and an old texture. The first phase of the study involved identifying and collecting the main sources of urban fire risk vulnerability. In the second phase, these data served as the foundation for developing and applying a novel urban fire risk assessment method.

GIS is a spatial and geographic information system used in fire risk management, especially in fire preparedness. It serves as the main organizational and analytical framework for processing data from various urban infrastructures (Masoumi et al. 2019). GIS has emerged as a critical technology for supporting firefighters in meeting their mission needs. The success of this system in managing fire hazards depends on evaluating the existing system, integrating GIS planning, leveraging it for new opportunities, and managing fire risk using GIS (Ferreira et al. 2016; Tikhonova et al. 2021). The steps and techniques used in this study were employed to compare two methods: logistic regression and the WLC model. The identification and selection of the optimal model for fire risk zoning in Kashan city is detailed in six steps in Table 1 and Figure 2. These steps are further examined in the following sections.

2.3. Data collection and standardization

Identifying influential criteria and indicators is crucial in urban fire risk zoning studies. This study employed the Delphi method using the Likert scale to collect expert opinions (Jangjoo 2021; Lee et al. 2019). The Delphi technique is a suitable and acceptable method for achieving consensus when developing a set of indicators (Lewis 1993).

In qualitative research, where the objective is to determine the importance of screen items, the Likert scale can gather expert opinions effectively. The seven-point Likert scale is directly related to the results of the t-test (Chisty and Rahman 2020; Oloke et al. 2021). No scale has outperformed the seven-point rating scale on any measure. For seven-point scales, measures with a mean below five are eliminated (Nyimbili and Erden 2020; Shariff 2015). The criteria were screened based on the research objective. The identified evaluation criteria are divided into two groups: vulnerable factors and capacity of mitigating factors, as shown in Table 2 (Chisty and Rahman 2020; Srivanit 2011).

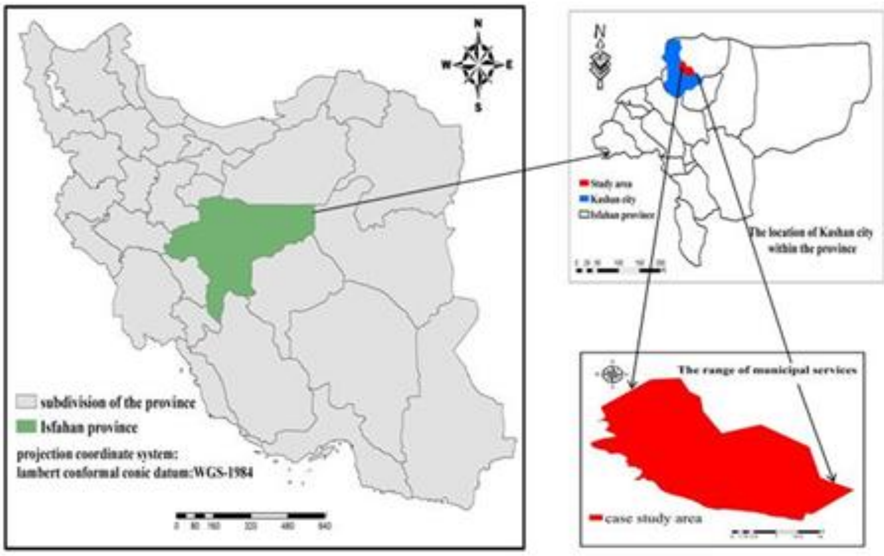

Figure 1. The location of the studied city

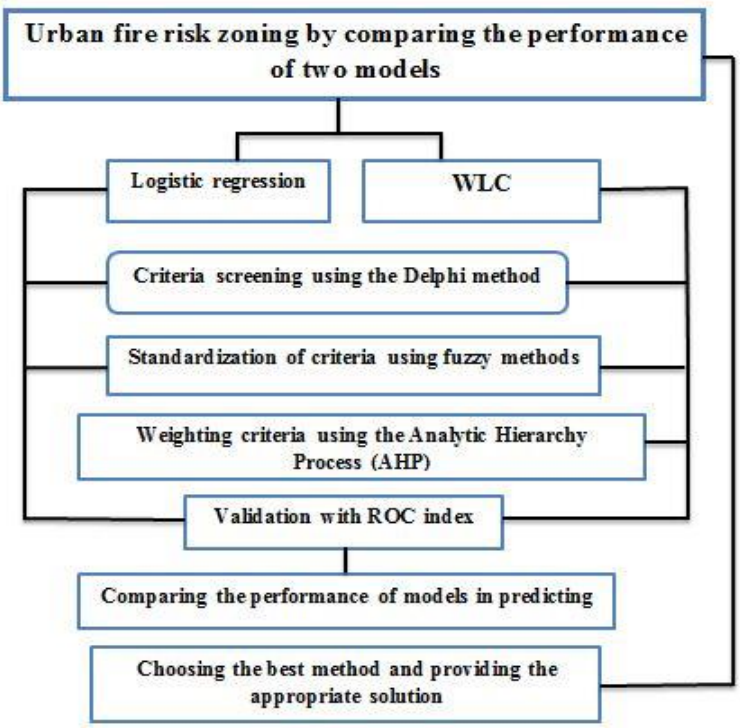

Figure 2. The flow chart of the research steps

Table 1. Research steps and techniques

Research steps and techniques	Step 1	Collecting and selecting the required data	Delphi Method
			(Kashan County Population Map for 2016)
	Step 2	Screening criteria according to the objective	Vulnerable Factors
			Capacity of Mitigation Factors
	Step 3	(Preparing data for spatial analysis)	Georeferencing Layers
			Conversion of Coordinate System to UTM and Zone 39
			Distance Analysis
			Classification
	Step 4	Standardizing layers	Fuzzy Logic Operators
			AHP Method
	Step 5	Identifying high-risk areas by comparing two methods	Logistic Regression
			WLC Method
	Step 6	Assessing accuracy	ROC Test

Table 2. Prioritization of key parameters in risk zoning of urban fires

Influential parameters		Priority Level
Vulnerable factors	Population density	1
	High land-high risk	4
	Fuel station	6
	Old texture	5
	Industrial unit	2
	Commercial-warehouse	3
Capacity of mitigation factors	Road	2
	Fire station	1
	Hydrant valve	3

The source of the map layers of commercial use warehouses, old texture, high-risk points, and population was derived from the land use map, and the layers of population, industrial town, roads, hydrant valves, fire stations, and fuel stations were extracted from thematic maps using GPS and information from the Kashan Fire organization, a location map of fire spots over the past 10 years was generated at a 1:25,000 scale.

A pixel size of 10 x 10 meters was considered for all map layers (Chhetri and Kayastha 2015). The data and layers were then prepared for analysis in the geographic information system (ArcGIS 10.4.1), with the necessary ground referencing of the layers and conversion of their coordinate system to UTM and zone 39 completed. The Euclidean distance method was utilized to analyze distance within the GIS environment (de Smith 2004). Euclidean distance can be calculated using Eq. (1).

$$d(q,p)=\sqrt{\sum_{i=1}^{n}(q_i-p_i)^2} \qquad (1)$$

According to Eq. (1), the Euclidean distance of two vectors, *p* and *q*, is equal to the sum of the square root of the difference of the coordinates of the vectors in the coordinate system. The output of these calculations is a raster layer that displays the distance between pixels or target points on the map (Lyimo et al. 2020). Figure 3 illustrates an example of the output layer generated from distance analysis in the ArcGIS environment.

In the next step, the layers were standardized using fuzzy logic. At first, the distance function was applied to the criteria in the IDRISI environment (IDRISI Selva 17.0) to determine the distance from each phenomenon. Subsequently, all criteria within the range of 0 to 255 were standardized using the fuzzy method (sadollah 2018). The type of function used in the fuzzy logic approach was linear, and the function type and thresholds were selected based on the review of sources and expert opinions, as shown in Table 3.

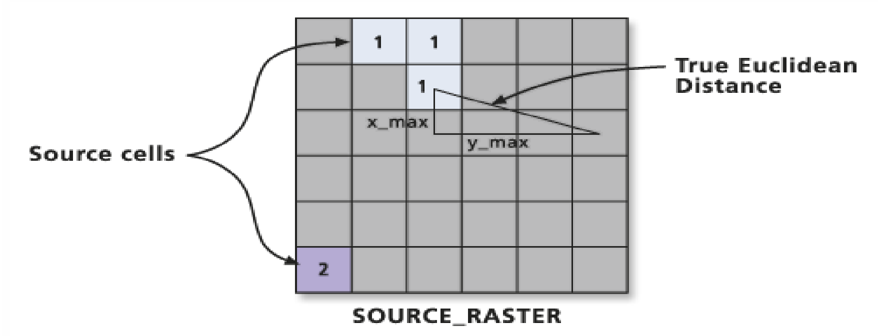

Figure 3. The Euclidean distance calculation algorithm in the ArcGIS environment

Table 3. Criterion threshold, shape, and type of membership function

Key criteria	Membership function form	Standardization	Membership amount
Population	Linear- Additive	<200< 200-700 >700>	0 0-255 255
Industrial and workshop	Linear- Additive	0-30 30-1000 >1000	255 0-255 0
Commercial-warehouse	Linear- Additive	0-10 10-300 >300	255 0-255 0
High-rise building	Linear- Additive	0-20 20-500 >500	255 0-255 0
Old texture	Linear- Additive	0-20 20-1000 >1000	255 0-255 0
Gas station	Linear- Additive	0-50 50-500 >500=0	255 0-255 0
Distance from the fire station	Linear- Additive	0-2500 >2500	0 255
Distance from access	Linear- Additive	0-25 25-150 >150	0 0-255 255
Distance from hydrant	Linear- Additive	0-60 60-800 >800	0 0-255 255

This method uses a linear function between minimum and maximum values (Eq. (2)). The values below the minimum threshold have no membership degree, while those above the maximum threshold have a full membership degree, receiving a value of 1 (de Smith 2004; Lyimo et al. 2020).

$$\mu(x) = 0 \ if \ x < min, \ \mu(x) = 1 \ if \ x > max, \ otherwise \ \mu(x) = \left(\frac{(x-min)}{(max-min)}\right) \quad (2)$$

The chosen thresholds for the linear functions, as detailed in Table 3, were calibrated based on expert consensus. To verify that the model was not overly sensitive to these particular breakpoints, a brief sensitivity analysis was performed. Thresholds of the key layers (population density and industrial distance) were varied by ±10 % and the effect of the resulting change was examined.

2.4. Integration of criteria by logistic regression method

Logistic regression is a multivariate model employed to predict a binary outcome based on predictor variables (Yalcin et al. 2011). Its primary advantage is that by incorporating a suitable link function into standard linear regression, it accommodates predictor variables (continuous, discrete, or mixed) without requiring a normal distribution (Tomaszewski 2020). The logistic regression model in this study was implemented using the Logit link function, which transforms the probability of fire occurrence into a continuous log odds scale. The Logit function was selected because it is the standard and most interpretable link for binary event modeling in spatial risk analysis (Kost et.al 2021). Unlike other multivariate statistical methods, such as multiple regression and discriminant analysis, this model is restricted to a dependent variable with only two possible states, predicting the probability of an event occurring versus the probability of it not occurring. The dependent variable is binary, where zero means the event does not occur and one means the event does occur. The model output has coefficients between zero and one, giving probabilities higher than 0.5 the value of one (fire occurrence) and probabilities lower than 0.5 the value of zero (fire absence), thus producing a Boolean risk map (Eq. (3)) (Pan et al. 2016).

$$p\left(\frac{y-1}{x}\right) = \frac{\exp\left(\sum BX\right)}{1+\exp\left(\sum BX\right)} \quad (3)$$

In this formulation, *P* represents the probability that the dependent variable equals 1, *X* denotes the independent variable, *B* is the calculated constant estimate, and *Y* stands for the dependent variable, which in this context is "fire". To linearize the above equation, a logarithmic change is made to it as Eq. (4).

$$\text{Loge}\left(\frac{p}{1+p}\right) = C_0 + C_1.X_1 + C_2.X_2 + \ldots + C_n{:}X_n + \text{error term} \quad (4)$$

C_0 serves as the model's intercept, and C_1, C_2, …, C_n are coefficients used to measure how much each independent factor X_1, X_2, …, X_n contributes to the observed changes in *Y*.

Coefficient estimation was performed using an iterative Newton–Raphson optimization algorithm, the default estimation method in IDRISI Selva, which minimizes the deviance between predicted and observed events. A fixed random seed was applied during the iterative coefficient estimation process to guarantee the reproducibility and stability of the logistic regression results.

Also, prior to fitting the Logistic Regression model, a multicollinearity diagnostic was performed to ensure that the explanatory variables were sufficiently independent. The potential correlation among variables was examined through both a Pearson correlation matrix and the Variance Inflation Factor (VIF) test within the IDRISI environment.

2.5. Identification of fire points

To understand the spatial patterns of fire incidents in the county, this investigation seeks to analyze the geographical relationships while assessing the influence of the underlying factors driving these occurrences. All fire points over the past 10 years (2014 to 2023) were extracted from the logistic regression model and converted into a raster map. For logistic regression modeling, non-fire pixels were generated by randomly sampling locations that had no recorded fire events in the past ten years. Random sampling was applied within each land-use type to ensure representativeness and spatial independence. A minimum distance of 200 m from recorded fire points was set to avoid spatial autocorrelation (Chhetri and Kayastha 2015; de Bem et al. 2019). The dataset included equal numbers of fire and non-fire pixels to maintain class balance. Figure 4 illustrates all the fire points listed in Table 4, categorized by the type of use and the number in one year. These points were assigned a weight of 1, while other points received a weight of zero.

2.6. AHP model

In line with the standardization stage of the criteria maps, the determined criteria were weighted using the AHP (Expert Choice 11) to integrate them into the WLC model. In the AHP method, the weight of each criterion signifies its importance and value compared to other criteria. Therefore, an informed and accurate selection of weights is of great help in achieving the goal (Nyimbili and Erden 2020). AHP serves as an effective tool for verifying the logical consistency of assessments made by decision-makers, thereby minimizing subjective bias in the final decision. Its utility is demonstrated across various fields, including suitability analysis, regional planning, site selection, and fire risk sensitivity studies (Srivanit 2011; Chhetri and Kayastha 2015; Faramarzi et al. 2021). In this study, first, the pairwise comparison matrix was constructed based on expert judgments regarding the relative importance of each criterion. An expert panel of nine specialists participated, including members from the Kashan Fire organization, municipal urban planners and academic researchers. Each expert independently completed the comparison matrices using the Saaty 1–9 importance scale (Noori et al. 2023). To obtain a consolidated judgment, the geometric mean of all expert pairwise scores was calculated to form a single aggregated matrix, ensuring a balanced representation of opinions. After the weights of the indicators were determined, all layers were combined in IDRISI software based on the WLC logic.

2.7. Weighted linear combination method (WLC)

GIS is an essential tool for spatial planners in multi-criteria evaluation, owing to its extensive capabilities in data handling (storage, editing, and collection) and spatial analysis/modeling. Ultimately, the use of GIS in this context is to directly aid in planning and decision-making (Xhafa and Kosovrasti 2015). Therefore, in this research, this system and the WLC method were used to analyze and evaluate several land suitability criteria.

AHP and WLC methods are preferred for multi-criteria decision analysis. Among the various techniques available for multi-criteria decision-making, the WLC approach is widely regarded as one of the most prevalent (Zhao 2008; Ayalew et al. 2004). In this method, decisions are made by directly assigning relative importance weights to each attribute. Afterwards, each alternative receives an overall score, obtained by multiplying the importance weight of every attribute by its corresponding normalized value for that alternative. These weighted values are then summed to produce the final score. Once total scores for all alternatives are computed, the one with the highest score is chosen as the best option (Hendry et al. 2008; Ghosh et al. 2012).

The evaluation process comprises different steps. The WLC method is generally composed of the following steps: first, each factor is multiplied by its corresponding weight; then, by summing the results and multiplying it by the product of the restrictions, inappropriate areas are removed, and a fire risk map in the area is obtained (Eq. (5)).

$$S = Wi\ Xi\ I\ cj \tag{5}$$

In which *S* represents desirability, *Wi* represent the factor weight, *Xi* represents the fuzzy factor value, *cj* represents the constraint criterion score, and *I* represents the product index. The final limit is obtained from Eq. (6) as follows:

$$C = I\ cj \tag{6}$$

In which *C* is the final limit, *Cj* is the constraint criterion score, and *I* is the product index. Weighting coefficients do not exist directly in a specific criterion but are instead assigned to a graded position of criterion values for a given option. The evaluation criterion with the highest value determines the first-degree weight after applying the criterion weights. The criterion with the next highest value determines the second-degree weight, and so on. After determining the weighting of the criteria and indicators using the previously mentioned formulas, the final map of fire risk was generated through the WLC technique (Zarin et al. 2021).

2.8. Validation with ROC index

The effectiveness of the two methods, WLC and logistic regression, used in this research was compared using validation with the ROC index. ROC validation was performed using all fire records from 2014 to 2023. Due to the limited number of annual observations, the full dataset was utilized to assess the overall performance of the spatial model to guarantee stable coefficient estimates. Here, IDRISI employs the ROC method to compare a Boolean map depicting “reality” (presence or absence of fire risk) with a probability map. The ROC scores range between 0.5 and 1, with 1 signifying a perfect match and 0.5 representing a random association (Lee and Pradhan, 2006). This easily interpretable disaggregation technique reveals the model’s predictive accuracy for the dependent variable. The statistic is visualized as a curve that relates the proportion of correctly predicted pixels (true positives) to those incorrectly predicted (false positives) (Schneider and Pontius 2001).

3. Results

This study investigated fire risk in a densely populated urban area in Kashan utilizing different types of spatial data and fire locations over a 10-year period. The primary processes included collecting spatial data and fire locations and combining this information through spatial analyses to compare LR and WLC models in order to identify and select the best model. To address this matter, a strong conceptual and analytical framework specifically designed for fire risk vulnerability assessment was implemented.

3.1. Logistic regression

The outcomes derived from the logistic regression method indicate the existence of both positive and negative linear functions. In the positive method, values below the minimum have no membership, while in the negative linear method, values above the maximum have no membership degree (Dey 2025).

After entering the data into the logistic regression statistical model, using the effective parameters in IDRISI software, the model coefficients were extracted according to Table 5. Prior to fitting the Logistic Regression model, a multicollinearity diagnostic using the VIF test was performed to ensure that the variables were sufficiently independent. The results confirmed that pairwise correlations between these variables were moderate and below 0.65. Generally, the VIF values for all independent variables were below the commonly accepted threshold of 5 (Marcoulides and Raykov 2019; Senaviratna, and Cooray 2019). These results indicate that no serious multicollinearity was present in the dataset, and the estimated coefficients (Table 5) reliably represent the independent contribution of each variable to fire risk occurrence. Consequently, the model's predictive strength and stability were not affected by variable interdependence, confirming its robust statistical validity. In this way, the coefficients for population, industrial and workshop, commercial-warehouse, old texture, high-rise building, and gas station are positive, indicating a relationship with fire occurrence. Conversely, the proximity to the fire station, road network, and hydrant valve demonstrated an inverse correlation with fire incidents within the research locale. Notably, the coefficient linked to "population density" was statistically significant, implying that population concentration exerts a more substantial impact on fire risk compared to all other variables (Pan et al. 2016; de Bem et al. 2019).

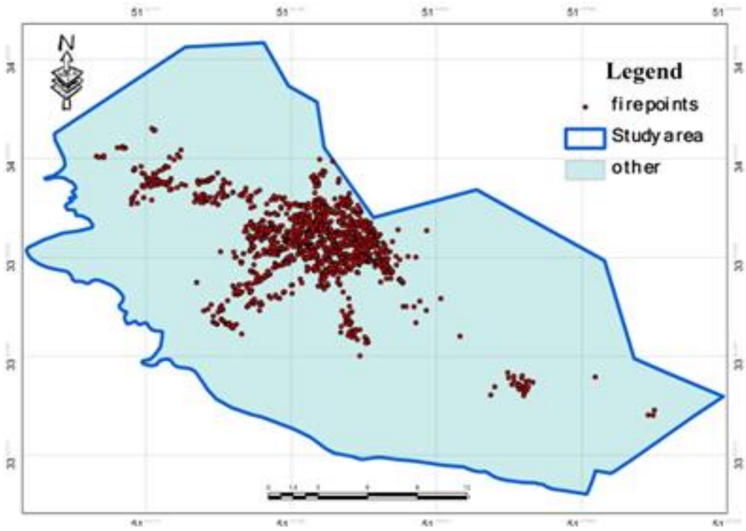

Figure 4. Fire spots in Kashan in the past 10 years

Table 4. Number of annual fires in Kashan (over 10 years)

User	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Factory	51	34	33	36	31	23	32	33	37	37
Residential	112	64	113	109	106	72	177	192	180	202
Aggregation	5	5	4	3	9	7	19	17	15	17
Commercial	56	75	51	56	50	56	68	67	72	75
Therapeutic	1	4	1	2	2	0	1	0	1	4
Store	26	22	10	8	3	12	12	18	22	27

Table 5. Coefficients derived from the logistic regression

	Independent variables	Coefficients
X_0	constant number	04.19804390
X_1	population	0.01024877
X_2	Distance from the fire station	-0.00154454
X_3	Industrial and workshop	0.00245561
X_4	Commercial - Warehouse	0.01493538
X_5	old texture	0.00260885
X_6	Distance from access	-0.00191017
X_7	petrol station	0.00029023
X_8	High-rise building	0.00397550
X_9	Distance from hydrant	-0.0361687

Since industrial estates serve as an indicator of high fire risk, and this risk lessens with increased distance from them, the fuzzy logic employed for this layer utilizes a reverse linear fuzzy logic function. Then, the influential parameters were prepared in ArcGIS and IDRISI software according to Figure 3. Figure 5 shows the standardized membership function diagrams of the factors affecting fire risk.

According to results, LR adequately models the relationship between fire risk and its contributing factors. Finally, a fire risk map was prepared using logistic regression. After validating the logistic regression model with the indicators (Figure 5), a fire risk zoning map of Kashan was produced. The continuous probability maps required discretization into five distinct fire risk classes: Very Low, Low, Moderate, High and Very High for practical management. As such, a quantile-based classification scheme was used to ensure that each of the five classes occupied approximately 20% of the total study area, thereby providing a balanced spatial representation (Schiavo 2025) (Table 6 and Figure 6). Table 6 presents the area in hectares and the percentage of the five classes. Based on the results, out of the total area of the study site, 1116.33 hectares (1.161%) have high risk, 788.96 hectares (0.820%) have very high risk, and 91% have very low risk for urban fire risk. Crucially, when overlaying these high-risk fire zones with data on industrial estates and densely populated areas, a significant overlap becomes apparent. This overlap suggests that areas with a heightened risk of fire incidents are also those susceptible to the release or concentration of anthropogenic pollutants, potentially exacerbating air quality issues and public health concerns.

However, it is important to note that although the logistic regression model assumes spatial independence among samples, the fire incidents exhibit partial spatial clustering, especially in dense residential and industrial zones. Visual inspection of the residuals in ArcGIS indicated no significant global clustering pattern beyond the influence of explanatory variables. Therefore, the standard logistic regression assumptions remain acceptable for the current spatial resolution (10 × 10 m pixel size). However, potential residual spatial autocorrelation is considered a limitation, and future research may employ spatial logistic regression or Geographically Weighted Regression (GWR) to better capture spatial non-stationarity and local variability (Ardianto et al. 2025).

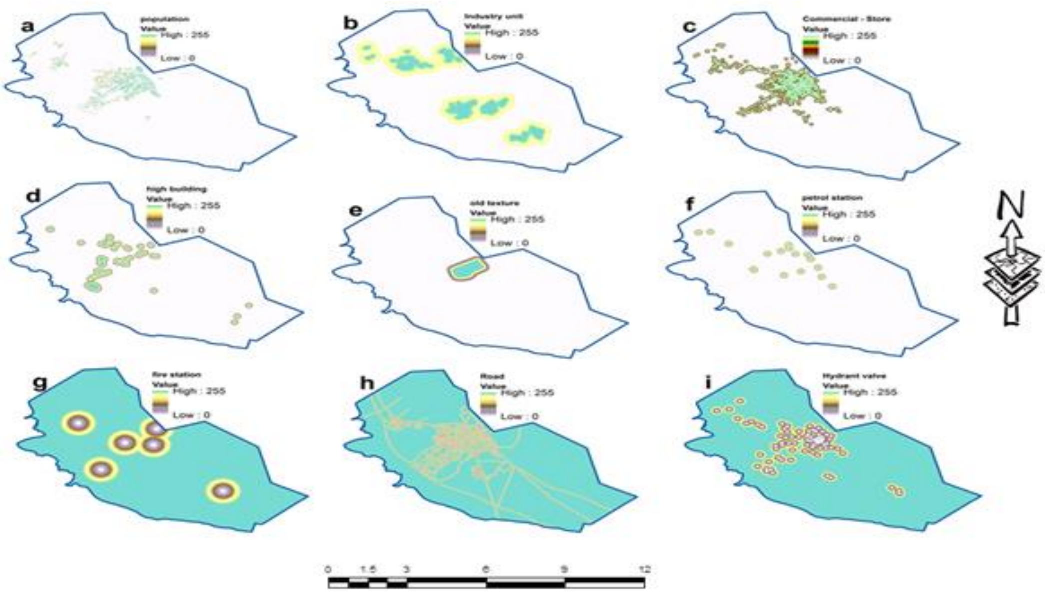

Figure 5. Fuzzy maps affecting urban fire occurrence and control: (a) population, (b) industrial unit, (c) commercial-warehouse, (d) high-rise building, (e) old texture, (f) fuel station, (g) distance from the fire station, (h) distance from the road, and (i) distance from the hydrant valve

Table 6. The results of the fire risk zoning by the logistic method

Value	Probability Range (P)	Percentage of area	Area per hectare	Percent
Very low risk	$0<P<P_{20}$	20%	87475.47	90.964
Low risk	$P_{20}<P<P_{40}$	20%	4669.03	4.855
Moderate risk	$P_{40}<P<P_{60}$	20%	2115.13	2.199
Medium risk	$P_{60}<P<P_{80}$	20%	1116.33	1.161
risk Too much	$P_{80}<P<1.0$	20%	788.96	0.820
Total	$0<P<1.0$	100%	96164.92	100

Px is the x-th percentile of the probability distribution of all pixels

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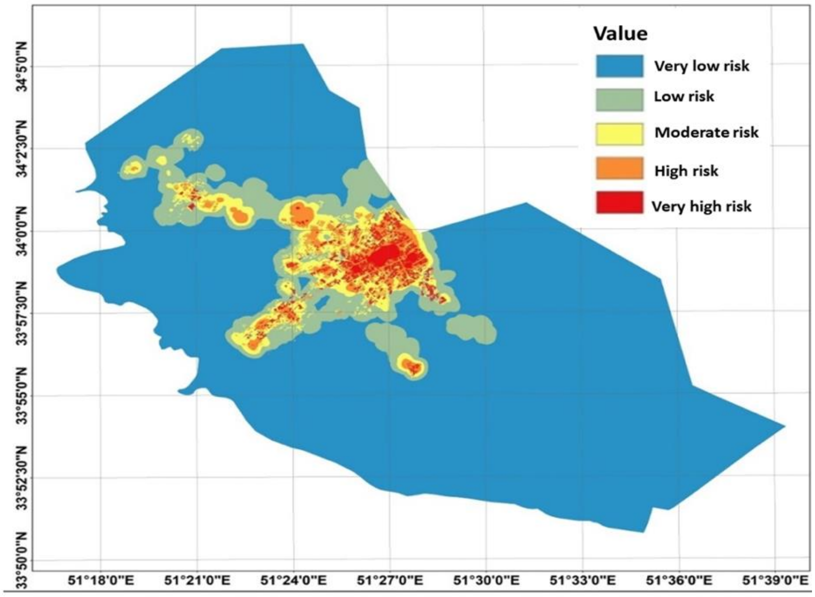

Figure 6. The fire risk zoning by the logistic method

3.2. AHP model

Based on the results of the AHP model, fire stations, population density, and existing industrial areas have the highest weights in the fire risk zoning of Kashan County with weights of 0.1998, 0.18648, and 0.14301, respectively. In contrast, hydrant valves carry the lowest importance with a weight of 0.06031. It should be noted the resulting matrix achieved a Consistency Ratio (CR = 0.01), well below the accepted threshold (0.10), confirming strong coherence among judgments and the methodological robustness of the weighting procedure (Figure 7). Finally, the decision matrix of the sub-criteria was multiplied by the decision matrix of the criteria in Excel to obtain the final weights. Table 7 presents the final weights obtained for combining layers based on WLC logic in IDRISI software.

This model, widely used and simple in multi-criteria evaluation, accounts for factor importance during the summation. This method is also based on fuzzy logic, which includes a range of proportionality. Therefore, the model's output includes alternatives of the degree of desirability for achieving a specific goal (Nebot and Mugica 2021). As is clear in Figure 8, which displays the findings of the WLC model in IDRISI software, the range of risk potential in the region varies between 0 and 178. The placement of control layers such as roads, fire stations, and hydrants reduced the potential for fire risk in the area, and as a result, the fuzzy value of 255 (maximum possible risk) was not recorded anywhere in the study area. On the other hand, the impact of industrial estates, densely populated areas, and commercial-warehouse uses on the formation and distribution of high-risk areas is evident.

To ensure the model wasn't unduly affected by the chosen breakpoints, the thresholds for the key layers such as population density and distance to industry were adjusted by ±10%. The change in the area classified as High-Risk under the WLC model remained below 5%, and the overall AUC stayed stable (within ±0.01). These results indicate that the fuzzy classification is robust to small variations in threshold definitions, supporting the view that the expert-driven calibration provides a consistent and defensible representation of risk gradients across the study area.

The classification of the WLC model findings into five groups (0-70 for very low risk, 70-100 for low risk, 100-110 for medium risk, 110-140 for high risk, and >140 for very high risk) reveals that out of the total area of the region, 969.5 hectares are high risk and 4833.30 hectares are very high risk. Therefore, more than 6% of the total area is at risk of fire, the distribution of which is shown on the map in Figure 9 and Table 8. Notably, the distribution of fire stations significantly impacts the spatial distribution of areas identified as having no or very low fire risk.

3.3. Assessing the accuracy of the LR model and WLC

The ROC method was used to evaluate the accuracy of the results obtained from the LR and WLC models (Figure 10). The validation results with the indicators used in LR method indicate that the value of 0.95 obtained from the ROC test indicates a very high correlation between the independent and dependent variables. The ratio of the ROC value of the fire hazard maps obtained from the WLC method is 0.74, reflecting the appropriate fit and efficiency of the model. The AUC was 0.85 for the logistic regression

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model. The data generally appears above the bisector, leading to a high True Positive Rate, which confirms the test has good diagnostic accuracy and power. However, in the WLC model, the AUC was 0.70, implying relatively good detection power.

By comparing the models' estimates of fire risk with each other and with historical fire locations in the study area, as well as the results obtained from the ROC test, it is evident that the logistic regression model provides a more appropriate estimate of the area than the WLC model.

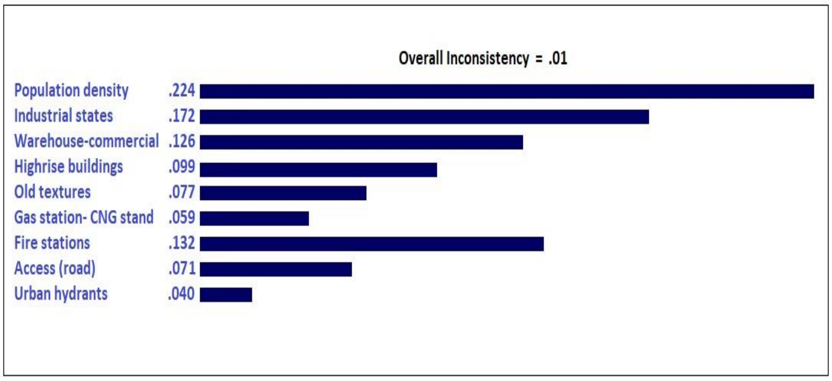

Figure 7. The weights obtained from the AHP model in the Expert Choice software

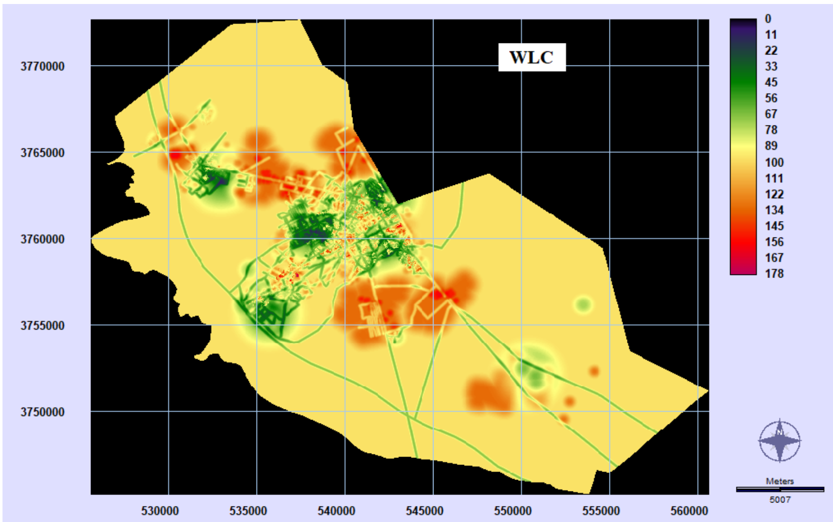

Figure 8. The results of the WLC model from IDRISI software output

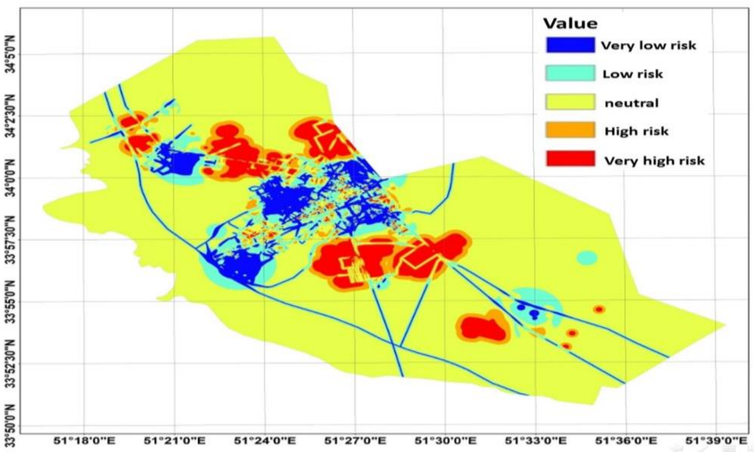

Figure 9. Classification of the results of the WLC model

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Table 7. The final weights of the criteria obtained from AHP

Criteria	Weights
Population density	0.18648
Industrial unit	0.14301
Commercial-warehouse	0.10521
High and dangerous places	0.08253
Old texture	0.06363
Gas station	0.04914
Fire station	0.1998
Road	0.10989
Hydrant valves	0.06031

Table 8. The results of the WLC model

Value	Area in hectares	Percent
Very low risk	50617.04	52.636
low risk	4722.85	4.911
Medium risk	35022.23	36.419
high risk	969.5	1.008
Very high risk	4833.3	5.026
Total	96164.92	100

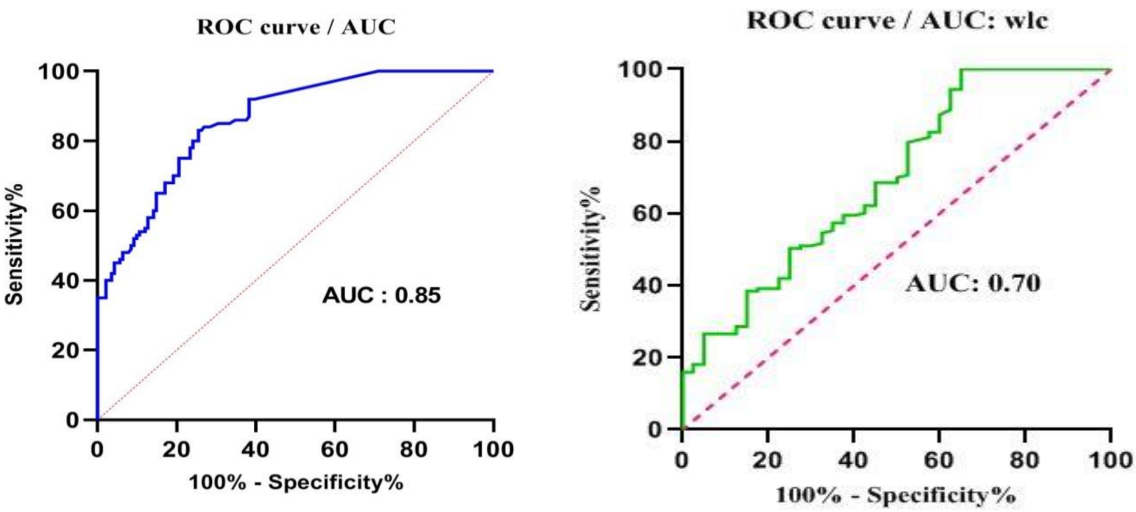

Figure 10. ROC statistics obtained to validate the LR method and the WLC model

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4. Discussion

In this study, 1950 fire incidents over the past 10 years were extracted from the Kashan Fire organization using “Mahar” software to analyze the spatial relationships among fire incidents in the city and the roles of factors affecting their occurrence using logistic regression and the WLC model. Previous studies, such as those by Yagoub and Jalil in the UAE, have utilized GIS for mapping incident spatial relationships. To optimize fire station placement, a network analysis was used to calculate emergency response times across the city, followed by a weighted overlay analysis to suggest the most suitable new station sites (2014). However, our research validation, confirmed by the ROC curve analysis which showed LR as the more accurate predictor, offers a critical insight into model superiority in the Kashan context. This finding supports the use of data-driven statistical approaches, like LR, over traditional MCDA methods, particularly where sufficient incident data allows the LR model to effectively capture the complex, non-linear relationships inherent in urban fire risk.

Moving to the specific results derived from the quantitative logistic regression model, the analysis clearly prioritizes key spatial drivers influencing fire events in Kashan. The highest positive correlations were identified with commercial warehouse areas and population density. This finding suggests that areas with concentrated commercial storage present a greater ignition or spread risk than other land use types. It is clear that areas with high fire risk have a higher potential for the emission of anthropogenic pollutants. This overlap highlights the need for integrated urban management to simultaneously address fire hazard and improve air pollution control.

Due to the direct correlation between fire station placement and the extent of low-risk areas, rapid emergency arrival is crucial. Consequently, Bandyopadhyay and Karar integrated AHP with GIS-based Weighted Overlay Analysis (WOA) to model ideal fire station locations. This approach successfully identifies sites that improve response time accessibility, target high population centers, and offer superior potential for reducing both property and life loss (2023). Nevertheless, the observed performance differential between LR and WLC highlights a key theoretical consideration in hazard modeling: the tradeoff between expert subjectivity (AHP/WLC) and data empiricism (LR) (Nyimbili and Erden, 2020). The WLC model relies heavily on the weights assigned through the AHP process. While this model is useful for integrating qualitative expert's opinion (as seen in Bandyopadhyay and Karar’s work on station location planning), it is not suitable alone for predicting urban fire occurrence. The latent variables captured by the LR model offer a more robust representation of underlying physical and socio-economic processes.

Comparing the fire risk estimation results from these models in Kashan, as well as ROC curve analysis, showed that the logistic regression model performs more accurately and provides a more appropriate estimate than the WLC model in identifying and predicting high-risk areas. Our findings suggest that for the spatial prediction of urban fires in Kashan, the data-driven complexity of LR (AUC=0.95) provided superior predictive accuracy compared to the expert-driven simplicity of WLC (AUC=0.74). While the WLC/AHP method offers high interpretability in the weighting phase, its predictive performance was significantly weaker. Conversely, LR, while more complex statistically, provided the most accurate estimation of the spatial risk distribution, as validated by the ROC index. Pan et al. also confirmed the validity of logistic models by studying forest fire occurrence and risk zoning in Shanxi Province, China (2002–2012). They achieved a forest fire risk zoning map at the provincial level using GIS to build a spatial logistic forest fire risk model based on historical fire locations and influencing factors. The resulting spatially sampled logistic model showed a good fit with the actual fire distribution and its causal factors ($p < 0.05$) (2016).

Finally, in this study, the logistic regression model was calibrated and validated using all fire incidents from 2014 to 2023 without a temporal split. Although this approach strengthened spatial estimation, it may introduce optimistic bias because the same dataset is used for training and validation. Future work should implement temporal cross validation or progressive annual hold out techniques to ensure less biased and more generalizable model evaluation. The validated fire risk maps derived from this research have direct practical utility for the Fire organization and Safety Services of Kashan Municipality. These maps delineate areas requiring intensified surveillance and proactive intervention planning. Furthermore, these maps provide new insight into the spatial relationship between human-induced hazards and environmental pollution, revealing how fire prone urban fabrics also act as potential hotspots for pollutant generation and dispersion.

Policy makers and urban planners can therefore employ these spatial products as dual purpose tools both for mitigating fire hazards and for reducing anthropogenic pollution impacts. Integrating dynamic parameters such as road network topology, station service capacity, and temporal variation of fire risk can further enhance the transition from static fire hazard mapping toward a dynamic model of urban environmental resilience. Future research should aim to couple fire risk models with urban air quality and atmospheric dispersion models to quantify the added environmental burden from recurrent fire incidents. Incorporating such interdisciplinary interaction will deepen the understanding of how human-induced fires contribute to anthropogenic pollution cycles within rapidly urbanizing environments.

5. Conclusion

This study provides a crucial methodological benchmark by rigorously comparing the predictive performance of a data-driven statistical model (Logistic Regression) against an expert knowledge driven approach (WLC/AHP) using robust validation metrics (AUC-ROC) for the first time across the entire urban area of Kashan. This comparison offers a validated framework for urban risk assessment in similar contexts that suggests that where historical incident data are robust, statistical models offer greater predictive power than purely subjective weighting methods.

The quantitative results from the logistic regression model provided clear, statistically significant priorities for mitigation. Specifically, the high correlation coefficients assigned by the LR model to Commercial Warehouse areas and Population Density provide a statistically robust confirmation that risk is not merely a function of distance to infrastructure, but is fundamentally linked to specific land use intensity and urban form characteristics. This refines the theoretical understanding of what drives fire risk compared to previous studies focusing solely on accessibility metrics. This result directly informs local policymakers in Kashan that risk mitigation efforts must move from spatially static factors (e.g., distance to station) towards dynamically prioritized variables identified by data- driven models, specifically emphasizing the enhanced safety protocols for commercial warehouse zones and population density risks. The use of such models in municipal management systems plays an effective role in promoting urban safety and optimizing preventive measures against fire.

In fact, a validated model serves as a deployable spatial planning tool. Unlike generalized risk indices, the resulting risk map (derived from the LR model) provides urban managers with a high- resolution probabilistic assessment and allows for optimal spatial allocation of limited emergency resources, which will directly contribute to the operational science of emergency management. In addition, integrating fire risk assessment into urban environmental policy and land use planning can contribute to pollution mitigation, improved air quality management, and the creation of cleaner, safer cities. The approach presented here establishes a spatially explicit framework for linking hazard mitigation and sustainable urban policy, a necessary step toward understanding and managing the intertwined challenges of urbanization, safety, and environmental health.

Based on the findings of this study, several recommendations are proposed for fire organization managers, urban planners, and future researchers:

For managers and planners:

-Since commercial and warehouse land uses have the highest positive coefficient in the model, the main focus should be on managing this sector. It is recommended that the enforcement of city safety codes for all industrial, workshop, and warehouse land uses be made mandatory and closely monitored. This includes strict control of heat sources and management of material and goods storage (reducing fire load) and considering separate and active fire stations to minimize the potential destruction after a fire incident.

-According to the output map from the WLC model and logistic regression, population density has been identified as the second-strongest risk driver. Considering the extensive old and densely populated texture in the city center (Districts 1 and 2) and the challenges of round-the-clock accessibility, it is essential to establish a new fire station in the city center. This action directly and positively affects the “distance from the station” factor, reducing the fire truck response time to the standard of less than five minutes and effectively mitigating the risk associated with high population density.

-To control long-term risk, the dispersion of factories and workshops should be prevented. It is recommended that specific locations be designated as industrial parks outside the urban boundary. This measure is related to the spatial management of risks associated with industrial and workshop areas and prevents the uncontrolled increase of risk within the urban fabric.

For researchers:

-Develop rolling-update risk maps that integrate recent incident data and urban growth.

-Extend the model to dynamic factors such as climate change, air dispersion, and spatial distribution of building materials, electricity/gas bifurcations, and urban safety infrastructure.

-Incorporate time as a factor using spatiotemporal models (e.g., Geographically Weighted Regression, spatiotemporal LR) to capture changes in risk over time and across locations.

-Sensitivity Analysis on AHP Weights: Applying Monte Carlo Simulation to the input weights derived from the AHP method used in the WLC model.

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-Incorporating real world constraints such as road network topology, dynamic traffic flow models, and station service capacity metrics as parameters affecting fire risk reduction.

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Authors Contribution

Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Data Curation, Writing- Original draft preparation were performed by Mohammad Amin Vakil alRoaya; Conceptualization, Project administration, Writing- Original draft preparation, and Reviewing were performed by Saeed Malmasi and Supervision, Validation and Editing were performed by Mojgan Zaeimdar and Mahnaz Mirza Ebrahim Tahrani. All authors read and approved the final manuscript.

Availability of data and materials

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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