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Advancements in Wildfire Detection and Prediction: An In-Depth Review

Reem SALMAN, Ali KAROUNI, Elias RACHID, Nizar HAMADEH

Abstract: ***Wildfires pose a significant hazard, endangering lives, causing extensive damage to both rural and urban areas, causing severe harm for forest ecosystems, and further worsening the atmospheric conditions and the global warming crisis. Electronic bibliographic databased were searched in accordance with PRISMA guidelines. Detected items were screened on abstract and title level, then on full-text level against inclusion criteria. Data and information were then abstracted into a matrix and analyzed and synthesized narratively. Information was classified into 2 main categories- GIS-based applications, GIS-based machine learning (ML) applications. Thirty articles published between 2004 and 2023 were reviewed, summarizing the technologies utilized in forest fire prediction along with comprehensive analysis (surveys) of their techniques employed for this application. Triangulation was performed with experts in GIS and disaster risk management to further analyze the findings. Discussion includes assessing the strengths and limitations of fire prediction systems based on different methods, intended to contribute to future research projects targeted at enhancing the development of early warning fire systems. With advancements made in technologies, the methods with which wildfire disasters are detected have become more efficient by integrating ML Techniques with GIS.***

Keywords: ***Wildfire, Detection, Prediction, Machine Learning, GIS***

I. INTRODUCTION

Forests are one of the main natural resources acting as critical component in maintaining global ecological balance and ensuring the sustainability of human civilization. Forests cover 31% of the global land surface and are of great importance in the wildland ecosystem [1]. One of the primary challenges to forest preservation is fire, which results in significant monetary and ecological damages as well as fatalities. Every year, forests covering millions of hectares are burnt globally, even though there has been a lot of effort and money put into monitoring and controlling forest fires. Moreover, climate change contributes to increased frequency and intensity of wildfires.

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******Correspondence Author(s)*
Reem SALMAN, Lebanese University, EDST, Lebanon, Beirut. E-mail: reemsalman93@hotmail.com, ORCID ID: 0000-0002-1499-7214
Ali KAROUNI, Lebanese University Faculty of Technology, Lebanon, Saida. E-mail: ali.karouni@gmail.com, ORCID ID: 0000-0002-5052-8773
Elias RACHID, Saint-Joseph University, Ecole Supérieure D'ingénieurs de Beyrouth, Lebanon, Beirut. E-mail: elia.rachid@usj.edu.lb, ORCID ID: 0000-0002-1302-1922
Nizar HAMADEH*, Lebanese University Faculty of Technology, Lebanon, Saida. E-mail: nizar.hemadeh@ul.edu.lb, ORCID ID: 0009-0009-3071-3929

Most wildfires occur under dry circumstances, usually during drought and amid fierce winds. Forests are often remote, unmanaged places with trees, dried wood, and leaves that serve as a fuel source for forest fires, causing a hazard. These elements combine to create a highly flammable substance that provides the idea environment for the initial ignition of the fire and serves as fuel for the fire spread. Failing to suppress fires before they get out of control makes the task of containing wildfires a more challenging and lengthy process [2]. It is anticipated that the ecosystem's fire control tactics would benefit from the development of models for forecasting.

The Mediterranean area is known for its extremely diversified natural vegetation, which protects many species of plants and animals that are endangered [3,4]. Additionally, one of the most significant foundations of bio-economic life in the Mediterranean basin countries is forests [5, 6]. In light of the Mediterranean region's environmental changes, forest fires have emerged as a significant and predominant factor responsible for the substantial degradation of vast forested areas.

This calls for a need to accurately assess burnt areas as they relate to greenhouse gas emissions into the atmosphere as well as for managing post-fire environmental impacts, such as regeneration and erosion [7].

The combination of several factors like fuels compositions, ignition sources, topography and weather conditions lead to Wildfires [8]. The Wildfire growth process is affected by the terrain mosaic such as, spread rate, frequency and fire ignition, energy released and intensity [9]. In order to, proactively address wildfire hazards, a significant challenge possessed in terms of modelling and simulation. That is, improving forest management plans and silvicultural practices to create resilient landscapes and minimizing damages. [10–11]. Also, It has been shown that environmental factors and the likelihood of forest fires are strongly correlated such as dry and hot conditions in addition to anthropogenic activities.

Furthermore, innovations in wildfire management have predominantly centered around advances in operational research methodologies. Limited experience to take the potential advantages of ML or deep learning techniques to enhance decision support in wildfire management. (e.g., [9,12][46][47][48]). This served as a motivation for conducting a comprehensive review of ML techniques and their potential applications. It aims to provide insights into how these methods can be leveraged to tackle the complexity in a holistic approach to fire management.

This review seeks to establish a scope of the most applications for wildfire prediction and management, covering the last 18 years of publications (from 2004 to the present). The following is what this review aims to provide:

- A summary of applications developed in the mentioned studies;
- A classification based on the analyzed attributes is as follow: (Author's name, place of study, ML technique employed, and model performance metrics).

By examining detected methods' strengths and limitations, the discussion aims to highlight the most appropriate technology to build a reliable spatial prediction and detection of potential forest fire hazard areas.

II. SYSTEMATIC REVIEW METHODOLOGY

A. Search Strategy

The review was built utilizing mainly Pubmed, with additional sources retrieved through Google Scholar and triangulation with experts from the Lebanese Red Cross, from articles previously utilized in operational products by technical leads. Three main search areas were included in the search strategy including corresponding key terms for: wildfire, detection and prediction, with particular focus on tools/ methods utilized, such as ML and GIS.

B. Eligibility Criteria

The following criteria were employed in the selection of the database search outcomes: (i) classifying the document type as a scholary research article or review article; (ii) a title and abstract that are appropriately aligned with the work's objective; (iii) thorough analysis to determine its technical significance.

C. Data Collection Results

The results of each filtering stage within the systematic review methodology are presented numerically in Figure 1. The initial search encompassed 3462 articles while the final stage, which included documents meeting the eligibility criteria for this review, consist of 30 articles.

D. Timing

There are no specific time-bound constraints imposed; nonetheless, due to the innovative nature of the subject matter, the included relevant materials lie within the period spanning from the year 2004 to the present day.

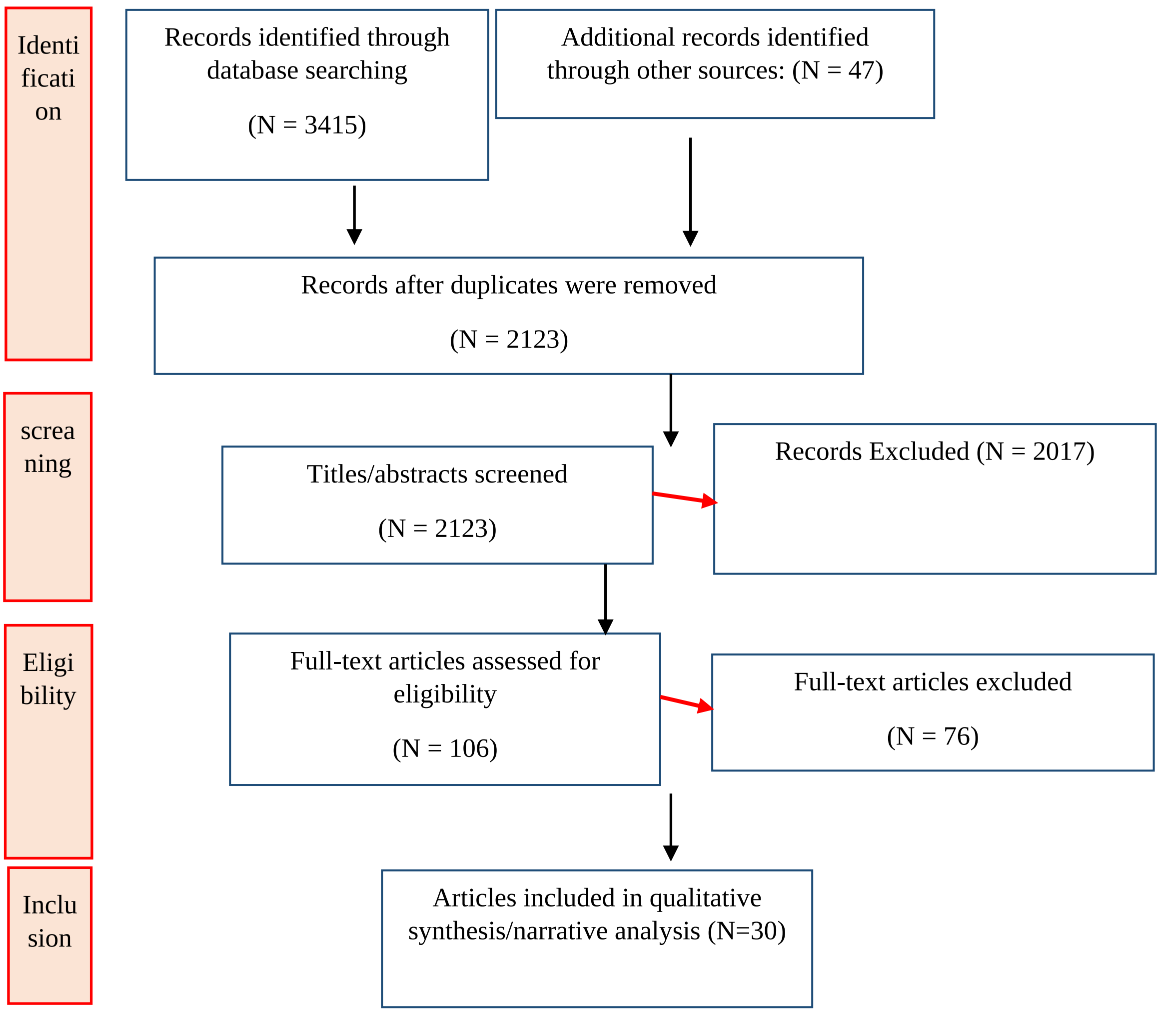

Figure 1: PRISMA Diagram

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III. RESULTS

The applications are classified into two main categories: GIS-based, and ML integrated with GIS. Thirty articles published between 2004 and 2023 were included in this review. Fifteen of them utilize remote sensing and GIS technology to analyze various parameters and develop forest fire risk models with employment of different statistical tools. Fifteen other studies employ GIS-based/ ML techniques to generate accurate flame propagation maps and predict fire spread in different areas. The included articles are sourced from various geographical areas, encompassing Asia, Europe, North America, and Africa, reflecting low, middle, and high-income countries. In Table 1, we provide a summary of the application, author's name, case study location, the utilized ML method, parameters and model performance metrics for articles that thoroughly explain the ML methodology employed. This summary aims to assist in discussing the findings and facilitate further references, particularly for applications where ML methods were adopted.

A. GIS-Based – Applications

The studies in this article included to some extent both GIS technology as well as remote sensing techniques. Remote sensing has a lot of applications in fire science, particularly associated with fuel load and moisture content, creating fire risk maps, detecting fires, determining rate of spread and assessing burn severity.

In [13], used GIS and remote sensing as well as statistical tools for developing forest fires risk map in two major landscapes TAL and CHAL in Nepal.

In [14], aimed to assess the impact of fire and identify fire risk areas in Amos ancient city/Marmaris Turkey using GIS and remote sensing methods, specifically the NBR and dNBR indices. However, the limitations of the study included the lack of data on the borders of the Amos ancient city, which led to the calculation of fire risk zones by measuring the buffer from a point.

In [15], aimed to assess the effect of fire and identify fire risk areas in Bizerte region, Tunisia using GIS and remote sensing methods, specifically the NBR indices.

In [16], tended to develop a risk model for fire spreading using a combination of remote sensing and GIS data in Mediterranean countries. A map of vegetation and land use was prepared using Landsat TM data, with classification accuracy results 90.26 and 93.75 respectively.

In [17], produced risk map using GIS in in the Geyve district of Sakarya province, Turkey indicating the varying levels of fire risk in different regions of the district based on five factors. The results showed that 29.97% of the southern slopes of the land highly increase the forest fire risk. Additionally, high-risk areas are within 400m from the road and 4000m from the settlements, which increases the importance of proximity to road and settlements as a mapping factors.

In [18], focused on assessing the anthropogenic factors on forest fires in the Nahr Ibrahim watershed in Lebanon. The integration of human factors resulted in an increase in high-risk zones and a decrease in low-risk zones.

The most common methods used in fire probability modeling are multicriteria decision analysis. Several studies included factors, such as vegetation, topography, weather, and anthropogenic factors, and weights were assigned by pairwise comparisons, based on either relative literature or expert opinions [19]. A similar approach for weight assignment was employed by Mazzeo [19] in Italy using MCDS, and Lamat [20] in India using MCDM with AHP to compare the parameters. Additionally, Majlingová [21] in Slovakia used MCDA, and Pourghasemi [22] in Golestan Province, Iran used Mamdani fuzzy logic (MFL) and modified-AHP models with AUC's 88.20% and 77.72%, respectively. Also, Semeraro [23] in Apulia Region, southern Italy used multi-criteria analysis based on Fuzzy expert system (FES).

In [24], fire-prone areas were identified in Harenna forest using remote sensing and GIS techniques along with MCDM. A fire susceptibility map was created, categorizing the forest into four levels of risk: very high risk, high risk, moderate risk, and low risk .

In [25], showed that enhanced accuracy could be achieved through the integration of GIS, Weights of Evidence (WOE) method and AHP. They noticed that the most fire-prone regions were found in forests with an NDVI exceeding 0.3 and at elevations higher than 600 meters in the Huichang County, China.

In [26], aimed to assess and compare the performance of the frequency ratio (FR) and AHP methods in mapping forest fire vulnerability in the Al-Draikich region of western Syria. Compared to the AHP approach, that achieved an AUC value of 0.838, the FR method had a greater accuracy, with a value of 0.864.

In [27], compared the bivariate Dempster-Shafer-based evidential belief function (EBF) model and the multivariate logistic regression (LR) model for mapping wildfire probability in the Zagros ecoregion, Iran. In comparison to the EBF model, the LR model offered a more precise forecast for future fires and their spatial distributions. However, the LR model assumes a linear relationship between variables and the likelihood of fire occurrence, which may not capture the complex nature of natural hazards, whereas the EBF model assigns equal weights for all variables and doesn't prioritize their significance.

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Table 1. Results: GIS-Based – Applications

Nb	Author's Name, Year	Case Study Location	Method used	Parameters	Performance Metrics
13	Parajuli et al., 2020	TAL and CHAL landscapes in Nepal	GIS and remote sensing and statistical tools	8 factors (aspect, slope, vegetation, proximity to roads and settlements, topographic factors, land surface and temperature)	Forest Fire Risk Map was created, indicating 65.4% of TAL falls under a high fire risk zone; whereas, only 21.54% in CHAL. In Nepal, April is the month when forests are most vulnerable to wildfires.
14	Tükel et al., 2022	Amos ancient city/ Marmaris Turkey	GIS and Remote Sensing / using NBR and dNBR as indices	Creation of fire risk classes by assessing fire affected areas using NBR & dNBR as indices. Areas were evaluated by applying three different buffer zones (500m, 1 kilometer, and 2 kilometer) to the unburn and burn areas	The results showed that the area with high and severe burn areas was close to the Amos ancient city in Marmaris
15	Saidi et al,.2021	Bizerte region, Tunisia	GIS and remote sensing / using NBR	Topo morphology index, Climatic index, Human index	Sensitivity analyses showed that human activities and climatic conditions play a crucial role in triggering wildfires
16	Erten et al., 2004	Gallipoli Peninsula	GIS and Remote sensing	9 factors (topography, vegetation, land use, population, fire stations, intervention places, settlements, forest fire towers, and transportation)	A vegetation map and land use was developed using Landsat TM data, and the classification accuracy results were 93.75 and 90.26
17	Güvendi et al.,2022	Geyve district of Sakarya province, Turkey	GIS and Remote Sensing	5 factors (Forest type, aspect, slope, road distance, and proximity to settlements)	The forest fire risk map showed that 0.05% was high risk, 9.03% was risky, 38.85% was medium risk, 48.45% was low risk and 3.62% was risk-free region. As for tree species, the places where Red Pine, as well as those with steep slopes, southern slopes, and closer proximity to roads and settlements were identified as higher risk areas
18	A.Assaker, 2012	Nahr Ibrahim watershed in Lebanon	GIS and Remote Sensing	6 factors (natural factors: climate, vegetation, topography anthropogenic factors: urban settlements, proximity to roads, agriculture)	The results show that anthropogenic factors enhance the probability of forest fire in high-risk areas and moderate risk areas by 5% to 38% and 7% to 25% respectively. While areas with low risk declined by 50% and nearly vanished in extremely low risk areas.
19	Mazzeo et al.,2022	Italian territory	GIS and Remote Sensing	Satellite data/products, land cover, NDVI for fuel moisture, due point temperature, fire identification images; temperature, wind, slope and aspect.	Classified Forest Fire Risk Map
20	Lamat et al., 2021	Maghalaya, India	GIS based / MCDM method for mapping and AHP to compare the selected parameters	8 factors (slope, aspect, elevation, population density, land use/land cover (LULC), wind speed, temperature, and rainfall)	32.86%, of the study area having high fire susceptibility, followed by 27.39% for high risk, 15.93% for moderate risk, and 15.93% for low risk
21	Majlingová et al., 2015	Slovakia, Slovensky raj Mts. territory	GIS / MCDA method	14 factor (terrain landforms, slope, aspect, tree species composition factor, stand age, forest health condition, damaged forest stands, fuel, urban settlements, proximity to roads, fruit collection, harvesting factors, silvicultural activities, tourism factorand recreation)	when considering the natural factors, forest fuel and geographical factors are the most cricial

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22	Pourghasemi et al., 2016	Golestan Province, Iran	GIS / Mamdani fuzzy logic (MFL) models and modified analytical hierarchy process (M-AHP)	Topography, distance to roads, water bodies and settlements, land cover.	The findings showed that the MFL model outperformed the M-AHP model with AUC's 88.20% and 77.72%, respectively.
23	Teodoro Semeraro,	Torre Guaceto (Apulia Region, southern Italy)	GIS / MCDA method with fuzzy system	-	The GIS fuzzy expert system efficiently manage natural protected areas and assist in decision-making
24	Venkata and Suryabhagavan,2016	Harenna forest, Ethiopia	remote sensing and GIS techniques, along with multi-criteria decision analysis	6 factors (elevation, aspect, slope, vegetation type, proximity to settlements and roads)	The extent of forest cover at very high risk was 22,981 ha (3.4%), while high-risk areas covered 1,59,229 ha (24%)
25	Hong et al., 2019	Huichang County, China	GIS / integrated WOE-AHP model	9 factors (land use and proximity to rivers, roads and human settlements, slope, annual rain, elevation, NDVI, wind speed)	Areas that are most prone to fire were found in forests with NDVI exceeds 0.3 and at elevations higher than 600m. Where AUC success rate = 0.94 and AUC prediction rate = 0.91
26	Ghassan et al.,2022	Draikich/ western region of Syria	GIS / frequency ratio (FR) and analytic hierarchy process (AHP)	13 factor (slope, aspect, curvature, elevation, NDVI, NDMI, topographic wetness index (TWI), wind speed, rainfall, temperature, proximity to settlements, roads and rivers)	The FR method achieved a higher accuracy with an area under the curve (AUC) of 0.864, compared to the AHP method which had an AUC of 0.838
27	Abolfazl et al., 2019	Zagros ecoregion, Western Iran	GIS / EBF and LR models	12 factor (altitude, , slope degree, aspect, TWI, annual temperature, wind effect, rainfall, land use, NDVI, and distance to roads, rivers, and urban areas)	The results showed that, the EBF model had an AUC of 0.701 and the LR model had an AUC of 0.728. However, the ensemble modeling approach improved the predictive accuracy with an AUC of 0.864

B. GIS Based – Machine Learning Applications

ML methods have emerged globally over the last decades as alternative approaches for complex problems and critical decision making especially in the domain of disaster risk reduction, as is the case with wildfire prediction and management. Hereby, we examine the contributions and outcomes of several studies on wildfire vulnerability modeling as identified in the analysis of the review findings.

In [28], developed an evolutionary optimized gradient boosted decision tree (EO-GBDT) for susceptibility fire mapping. The suggested outperformed 8 other models including RF, SVM and ANN in terms of performance with the highest accuracy.

In [29], implemented ANN, RF and SVM for forecasting wildfire susceptibility with the RF model achieving the best performance.

In [30], three methods were employed for multi-hazard modeling in Chaharmahal and Bakhtiari Province, Iran: support vector machine (SVM), generalized linear model (GLM), and functional discriminant analysis including landslides, floods, wildfires, and land subsidence and snow avalanches. GLM produced the best results for predicting wildfires risk, followed by the others.

In [31], three approaches were used to map fire susceptibility in Golestan Province, Iran: the general additive model (GAM), the multivariate adaptive regression spline (MARS), the support vector machine (SVM), in addition to the ensemble GAM-MARS-SVM. SVM was shown to be the least accurate approach out of these, and the ensemble had the best predicted accuracy.

In [32], five hybrid ML algorithms were employed to model forest fire susceptibility in Morocco by integrating frequency ratio (FR) with various ML models: FR-MLP, FR-LR, FR-SVM, FR and Classification and Regression Tree (FR-CART), and FR-RF. Each of these algorithms performed very high predictive accuracy, especially the FR algorithm.

In [33], assessed a thorough wildfire susceptibility study in Amol County, Iran using several statistical and ML models such as NN, RF,SVM, decision tree, radial basis function, least angle regression and logistic regression. According to the accuracy evaluation, RF indicated the highest accuracy in wildfire prediction with an AUC of 88%, followed by SVM with 79% AUC.

In [34], applied Logistic Regression (LR) and ANN to estimate the probability of wildfires in Italy. High classification accuracy achieved by 0.68 for the subalpine and alpine region and 0.76 for the peninsular and insular region. Also, the study assessed that the most important factor in the Insular and peninsular region was the climate, while the presence of forest in the Alpine and subalpine region.

In [35], attempted to enhance existing models by integrating GIS, the weather prediction model - Aladin and MODIS satellite data using various data mining techniques for three datasets for several areas of Slovenia: Kras, Primorska and continental Slovenia. The experimental findings showed that bagging of decision trees outperforms other methods for the three different areas in terms of predicted accuracy, kappa statistics and precision.

In [36], aimed to assess and map the forest fire vulnerability zones in Uttarakhand, India using GIS-based with five distinct ML techniques i.e. ANN, RF, LR, SVM, and ensemble using 13 factors.

The results showed that the ensemble ML achieved the highest accuracy of value AUC=0.977, followed by the RF of value AUC=0.973 and ANN of value AUC=0.972. The contribution of all the parameters aids in understanding the influence of each parameter for forest fire susceptibility such as, temperature, aspect and distance to religious centers had less influence than other factors. Additionally, it provided new perspectives on how to build ML model integrated with DNN for scientific modeling.

In [37], the evidential belief function (EBF) method was applied to map the vulnerability of wildfires in the Hyrcanian ecoregion, northern Iran using 14 predicting factors and 1162 wildfire points. The results showed that the GIS-based EBF model was effective in predicting the probability of wildfires achieving an AUC value 84.14 %.

In terms of non-comparative works, Vacchiano [38] had implemented maximum entropy (MaxEnt) method in Aosta Valley in the Italian Alps with fire ignition data of a 15-year period, and reported competitive AUC scores ranging from 0.90 to 0.95.

In [39], utilized a Deep Learning model for assessing wildfire risk and susceptibility in Sydney, Australia's Northern beaches. The model incorporated 36 essential factors in assessing wildfires risk. As for the factors they were spatially mapped considering a variety of factors such as social, physical, anthropogenic factors, climate, topography and morphology that contributes in the adaptation in different regions of Australlia with minor localization requirements. The findings showed how accurately the model predicted wildfires vulnerability by achieving high precision against accuracy assessment metrics of PRC = 93.8%, ROC = 95.1%, and k coefficient = 94.3%.

In [40], introduces an ANN framework to forecast the propagation of wildfires in Heilongjiang Province, China and compares it with another model that combines cellular automata (CA) and Wang Zhengfei's model. In comparison to the combined model, the ANN model demonstrates better prediction accuracy since it considers several environmental factors and combustion factors

In [41], aimed to create forest fire susceptibility mapping (FFSM) in Chaharmahal and Bakhtiari Province, Iran using GIS and ensemble models, ANFIS-GA-SA and RBF-ICA. The ROC-AUC index was used to verify the maps. The spatial autocorrelation analysis revealed that fire occurrences in the study area is clustered with spatial dependence associated with factors such as rainfall, soil type, and settlement distance. The spatial autocorrelation analysis, failed to analyze the underlying reasons driving these relationships, however, it identified the variables with spatial dependency.

In [42], introduced a spatial forecasting model for forest fire susceptibility in Yunnan Province, China, using a Convolutional Neural Network (CNN) and historical data of prior forest fires locations from 2002 to 2010, alongside 14 factors. The findings demonstrate that the proposed CNN model outperformed benchmark classifiers such as random forests, SVM, NN, and kernel logistic regression in terms of accuracy (AUC=0.86).

Table 2. Results: *GIS Based* – Machine Learning Applications

Nb	Author's Name, Year	Case Study Location	Mthod used	Parameters	Performance Metrics
28	Sachdeva et al.,2018	Nanda Devi, India	Machine Learning / A comparative study between EO-GBDT, ANN, RF, DT, SVM, NB, LR, GBDT, PSO-SVM	18 factor (aspect, slope, elevation, plan curvature, topographic position index, TWI, NDVI, soil texture, temperature, evapotranspiration, relative humidity, rainfall, aridity index, potential wind speed, land cover and proximity to rivers, roads and habitations)	The best model is the EO-GBDT with Accuracy = 95%
29	Ghorbanzadeh et al. ,2019	Amol County, Iran	GIS based, Machine learning / ANN, SVM, RF	topographic, vegetation, meteorological, anthropological, and hydrological factors	The resulting 4-fold cross-validation (CV) accuracies for the ANN, SVM and RF, were 74%, 79% and 88%, respectively. The RF AUC = 0.88 is the best one
30	Yousefi,2020	Chaharmahal and Bakhtiari Province, Iran	GIS based Machine Learning / FDA, GLM, SVM	topographic, climatic, geological, morphological social factors	SVM is the effective in forecasting the risks of land subsidence, landslides, and flood hazards in the study area. GLM is the best algorithm for mapping wildfires with AUC = 0.837l , and FDA is the most reliable for estimating the risk of snow avalanches
31	Eskandari et al.,2021	Golestan Province, Iran	Machine Learning / GAM, MARS, SVM, ensemble GAM-MARS-SVM.	10 factors (slope angle, elevation, annual mean rainfall, annual mean temperature, wind effect, TWI, plan curvature, distance to rivers, roads, and villages)	With an AUC = 0.830 the new ensemble model is the best. Additionally, annual mean rainfall, the distance to the village, and elevation were the most crucial in predicting fire.

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32	Mohajane et al.,2021	Tanger-T´etouan-Al Hoceima region, Morocco	GIS Based Machine Learning / FR-MLP, FR-LR, FR-RF, FR-SVM, FR-CART	10 factors (slope angle, aspect, elevation, distance to roads and residential, temperature, wind speed, rainfall, Land use, and NDVI)	In the forecasting of the forest fire RF-FR performed best (AUC = 0.989), followed by SVM-FR (AUC = 0.959), MLP-FR (AUC = 0.858), CART-FR (AUC = 0.847), and LR-FR (AUC = 0.809)
33	Gholamnia,2020	Amol County, Iran	Machine Learning / ANN, dmine regression (DR) , radial basis function (RBF), DM neural, LARS, multi-layer perceptron (MLP), RF, self-organizing maps (SOM), SVM, DT	16 factor (Distance to Stream, Annual Temperature, Land use, NDVI, TWI, Slope, Aspect, Annual Rainfall, Wind Effect, Distance to settlements, Altitude, Potential Solar Radiation, distance to Road, Recreation Area, Landforms, Plan Curvature (100/m))	RF with accuracy 88% outperformed both SVM and LR models with an accuracy values 79% and 65% respectively.
34	Elia et al., 2020	Itlay	Machine Learning/ ANN and Logistic Regression	12 factor (relative humidity, maximum temperature, wind speed, land cover, tree cover percentage, settlement locations, population, distance to roads, rails, fire climatic index, elevation, and slope)	The LR model was outperformed by the ANN model with an AUC value of 0.78 for the Subalpine and Alpine region and 0.65 for the peninsular and insular region compared to AUC values of 0.82 and 0.76 respectively.
35	Stojanova et al., 2006	Slovenia	GIS based Machine learning/ logistic regression, random forests, decision trees (J48), bagging and boosting ensemble methods	9 factors (relative humidity and temperature, precipitation, sun radiation energy, wind speed, wind direction, evapotranspiration, transpiration, evaporation)	Compared to the other algorithms, Bagging of decision trees shows the best results in terms of predictive accuracy, kappa statistics and precision
36	Mohd Rihan et al., 2023	Uttarkhand/ India	GIS based Machine learning – Deep Learning (ANN,RF,LR, SVM, Ensemble ML)	13 factors listing 10 (wind speed, temperature, aspect, annual rainfall, evapotranspiration, distance to tourist spots, religious centers, agriculture, urban and roads)	The results showed the ensemble ML achieved the highest accuracy of value AUC=0.977, followed by the RF of value AUC=0.973 and ANN of value AUC=0.972
37	Nami et al., 2017	Hyrcanian ecoregion, northern Iran	GIS-based EBF model	-	The validation outcomes validated the effectiveness of the GIS-based EBF model which obtained AUC values of 84.14 and 81.03% for success and prediction rates, respectively
38	Vacchiano et al.,2018	Aosta Valley, Italy	Machine Learning / MaxEnt	10 factors (Temperature, precipitation, elevation, slope, aspect, heat load index, distance from main roads and buildings, number of enterprising with grazing animals and number of grazing domestic animals)	AUC (winter, forest) = 0.95, AUC (summer) = 0.90 AUC (winter, grasslands) = 0.94
39	Naderpour el al., 2021	Northern Beaches area in the state of NSW in Australia	GIS Based / Machine Learning -Deep Neural Network	36 factors such as (slope, aspect, NDVI, altitude, annual temperature, rainfall, humidity, and wind speed, road density, land cover, distance to roads, distance to rivers)	The results show that the developed model has high precision against accuracy assessment metrics of PRC = 93.8%, ROC = 95.1%, and k coefficient = 94.3%
40	Zechuan Wu et al., 2022	Heilongjiang Province in China	GIS Based - Artificial Neural Network	9 factors (humidity, temperature, precipitation, slope, aspect, elevation, moisture content, wind speed and wind direction)	The ANN model achieved sensitivity, average accuracy, and F-measure values of 95.26%, 85.02%, and 89.85%, respectively.
41	Seyed Vahid and Razavi-Termeh, 2020	western Zagros Mountain in Chaharmahal and Bakhtiari province, Iran	GIS based Machine learning / Adaptive neuro fuzzy interface system (ANFIS) with genetic (GA) and simulated annealing (SA) algorithms (ANFIS-GA-SA) and an ensemble of radial basis function (RBF)	10 factors (Slope angle, rainfall, distance to roads, distance to settlements, altitude, slope aspect, temperature, wind effect, soil and land use)	The results shows that ANFIS-GA-SA had an accuracy of 0.903, while the accuracy of the mapping prepared using RBF- ICA model was 0.878
42	Guoli Zhang et al., 2019	Yunnan Province, China	GIS based / Machine Learning Convolutional Neural Network	11 factor (Forest coverage ratio, Aspect, Slope, NDVI, Elevation, Precipitation, Distance to rivers and roads, Surface roughness, Temperature, Wind speed)	Area under curve = 0.86

IV. DISCUSSION

This review highlights that there is an obvious potential for adopting ML methods for forecasting and classification. In the literature, it is observed that researchers and decision-makers rely on ML methods to evaluate and spatially map wildfire susceptibility; However, the model outcomes such as the interpretation and the explanation should be explained very well. Numerous statistical and ML approaches for spatially explicit wildfire probability prediction have been developed as a result of enhanced knowledge of GIS and data-processing tools [25, 27]. It is challenging to determine the most suitable modeling approach for predicting wildfire probability. Despite efforts to assess the predictive capabilities for the different models, there remains a lack of guidance on the most effective model for forecasting the spatial pattern of wildfires across different terrains. LR was preferred by different researchers [27, 45]. Several other researchers have produced probability maps using different techniques including SVM, random forest, ANN, ANFIS, WOE, frequency ratio, evidential belief function, index of entropy, and analytic hierarchy process [43][44].

While these models have effectively forecast wildfire probabilities, they do have certain drawbacks. ANN, SVM, and ANFIS are three examples of automated techniques that are not reliable since modelers must manually adjust the parameters through a time-consuming trial and error procedure [25,27]. The real relationships between wildfires and their causes are obscured by statistical and probabilistic models because they are so sensitive to the input data [27]. Due to biased expert opinions by viewing some factors as more important or vulnerable than others, according to their experience in the field of forest fire, AHP and other analytic methods have become more subjective.

Each method exhibits differences in the input processes, computations, and predictive precision. Decision makers involved in fire management and planning continue to struggle with un-reluctantly selecting the most suitable approach for various environmental settings, even though great efforts to pinpoint fire-prone areas using these methods and several comparative studies aimed to identify the most appropriate for predicting future fire [37].

In the literature, extensive research has been conducted on Multi criteria decision analysis and statistical-based methods, which are among the commonly used GIS based models for wildfire modeling [44].

The integration of multi-criteria decision-making (MCDM) methods in GIS offers a practical framework for merging various spatial information and tackling several environmental issues, such as mapping and evaluation of fire vulnerability.

The selection of the aggregation technique, determining weights, managing linguistic variables and attributes provide several challenges, as they do in many multi-criteria decision procedures. Numerous solutions are offered in the literature to deal with these issues, but only few methods are able to resolve these issues. One such method is the FES which provides the ability to deal with fuzzy logic-supported non-linear aggregation techniques.

Moreover, the key benefit of integrating ML techniques with GIS is often a better performance in predicting wildfires and a faster data processing rate when compared to traditional methods like MCDA [27].

V. STRENGTHS

This review aids in consolidating a comprehensive research effort that encompasses various articles from diverse regions worldwide, spanning low, middle, and high-income countries, all within a single article. This approach offers a different perspective by incorporating insights from various models and references. This contributes significantly to informing decision-making processes related to forest fires for relevant stakeholders and Disaster Risk Reduction. It is especially pertinent given the heightened global attention to natural hazards, heavily influenced by climate change, which can play a pivotal role in shaping decision-making approaches.

VI. LIMITATIONS

The primary limitations are that the studies did not provide information about the computational time required for the modelling process, an important aspect for assessing models' applicability in some critical fields as disaster management for decision making. Also, there are still few datasets for extensive wildfires, and the majority of models are constructed using smaller wildfire incidents for training, which may not accurately capture the conditions of extreme wildfire events. Studies focus on a specific region, thus their results may not be easily applicable to other regions with different socio-economic and environmental conditions. Most papers do not discuss the potential impact of climate change or future scenarios on forest fire susceptibility, which could be important factors to consider for long-term forest management strategies. Even though this review provides a holistic understanding of the breadth of applications utilized in fire detection and prediction, questions remain on the implementation across various settings which are not covered in-depth in the literature, and ways to overcome highlighted limitations.

VII. CONCLUSION

This study was based on a base set of 30 articles that explored various methods for forecasting and identifying wildfires. The integration of GIS, fieldwork, Remote Sensing data, and statistical methods can build reliable spatial prediction for potential forest fire hazard zones across various geographical areas by choosing a reliable environmental data that may feed in fire prediction. Limitations of tools presented are also highlighted in this study, calling for contextualization of implementation in various contexts. Moreover, continuous enhancement is essential, especially when aiming for faster models and better understanding of the results which still a critical factor in ML based models. Finally, there is a need to bridge the gaps between monitoring, learning, and decision-making process.

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AUTHORS PROFILE

Reem Salman, Engineer, received her MS Diploma in the Computer and Telecommunication Engineering Department at Lebanese International University. Currently, she is a doctoral student at the Lebanese University. Reem is an expert researcher at the Disaster Risk Reduction Unit at the Lebanese Red Cross, and she has a keen interest in utilizing Machine Learning and GIS methods to mitigate environmental disasters in Lebanon and Mediterranean.

Ali Karouni received his degree in electrical and electronics engineering from the Faculty of Engineering, Lebanese University in 2009. He also received his master degree in industrial control from the Ecole Doctorale des Sciences et de Technologie (EDST)-Lebanese University in collaboration with Université de Technologie de Compiegne-France in 2010. He then was granted a diploma of master in renewable energies from Saint Joseph University-Faculty of Engineering ESIB-Lebanon in collaboration with EDST-Lebanese University. In 2014, he obtained his PhD in Engineering Sciences - Informatique et Applications- from the Université d'Angers-France collaborated with EDST-Lebanese University. Currently, he is an assistant professor at the Faculty of Technology, Lebanese University. His research interests include data mining, multi-agent systems, pattern recognition, decision theory, optimization and cooperative intelligent systems.

Elias A. Rachid: was born in Lebanon, in 1966. He received the M.S. degree in telecommunications engineering from the University of Saint-Joseph (USJ) (Ecole Supérieure d'Ingénieurs de Beyrouth ESIB), Beirut, Lebanon, in 1990, and the Ph.D. degree in electronics and signal processing (microwave) from University Marnes La Vallée, Paris, and the National Institute of Telecom Evry, France, in 2004. He joined the ESIB, in 1990, where he is a Full Professor and the Director of the CINET Center of Electrical and Telecommunications Industries (CINET), ESIB, Université Saint-Joseph

Nizar Hamadeh, obtained his Ph.D. in computer engineering from the University of Angers, France. In 2021, he was awarded the highest international degree (HDR) in machine learning from the Lebanese University. His research interests lie in Machine Learning and Artificial Intelligence. Currently, he holds the position of an associate professor at the Faculty of Technology, Lebanese University. His research encompasses areas such as data mining, multi-agent systems, pattern recognition, decision theory, optimization, and cooperative intelligent systems.