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

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***Abstract:** Wildfires pose a significant hazard, endangering lives, causing extensive damage to both rural and urban areas, causing severe harm to forest ecosystems, and further worsening the atmospheric conditions and the global warming crisis. PRISMA guidelines searched electronic bibliographic databases. Detected items were screened at the abstract and title levels, followed by full-text screening against the inclusion criteria. Data and information were then abstracted into a matrix and analysed and synthesised narratively. Information was classified into two main categories: GIS-based applications and GIS-based machine learning (ML) applications. Thirty articles published between 2004 and 2023 were reviewed, summarising the technologies used in forest fire prediction along with comprehensive analyses (surveys) of the techniques employed for this application. Triangulation was performed with experts in GIS and disaster risk management to analyse the findings further. The discussion involves assessing the strengths and limitations of fire prediction systems based on various methods, to contribute to future research projects that aim to enhance 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 primary natural resources, acting as a critical component in maintaining global ecological balance and ensuring the sustainability of human civilisation. 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 burned globally, despite considerable effort and investment in monitoring and controlling forest fires. Moreover, climate change contributes to the increased frequency and intensity of wildfires. Most wildfires occur under dry conditions, typically during droughts and in the presence of fierce winds. Forests are often remote, unmanaged areas with trees, dried wood, and leaves that serve as a fuel source for forest fires, posing a significant hazard. These elements combine to create a highly flammable substance that provides the ideal 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 forecasting models.

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 environmental changes in the Mediterranean region, forest fires have become a significant and predominant factor contributing to 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 fuel compositions, ignition sources, topography and weather conditions leads to Wildfires [8]. The Wildfire growth process is affected by the terrain mosaic, such as spread rate, frequency, fire ignition, energy released and intensity [9]. To proactively address wildfire hazards, a significant challenge is posed in terms of modelling and simulation. That is, improving forest management plans and silvicultural practices to create resilient landscapes and minimise damage. [10–11]. Additionally, it has been shown that environmental factors and the likelihood of forest fires are strongly correlated, including dry and hot conditions, as well as anthropogenic activities.

Furthermore, innovations in wildfire management have primarily focused on advancements 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]). 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.

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This review aims to establish the scope of wildfire prediction and management applications, 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 analysed attributes is as follows: (Author's name, place of study, ML technique employed, and model performance metrics).

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

II. SYSTEMATIC REVIEW METHODOLOGY

A. Search Strategy

The review was built primarily using PubMed, with additional sources retrieved through Google Scholar and triangulated with experts from the Lebanese Red Cross, as well as articles previously utilised 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 utilised, 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 scholarly 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 yielded 3,462 articles, while the final stage, which included documents meeting the eligibility criteria for this review, comprised 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 span the period from 2004 to the present day.

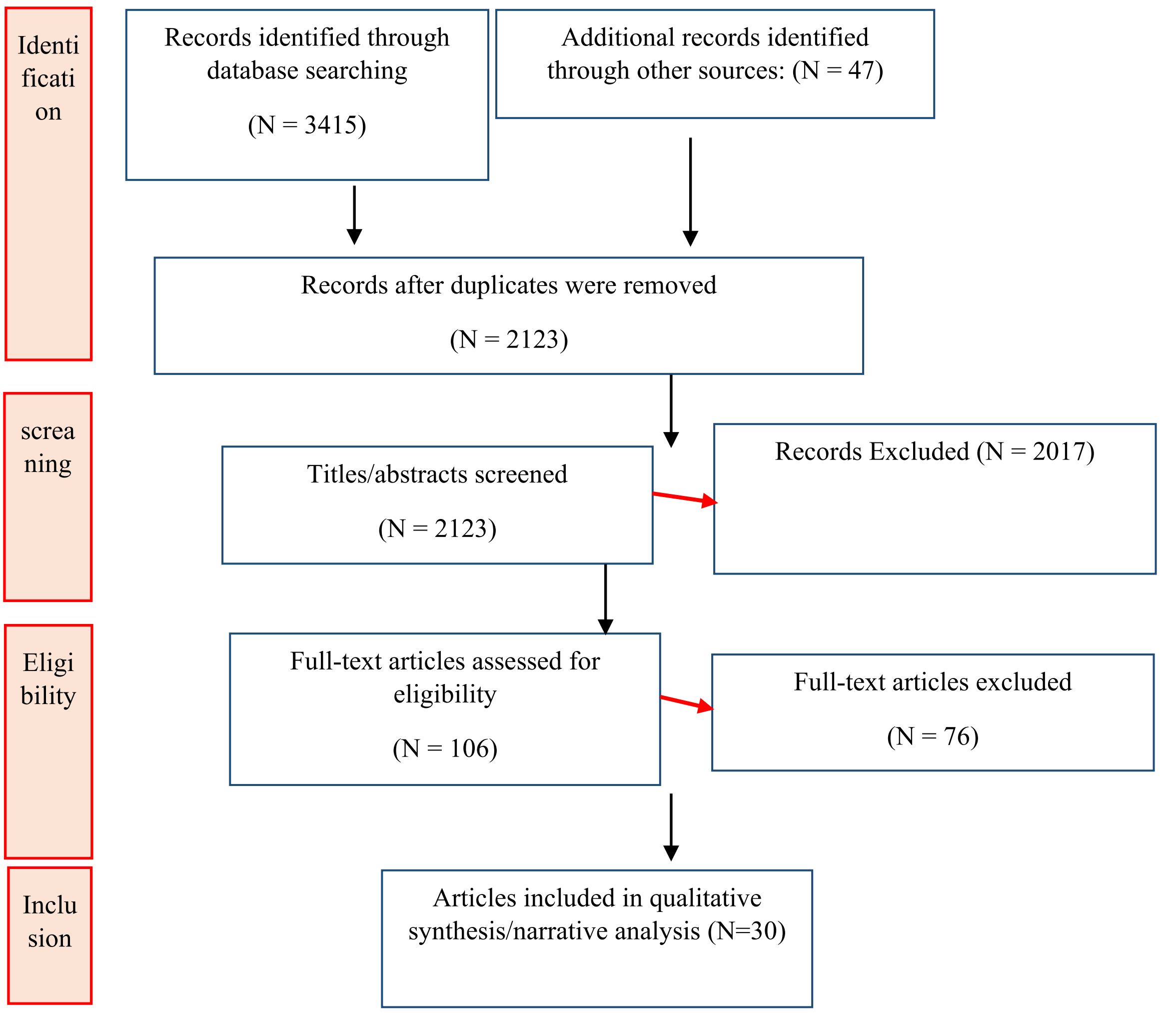

Figure 1: PRISMA Diagram

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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 utilise remote sensing and GIS technology to analyse various parameters and develop forest fire risk models, employing 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 regions, encompassing Asia, Europe, North America, and Africa, reflecting countries with low, middle, and high incomes. In Table 1, we provide a summary of the application, the author's name, the case study location, the utilised 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, to some extent, incorporated both GIS technology and remote sensing techniques. Remote sensing has numerous applications in fire science, particularly in determining fuel load and moisture content, creating fire risk maps, detecting fires, assessing the rate of spread, and evaluating burn severity.

In [13], used GIS and remote sensing as well as statistical tools for developing forest fires risk map in two significant 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 study's limitations included the lack of data on the borders of the ancient city of Amos, which led to the calculation of fire risk zones by measuring the buffer from a single 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 of 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 have a high risk of forest fires. Additionally, high-risk areas are within 400m of the road and 4000m of the settlements, which increases the importance of proximity to roads and settlements as a mapping factor.

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]. Mazzeo employed a similar approach for weight assignment [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, categorising 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, the 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 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, which achieved an AUC value of 0.838, the FR method showed 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. In contrast, the EBF model assigns equal weights to all variables and doesn't prioritise their significance.

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, remote sensing, and statistical tools	8 factors (aspect, slope, vegetation, proximity to roads and settlements, topographic factors, land surface and temperature)	A Forest Fire Risk Map was created, indicating that 65.4% of TAL falls under a high fire risk zone, whereas only 21.54% of CHAL does. 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 kilometre, and 2 kilometres) to the unburned and burned areas	The results showed that the area with high and severe burn areas was close to the ancient city of Marmaris
15	Saidi et al, of Amos, .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 were 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 indicated that 0.05% of the area was at high risk, 9.03% was at risk, 38.85% was at medium risk, 48.45% was at low risk, and 3.62% was a 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 increase the probability of forest fires 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 regions.
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 has 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 factors (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 factor, and recreation)	When considering the natural factors, forest fuel and geographical factors are the most critical

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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 AUCs of 88.20% and 77.72%, respectively.
23	Teodoro Semeraro,	Torre Guaceto (Apulia Region, southern Italy)	GIS / MCDA method with fuzzy system	-	The GIS-based fuzzy expert system efficiently manages natural protected areas and supports informed decision-making.
24	Venkata and Suryabhagav. An,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 most prone to fire were identified in forests with NDVI values exceeding 0.3 and at elevations higher than 600 meters. 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 factors (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 modelling 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 few 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 modelling 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 model outperformed eight other models, including RF, SVM, and ANN, in terms of performance, achieving 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 wildfire 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 with 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 an AUC of 79%.

In [34], applied Logistic Regression (LR) and ANN to estimate the probability of wildfires in Italy. High classification accuracy was achieved, with values of 0.68 for the subalpine and alpine regions and 0.76 for the peninsular and insular areas. Additionally, the study found that climate was the most critical factor in the Insular and peninsular areas. At the same time, the presence of forests was more significant in the Alpine and subalpine zones.

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

In [36], the authors aimed to assess and map the forest fire vulnerability zones in Uttarakhand, India, using GIS-based methods 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, with an AUC value of 0.977, followed by the RF, with a value of 0.973, and the ANN, with a value of 0.972. The contribution of all the parameters aids in understanding the influence of each parameter on forest fire susceptibility, such as temperature, aspect, and distance to religious centres, which had less impact than other factors. Additionally, it provided new perspectives on how to build an ML model integrated with a DNN for scientific modelling.

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 of 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 determining wildfire risk. As for the factors, they were spatially mapped, considering a variety of factors, such as social, physical, and anthropogenic factors, climate, topography, and morphology, that contribute to adaptation in different regions of Australia with minimal localisation requirements. The findings demonstrated the model's accuracy in predicting wildfire vulnerability, 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 for. Est 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 are clustered with spatial dependence associated with factors such as rainfall, soil type, and settlement distance. The spatial autocorrelation analysis failed to identify the underlying reasons driving these relationships; however, it did identify 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 fire locations from 2002 to 2010, alongside 14 factors [45]. The findings demonstrate that the proposed CNN model outperformed benchmark classifiers, including 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	Method 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 factors (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.al and Bakhtiari Province, Iran	GIS-based Machine Learning / FDA, GLM, SVM	topographic, climatic, geological, morphological, and social factors	SVM is 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 an AUC = 0.837, 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, distance to the village, and elevation were the most significant factors in predicting the occurrence of fires.
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 achieved an accuracy of 88%, outperforming both SVM and LR models, which achieved accuracy values of 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 AUC values of 0.78 for the Subalpine and Alpine regions and 0.65 for the peninsular and insular areas, 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., 202.3	Uttarakhand/ 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 centres, 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	The Northern Beaches area in the state of NSW, 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 Mountains 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 show that ANFIS-GA-SA had an accuracy of 0.903, while the accuracy of the mapping prepared using the ICA model was 0.878
42	Guoli Zhang et al., 2019	Yunnan Province, China	GIS-based / Machine Learning Convolutional Neural Network	11 factors (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 interpretation and explanation, should be clearly explained. 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 modelling approach for predicting wildfire probability. Despite efforts to assess the predictive capabilities of the different models, a lack of guidance remains on the most effective model for forecasting the spatial pattern of wildfires across various terrains. Different researchers preferred LR [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 modellers must manually adjust the parameters through a time-consuming trial and error procedure [25,27]. Statistical and probabilistic models obscure the genuine relationships between wildfires and their causes because they are so sensitive to the input data [27]. Due to biased expert opinions that view some factors as more critical or vulnerable than others, based on their experience in the field of forest fires, AHP and other analytical 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 significant efforts have been made 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 modelling [44].

The integration of multi-criteria decision-making (MCDM) methods in GIS provides a practical framework for combining various spatial information and addressing multiple environmental issues, such as mapping and evaluating fire vulnerability.

The selection of the aggregation technique, determining weights, and managing linguistic variables and attributes present several challenges, as they do in many multi-criteria decision procedures. Numerous solutions are offered in the literature to address these issues; however, only a few methods can effectively resolve them. One such method is the FES, which enables the use of 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 consolidates 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. This is especially pertinent given the heightened global attention to natural hazards, which are heavily influenced by climate change, and 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 essential aspect for assessing the models' applicability in critical fields such as disaster management for decision-making. Additionally, there are still a few datasets available for extensive wildfires, and the majority of models are constructed using minor 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 readily applicable to other areas 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

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management strategies. Although this review provides a comprehensive understanding of the diverse applications employed in fire detection and prediction, questions remain regarding the implementation across various settings that are not thoroughly addressed in the literature, as well as strategies to overcome the 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 predictions for potential forest fire hazard zones across various geographical areas by selecting reliable environmental data that can inform fire prediction. The limitations of the tools presented are also highlighted in this study, underscoring the need for their contextualization in diverse settings. Moreover, continuous enhancement is essential, especially when aiming for faster models and a deeper understanding of the results, which remains a critical factor in ML-based models. Finally, there is a need to bridge the gaps between monitoring, learning, and the decision-making process.

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REFERENCES

1. C. Lai, S. Zeng, W. Guo, X. Liu, Y. Li, B. Liao, "Forest Fire Prediction with Imbalanced Data Using a Deep Neural Network Method," Forests, 2022, 13, 1129. [DOI: 10.3390/f13071129] https://doi.org/10.3390/f13071129
2. Alkhatib, "A Review on Forest Fire Detection Techniques," March 2014. [DOI: 10.1155/2014/597368] https://doi.org/10.1155/2014/597368
3. Ibrahem, E. Koubaily, A. Thabeet, "Modelling the natural regeneration of Cedrus libani A. Richard in Slenfeh, Syria, using binary logistic regression," 2021. [DOI: 10.1007/s40808-020-00939-y] https://doi.org/10.1007/s40808-020-00939-y
4. F. Recanatesi, C. Giuliani, M. Ripa, "Monitoring Mediterranean Oak decline in a peri-urban protected area using the NDVI and Sentinel-2 images: The case study of Castelporziano State Natural Reserve," 2018. https://doi.org/10.3390/su10093308
5. H. Almohamad, A. Knaack, B. Habib, "Assessing spatial equity and accessibility of public green spaces in Aleppo City, Syria," Forests, 2018. https://doi.org/10.3390/f9110706
6. P. Verkerk, J. Fitzgerald, P. Datta, M. Dees, G. Hengeveld, M. Lindner, S. Zudin, "Spatial distribution of the potential forest biomass availability in Europe," Forest Ecosystems, 2019. https://doi.org/10.1186/s40663-019-0163-5
7. H. Abdo, H. Almohamad, A. Al Dughairi, Motirh Al-Mutiry, "GIS-Based Frequency Ratio and Analytic Hierarchy Process for Forest Fire Susceptibility Mapping in the Western Region of Syria," 2022. [DOI: 10.3390/su14084668] https://doi.org/10.3390/su14084668
8. Jain, P.; Coogan, S.C.P.; Subramanian, S.G.; Crowley, M.; Taylor, S.; Flannigan, M.D. "A review of machine learning applications in wildfire science and management," Environmental Reviews, 2020, 28, 478–505. https://doi.org/10.1139/er-2020-0019
9. Pais, C.; Miranda, A.; Carrasco, J.; Shen, Z.-J.M. "Deep fire topology: Understanding the role of landscape spatial patterns in wildfire occurrence using artificial intelligence," Environmental Modelling & Software, 2021, 143, 105122. https://doi.org/10.1016/j.envsoft.2021.105122
10. Botequim, B.; Fernandes, P.M.; Garcia-Gonzalo, J.; Silva, A.; Borges, J.G. "Coupling fire behaviour modelling and stand characteristics to assess and mitigate fire hazard in a maritime pine landscape in Portugal," European Journal of Forest Research, 2017, 136, 527–542. https://doi.org/10.1007/s10342-017-1050-7
11. Pacheco, A.P.; Claro, J.; Fernandes, P.; de Neufville, R.; Oliveira, T.M.; Borges, J.G.; Rodrigues, J.C. "Cohesive fire management within an uncertain environment: A review of risk handling and decision support systems," Forest Ecology and Management, 2015, 347, 1–17. https://doi.org/10.1016/j.foreco.2015.02.033
12. Miranda, A.; Carrasco, J.; González, M.; Pais, C.; Lara, A.; Altamirano, A.; Weintraub, A.; Syphard, A.D. "Evidence-based mapping of the wildland-urban interface to better identify human communities threatened by wildfires," Environmental Research Letters, 2020, 15, 094069. https://doi.org/10.1088/1748-9326/ab9be5
13. Parajuli, A. Gautam, S. Sharma, K. Bhujel, G. Sharma, P. Thapa, B. Bist, S. Poudel, "Forest fire risk mapping using GIS and remote sensing in two major landscapes of Nepal," Geomatics, Natural Hazards and Risk, 2020, 11:1, 2569-2586. [DOI: 10.1080/19475705.2020.1853251] https://doi.org/10.1080/19475705.2020.1853251
14. E. Tukil, K. Kalkan, "Analysis of the threat of forest fires to ancient cities by GIS and Remote Sensing methods," 2022. [DOI: 10.48053/turkgeo.1140975] https://doi.org/10.48053/turkgeo.1140975
15. S. Saidi, A. Ben Younes, B. Anselme, "A GIS-remote sensing approach for forest fire risk assessment: case of Bizerte region, Tunisia," 2020. [DOI: 10.1007/s12518-021-00369-0] https://doi.org/10.1007/s12518-021-00369-0
16. Erten, Esra & Kurgun, V. & Musaoglu, Nebiye. "Forest fire risk zone mapping from satellite imagery and GIS: A case study." Congress of the International Society for Photogrammetry and Remote Sensing, Istanbul, Turkey, 2004, 222-230.
17. Ş. Güvendi, A. Şişman, "Forest fire risk analysis using GIS; Example of Geyve," Advanced Land Management, 2(1), 13–20, 2022.
18. Assaker, T. Darwish, G. Faour, "Use of Remote Sensing and GIS to Assess the Anthropogenic Impact on Forest Fires in Nahr Ibrahim Watershed," Lebanese Science Journal, 2012.
19. Mazzeo, G., De Santis, F., Falconieri, A., Filizzola, C., Lacava, T., Lanorte, A., Marchese, F., Nol`e, G., Pergola, N., Pietrapertosa, C., Satriano, V., 2022. "Integrated satellite system for fire detection and prioritisation." Remote Sensing, 14 (2), 335. [DOI: 10.3390/rs14020335]

https://doi.org/10.3390/rs14020335
20. R. Lamat, M. Kumar, A. Kundu, D. LAL, "Forest fire risk mapping using analytical hierarchy process (AHP) and earth observation datasets: a case study in the mountainous terrain of Northeast India," 2021. https://doi.org/10.1007/s42452-021-04391-0
21. Majlingová, A., "Automated procedure to assess the susceptibility of forest to fire," Journal of Forest Science, 2015, 61 (6), 255–260. https://doi.org/10.17221/18/2015-JFS
22. Pourghasemi, H.R., Beheshtirad, M., Pradhan, B., "A comparative assessment of prediction capabilities of modified analytical hierarchy process (M-AHP) and Mamdani fuzzy logic models using Netcad-GIS for forest fire susceptibility mapping" Geomatics Natural Hazards Risk, 1–25 (ahead-of-print), 2016.
23. Semeraro, T., Mastroleo, G., Aretano, R., Facchinetti, G., Zurlini, G., Petrosillo, I., "GIS fuzzy expert system for the assessment of ecosystems vulnerability to fire in managing Mediterranean natural protected areas," Journal of Environmental Management, 2016, 168, 94–103. https://doi.org/10.1016/j.jenvman.2015.11.053
24. K. Suryabhagavan, M. Alemu, Balakrishnan, "GIS-Based Multicriteria Decision Analysis Approach for Forest Fire Susceptibility Mapping: A Case Study in Harenna Forest, southwestern Ethiopia," 2016.
25. Hong, H., Jaafari, A., Zenner, E.K., "Predicting spatial patterns of wildfire susceptibility in the Huichang County, China: an integrated model to analyse landscape indicators," Ecological Indicators, 2019, 101, 878–891. [DOI: 10.1016/j.ecolind.2019.01.056] https://doi.org/10.1016/j.ecolind.2019.01.056
26. Abdo, H.G.; Almohamad, H.; Al Dughairi, A.A.; Al-Mutiry, M. "GIS-Based Frequency Ratio and Analytic Hierarchy Process for Forest Fire Susceptibility Mapping in the Western Region of Syria," Sustainability, 2022, 14, 4668. [DOI: 10.3390/su14084668] https://doi.org/10.3390/su14084668
27. Jaafari, Abolfazl, Davood Mafi-Gholami, Binh Thai Pham, and Dieu Tien Bui. "Wildfire Probability Mapping: Bivariate vs. Multivariate Statistics" Remote Sensing, 2019, 11, no. 6: 618. [DOI: 10.3390/rs11060618] https://doi.org/10.3390/rs11060618
28. Sachdeva, S., Bhatia, T., Verma, A., "GIS-based evolutionary optimized Gradient Boosted Decision Trees for forest fire susceptibility mapping," Natural Hazards, 2018. [DOI: 10.1007/s11069-018-3256-5] https://doi.org/10.1007/s11069-018-3256-5
29. Ghorbanzadeh, O., Valizadeh Kamran, K., Blaschke, T., Aryal, J., Naboureh, A., Einali, J., Bian, J., "Spatial prediction of wildfire susceptibility using field survey GPS data and machine learning approaches," Fire, 2019. [DOI: 10.3390/fire2030043] https://doi.org/10.3390/fire2030043
30. Yousefi, S., Pourghasemi, H., Emami, S., Pouyan, S., Eskandari, S., Tiefenbacher, J., "A machine learning framework for multi-hazards modelling and mapping in a mountainous area," Scientific Reports, 2020. [DOI: 10.1038/s41598-020-69233-2] https://doi.org/10.1038/s41598-020-69233-2
31. Eskandari, S., Pourghasemi, H., Tiefenbacher, J., "Fire susceptibility mapping in the natural areas of Iran using new and ensemble data mining models," Environmental Science and Pollution Research, 2021. [DOI: 10.1007/s11356-021-13881-y] https://doi.org/10.1007/s11356-021-13881-y
32. Mohajane, M., Costache, R., Karimi, F., Bao Pham, Q., Essahlaoui, A., Nguyen, H., Laneve, G., Oudija, F., "Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area," Ecological Indicators, 2021, 129, 107869. [DOI: 10.1016/j.ecolind.2021.107869] https://doi.org/10.1016/j.ecolind.2021.107869
33. Gholamnia, K., Gudiyangada Nachappa, T., Ghorbanzadeh, O., Blaschke, T., "Comparisons of diverse machine learning approaches for wildfire susceptibility mapping," Symmetry, 2020, 12, 604. https://doi.org/10.3390/sym12040604
34. Elia, M., D'Este, M., Ascoli, D., Giannico, V., Spano, G., Ganga, A., Colangelo, G., Lafortezza, R., Sanesi, G. (2020). Estimating the probability of wildfire occurrence in Mediterranean landscapes using artificial neural networks. Environmental Impact Assessment Review, 85, 106474. https://doi.org/10.1016/j.eiar.2020.106474. https://doi.org/10.1016/j.eiar.2020.106474
35. Stojanova, D., Panov, P., Kobler, A., Džeroski, S. (January 2006). Learning to Predict Forest Fires with Different Data Mining Techniques.
36. M. Rihan, A. Bindajam, S. Talukdar, Shahfahad, M. Naikoo, J. Mallick, A. Rahman. Forest Fire Susceptibility Mapping with Sensitivity and Uncertainty Analysis Using Machine Learning and Deep Learning Algorithms,2023. Vol. 72, Iss: 2, pp 426-443, https://www.doi.org/10.1016/j.asr.2023.03.026.
37. Nami, M., Jaafari, A., Fallah, M., Nabiuni, S. (2018). Spatial prediction of wildfire probability in the Hyrcanian ecoregion using an evidential belief function model and GIS. International Journal of Environmental Science and Technology, 15, 373–384. https://doi.org/10.1007/s13762-017-1371-6
38. Vacchiano, G., Foderi, C., Berretti, R., Marchi, E., Motta, R. (2018). Modelling anthropogenic and natural fire ignitions in an inner-Alpine valley. Natural Hazards and Earth System Sciences, 18, 935–948. https://doi.org/10.5194/nhess-18-935-2018. https://doi.org/10.5194/nhess-18-935-2018
39. Naderpour, M., Rizeei, H.M., Ramezani, F. (2021). Forest fire risk prediction: a spatial deep neural network-based framework. Remote Sensing, 13, 2513. https://doi.org/10.3390/rs13132513
40. Wu, Z., Wang, B., Li, M., Tian, Y., Quan, Y., Liu, J. (2022). Simulation of forest fire spread based on artificial intelligence. China. https://doi.org/10.1016/j.ecolind.2022.108653
41. Vahid Razavi-Termeh, S., Sadeghi-Niaraki, A., Choi, S. (2020). Ubiquitous GIS-Based Forest Fire Susceptibility Mapping Using Artificial Intelligence Methods. https://doi.org/10.3390/rs12101689
42. Zhang, G., Wang, M., Liu, K. (2019). Forest Fire Susceptibility Modelling Using a Convolutional Neural Network for Yunnan Province of China. International Journal of Disaster Risk Science, 10, 386–403. https://doi.org/10.1007/s13753-019-00233-1
43. Cai, J., Luo, J., Wang, S., Yang, S. (2018). Feature selection in machine learning: A new perspective. Neurocomputing, 300, 70–79. https://doi.org/10.1016/j.neucom.2017.11.077
44. Jaafari, A., Zenner, E.K., Pham, B.T. (2018). Wildfire spatial pattern analysis in the Zagros Mountains, Iran: a comparative study of decision tree-based classifiers. Ecological Informatics, 43, 200–211. https://doi.org/10.1016/j.ecoinf.2017.12.006
45. Catry, F.X., Rego, F.C., Bação, F.L., Moreira, F. (2010). Modelling and Mapping Wildfire Ignition Risk in Portugal. International Journal of Wildland Fire, 18(8), 921–931. https://doi.org/10.1071/WF07123

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