

GIS, Remote Sensing and Machine Learning Applications for Forest Fire Mapping, Susceptibility Assessment and Risk Analysis: A Systematic Review

Lucius Malalu

luciusmalalu2002@gmail.com

Malawi University of Science and Technology <https://orcid.org/0009-0004-5753-8386>

Henry Chinthuli

Mount Mulanje Conservation Trust

Systematic Review

Keywords: forest fire, wildfire, burned area mapping, GIS, remote sensing, spectral indices, machine learning, NBR, dNBR, Sentinel-2, Landsat, MODIS, burn severity, susceptibility mapping.

Posted Date: October 5th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11233692/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

GIS, Remote Sensing and Machine Learning Applications for Forest Fire Mapping, Susceptibility Assessment and Risk Analysis: A Systematic Review

Lucius Malalu^{1*}, Henry Chinthuli²

¹Ndata School of Climate and Earth Sciences, Malawi University of Science and Technology, P.O Box 5196, Limbe, Malawi.

²Mount Mulanje Conservation Trust, P.O Box 139, Mulanje, Malawi.

Corresponding author: Lucius Malalu, Ndata School of Climate and Earth Sciences, Malawi University of Science and Technology, P.O Box 5196, Limbe, Malawi. Cel: 265-0-885-070-761. Email: luciusmalalu2002@gmail.com

Abstract

Forest fires pose significant environmental and socioeconomic risks, increasing the need for reliable methods for spatial mapping, susceptibility assessment, and risk prediction. This systematic review synthesizes research on the application of remote sensing, Geographic Information Systems (GIS), and machine learning for forest fire mapping. A total of 202 articles were initially identified from five academic sources, of which 51 studies met the predefined inclusion criteria. The reviewed literature shows increasing research activity, with publications spanning 2021 to 2026. Asia accounted for the largest proportion of studies (62.7%, n=32), while Africa was represented by only four studies, indicating a geographical research gap. Among remote sensing datasets, MODIS was most frequently used (27 studies), followed by Sentinel-2 (14), while VIIRS and Landsat 8 were each used in six studies. Machine learning approaches dominated the analytical methods, with Random Forest being the most frequently applied model (28 studies), followed by XGBoost (20), Support Vector Machine (13), and Logistic Regression (12). Common predictor variables included temperature, precipitation, slope, aspect, elevation, distance to roads and settlements, land use/land cover, and vegetation indices. NDVI was the most frequently used spectral index, appearing in 43 studies. Key limitations included spatial resolution, data quality, data availability, and model performance. The review demonstrates a clear shift toward integrated GIS, remote sensing, and machine learning frameworks, including cloud-based platforms such as Google Earth Engine. Future research should prioritize improved spatial and temporal data resolution, broader geographical coverage, particularly in Africa, integration of multiple datasets and seasonal risk indices, advanced deep learning methods, continuous monitoring, and robust validation to reduce bias and improve model transferability. These advances can strengthen forest fire management and support evidence-based decision-making.

Keywords: forest fire; wildfire; burned area mapping; GIS; remote sensing; spectral indices; machine learning; NBR; dNBR; Sentinel-2; Landsat; MODIS; burn severity; susceptibility mapping.

Introduction

Forest fires are important environmental disturbances that affect terrestrial ecosystems, biodiversity, carbon cycling, atmospheric composition, and human communities. The increasing availability of Earth-observation data has strengthened the ability to monitor the occurrence, extent, and impacts of forest fires across different spatial and temporal scales. Remote sensing is particularly valuable because it provides repeated observations over large and often inaccessible areas, supporting the detection of active fires, delineation of burned areas, assessment of fire severity, and monitoring of post-fire environmental changes [1,2,3]. The development of improved satellite sensors and analytical techniques has further increased the potential for timely and spatially detailed forest-fire mapping [4,3]. Consequently, reliable information on the location, extent, timing, and characteristics of fire-affected areas is essential for environmental monitoring, fire management, disaster assessment, ecosystem restoration, and scientific investigations of fire dynamics.

Accurate mapping of forest fires provides fundamental information about the spatial and temporal distribution of burned areas. Conventional field surveys and manual interpretation can provide detailed information at local scales, but they are often difficult to implement consistently over large geographic areas. Satellite remote sensing provides an alternative by enabling systematic observations across extensive regions and over repeated time periods. Recent reviews have demonstrated that remote sensing has become a central component of wildfire monitoring, with optical, thermal, radar, LiDAR, and hyper spectral observations being used for different stages of the fire cycle [2,4]. The rapid expansion of cloud-processing platforms has further facilitated large-scale processing of satellite archives and automated generation of burned-area information [4].

Remote-sensing-based fire mapping generally involves two related but distinct applications: active-fire detection and burned-area mapping. Active-fire detection identifies thermal anomalies associated with ongoing or recently active combustion, whereas burned-area mapping identifies land surfaces that have already been affected by fire. The MODIS Collection 6 active-fire product represented an important development in satellite fire monitoring because improvements to the detection algorithm reduced some commission and omission errors and improved performance across several fire environments [1]. MODIS observations have subsequently remained an important source of active-fire information, while newer sensors such as the Visible Infrared Imaging Radiometer Suite (VIIRS) have provided additional observations at finer spatial resolution [1,2].

Burned-area mapping focuses on identifying the spatial extent of land affected by fire. The MODIS Collection 6 burned-area product represented a major development in this field by improving the detection of small burns, reducing temporal uncertainty in burn-date estimation, and decreasing the amount of unmapped area [5]. However, subsequent validation demonstrated that burned-area products can still experience substantial omission and commission errors, particularly in ecosystems where fires are small, fragmented, or spectrally difficult to distinguish from surrounding land cover [6]. Comparisons among global burned-area products have also demonstrated substantial differences in the amount, location, and timing of mapped fire activity, emphasizing the importance of understanding the characteristics and limitations of individual products [7].

The spatial and temporal resolution of satellite observations is therefore a major consideration in forest-fire mapping. Coarse-resolution sensors provide frequent observations and extensive geographic coverage, but they may not adequately resolve small or fragmented fires. Higher-resolution sensors provide greater spatial detail but may have lower temporal coverage, greater computational requirements, and increased susceptibility to cloud contamination. Global validation of the MODIS Collection 6 burned-area product demonstrated that omission errors were particularly important for smaller burned areas and that mapping performance varied considerably among biomes [6]. More detailed assessments have similarly shown that the spatial shape and boundaries of burned areas can be affected by the relatively coarse resolution of global products [8]. These limitations have encouraged increasing use of medium- and high-resolution satellite imagery for detailed fire mapping.

Several satellite platforms have consequently been investigated to improve the spatial detail of forest-fire mapping. Landsat provides a long-term archive and relatively fine spatial resolution, making it valuable for detailed burned-area mapping, historical fire analysis, burn-severity assessment, and validation. Sentinel-2 provides multispectral observations at spatial resolutions as fine as 10 m and a relatively frequent revisit cycle, providing opportunities for mapping small and fragmented burned areas. [9] Demonstrated the potential of Sentinel-2 multispectral observations for burned-area mapping in sub-Saharan Africa, including the generation of a database specifically designed to support small-fire detection. [10] further demonstrated that Landsat-8 and Sentinel-2 observations can be combined through multi-temporal change detection to produce medium-resolution burned-area information.

The combination of different optical sensors has subsequently become an important research direction. Integrating Landsat and Sentinel-2 observations can increase temporal sampling while retaining relatively high spatial resolution. This is particularly useful where cloud cover or satellite revisit intervals prevent the acquisition of a single suitable image immediately before or after a fire. More recent research has extended this concept to high-resolution commercial imagery. [11], for example, investigated deep-learning-based burned-area mapping by transferring information learned from Landsat-8 to PlanetScope imagery. Such approaches

demonstrate the potential for combining information across sensors with different spatial and temporal characteristics [11].

Synthetic Aperture Radar (SAR) provides complementary information for forest-fire mapping because radar observations are less dependent on cloud-free conditions than optical imagery. SAR can also provide information related to vegetation structure and surface characteristics that may change following fire. [2] Identified radar and LiDAR as important complementary technologies for burned-area assessment, while more recent research has demonstrated the potential of Sentinel-1 SAR for integration with optical Sentinel-2 data. [12] Developed a deep-learning approach that used the synergy of Sentinel-1 and Sentinel-2 observations for burned-area mapping and evaluated its performance across multiple fire events. These developments suggest that multi-sensor observations can provide complementary information that may improve fire mapping under conditions where individual sensors have limitations.

A range of spectral indices and change-detection techniques has also been developed for forest-fire mapping. Burned vegetation produces changes in spectral reflectance, particularly in the near-infrared and shortwave-infrared portions of the electromagnetic spectrum. The Normalized Burn Ratio (NBR), differential Normalized Burn Ratio (dNBR), and related spectral indices are therefore frequently used to identify fire-induced changes and assess burn severity. A comprehensive review of forest burned-area and burn-severity research found that spectral indices remain among the most frequently used approaches in remote-sensing-based fire studies [13]. More recent reviews have similarly identified NBR and NDVI among the most frequently applied indices in wildfire mapping research [3].

Image differencing and multi-temporal change detection are particularly useful because they compare surface conditions before and after a fire. These approaches can reduce confusion associated with spatial variability in vegetation and background conditions when appropriate pre-fire and post-fire observations are available. [10] Demonstrated the effectiveness of combining Landsat-8 and Sentinel-2 observations through a multi-temporal change-detection framework. More recent studies have extended change detection through automated spectral-index combinations and machine-learning approaches, including unsupervised burned-area mapping using automatically generated labels and ensemble learning [15]. These developments demonstrate a transition from manually defined thresholds toward increasingly automated approaches capable of exploiting multiple spectral and temporal characteristics.

The increasing availability of machine-learning techniques has further expanded the range of approaches available for forest-fire mapping. Machine-learning algorithms can integrate multiple spectral, spatial, temporal, and environmental variables and can model nonlinear relationships between satellite observations and burned surfaces. Random forests, support vector machines, decision trees, and ensemble methods have been applied to burned-area classification and related fire-mapping problems. Recent reviews indicate a continuing shift from conventional

threshold-based approaches toward machine learning and deep learning, particularly as larger satellite datasets and cloud-processing capabilities become available [4,3].

Deep learning has become particularly important for automated burned-area segmentation because neural networks can learn spatial and spectral features directly from image data. [16] Developed a U-Net-based approach for burned-area segmentation using Sentinel-2 imagery and demonstrated the potential of convolutional neural networks for automated fire mapping. [12] Subsequently demonstrated deep-learning-based mapping using the synergy of Sentinel-1 and Sentinel-2 observations. Burnt-Net, developed using post-fire Sentinel-2 imagery, further demonstrated the potential of deep morphological neural networks for automated burned-area segmentation (2022). These studies indicate that deep-learning approaches can reduce dependence on manually designed spectral features while providing pixel-level burned-area delineation.

Recent studies have continued to investigate different deep-learning architectures and strategies for improving burned-area mapping. [17] Compared a stacked auto encoder with several conventional classification algorithms for mapping burned forest areas from Sentinel-2 imagery. Their findings demonstrate the increasing application of deep learning for extracting burned areas from high-resolution multispectral imagery. More recent work has investigated super-resolution and transfer-learning approaches to overcome the trade-off between spatial and temporal resolution. [18], for example, developed DLSR-FireCNet to generate enhanced-resolution burned-area information from MODIS observations using deep learning and decision-level super-resolution.

The development of Transformer-based and attention-based architectures represents another recent stage in the evolution of deep-learning fire mapping. In 2026, context-aware Transformer-U-Net approaches were investigated for burned-area segmentation from Sentinel-2 imagery, combining spatial attention with Transformer-based self-attention to capture both local boundaries and broader contextual information. Such methods are intended to improve the delineation of irregular burn boundaries and reduce confusion between burned surfaces and spectrally similar land-cover features. The continued development of these architectures reflects a broader movement toward models capable of integrating spatial context and multi-scale information in high-resolution satellite imagery.

The accuracy of forest-fire mapping is influenced by numerous factors, including fire size, burn severity, vegetation type, canopy structure, topography, atmospheric conditions, spatial resolution, temporal frequency, and image-acquisition timing. Small fires may occupy only a fraction of a satellite pixel, while low-severity or understory fires may produce relatively weak spectral signals. Clouds and smoke can limit the availability of optical observations, while water bodies, shadows, agricultural disturbances, and other land-cover changes can produce spectral responses that resemble burned areas [2,6]. Recent studies have also shown that sensor

differences and regional environmental conditions can affect the transferability of machine-learning and deep-learning models between geographic locations [12, 17].

Accuracy assessment and independent validation are therefore essential components of forest-fire mapping research. Reliable validation requires reference data that accurately represent the spatial and temporal characteristics of burned areas. [19] Proposed a stratified probability-sampling design for regional-to-global burned-area product validation, emphasizing the importance of statistically rigorous sampling in accuracy assessment. [6] Subsequently applied a global validation framework using independently interpreted Landsat-8 image pairs. Other validation studies have shown that the performance of burned-area products can differ substantially depending on fire size, land-cover type, and environmental setting [20]. These findings highlight the importance of standardized validation approaches when comparing different fire-mapping methods and products.

Another important development is multi-sensor and multi-temporal data fusion. Individual satellite systems have limitations in terms of spatial resolution, temporal frequency, spectral coverage, cloud sensitivity, and data availability. Combining complementary observations can therefore provide more complete information about fire occurrence and burned-area evolution. Recent research has combined optical, thermal, radar, and active-fire observations, while multi-source approaches increasingly integrate MODIS, VIIRS, Landsat, Sentinel, and geostationary satellite data. In 2026, for example, Fire Cluster integrated MODIS, VIIRS, Landsat-8, and Himawari-8 observations using a hierarchical clustering framework to reconstruct wildfire events in space and time. Such multi-source approaches demonstrate the potential of combining complementary observations to improve fire-event characterization and reduce omissions caused by individual sensor limitations.

The use of cloud-based geospatial processing has further changed the way large volumes of satellite data can be analyzed. Platforms such as Google Earth Engine provide access to extensive satellite archives and computational resources, allowing researchers to process large areas without downloading and storing all imagery locally. [4] Identified cloud geoprocessing as one of the major developments influencing wildfire burned-area mapping, particularly for large-scale applications. These platforms can facilitate automated image preprocessing, spectral-index calculation, temporal compositing, classification, validation, and production of spatial fire products.

Recent literature also demonstrates a growing emphasis on near-real-time wildfire monitoring. Traditional burned-area products may experience delays because of satellite revisit intervals, cloud contamination, image-processing requirements, and product-generation procedures. The integration of active-fire observations with higher-resolution optical imagery can reduce these delays. Recent studies have investigated near-real-time burned-area mapping using Sentinel-2 and VIIRS observations, while newer multi-source approaches aim to characterize fire events

using observations acquired at different spatial and temporal resolutions[21]. These developments are particularly important for applications requiring rapid information for emergency response and post-fire assessment.

Despite substantial methodological progress, several research gaps remain. These include difficulties in detecting small and low-severity fires, limited availability of high-quality training and validation data, differences in model performance between geographic regions, uncertainty associated with multi-sensor data integration, and the computational requirements of increasingly complex deep-learning models. Recent systematic reviews have also identified uneven geographic representation in the literature and continuing challenges associated with model generalization, interpretability, and operational implementation [13,3]. The emergence of self-supervised learning, transfer learning, super-resolution, Transformer architectures, and multi-source data fusion provides promising directions for addressing some of these limitations, but their effectiveness requires further evaluation across diverse fire regimes and environmental conditions.

Given the rapid development of satellite technologies, analytical techniques, artificial intelligence, cloud computing, and multi-sensor data fusion, there is a growing need to synthesize the current evidence on forest-fire mapping. Previous reviews have examined remote-sensing approaches to forest burned-area estimation and post-fire assessment[13], while more recent reviews have focused on remote-sensing datasets, cloud-processing platforms, and emerging image-processing algorithms [4,3]. The continued emergence of high-resolution satellite observations, deep-learning architectures, and multi-source fire-monitoring systems means that the methodological landscape continues to evolve. A systematic review is therefore needed to consolidate the evidence, identify dominant approaches, examine methodological differences, and establish areas requiring further research.

Therefore, this systematic review examines the current state of forest-fire mapping using remote sensing and GIS technologies, with particular emphasis on literature published between 2021 and 2026. Specifically, the review examines the major satellite datasets and sensors used for forest-fire mapping; evaluates active-fire detection and burned-area mapping approaches; investigates the application of spectral indices and change-detection techniques; assesses the use of machine learning and deep learning; and examines multi-sensor, multi-temporal, and cloud-based processing approaches. The review also evaluates methods used for accuracy assessment and validation and identifies the principal challenges and research gaps affecting the reliability and operational applicability of forest-fire mapping. By synthesizing the evidence published during this period, the review aims to provide a comprehensive understanding of methodological developments and identify opportunities for improving the accuracy, timeliness, scalability, reproducibility, and practical application of remote-sensing-based forest-fire mapping.

Methodology

Planning Stage

During the planning stage (Fig. 1), the research team refined the central review question to explicitly investigate how forest fires have been mapped using GIS, remote sensing, and machine learning. This guided the development of a comprehensive search strategy incorporating terminology related to forest fire mapping, GIS, remote sensing, and machine learning.



Fig. 1 The plan review step by step process

Information Sources and Literature Retrieval

This systematic review was conducted to synthesize published evidence on forest-fire mapping using remote sensing, satellite Earth observation, geographic information systems (GIS), and related geospatial analytical techniques. The review focused on studies published between 2021 and 2026, thereby capturing recent developments in satellite-based fire detection, burned-area mapping, spectral-index methods, machine learning, deep learning, multi-sensor data integration, and cloud-based geospatial processing. The review process was structured in accordance with the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses

(PRISMA 2020) [22] to promote transparency and reproducibility in study identification, screening, eligibility assessment, and inclusion.

A comprehensive literature search was conducted using major multidisciplinary and technical databases, including MDPI, Science Direct, Taylor and Francis, Springer Link, and Google Scholar. These databases were selected to provide broad coverage of environmental science, remote sensing, Geoinformatics, computer science, and artificial-intelligence research relevant to forest-fire mapping. In addition to database searches, the reference lists of relevant articles were examined through backward citation searching, while forward citation searching was used to identify subsequent studies that cited key publications. This approach was intended to reduce the likelihood of missing relevant studies that were not retrieved through the primary database searches.

The search focused on publications addressing the detection, delineation, classification, or characterization of forest-fire-affected areas using remotely sensed or geospatial data. Particular attention was given to studies employing commonly used satellite systems, including MODIS, Landsat, Sentinel-1, Sentinel-2, and other optical, thermal, and synthetic aperture radar (SAR) datasets. Studies applying conventional image-processing techniques as well as machine-learning and deep-learning approaches were considered to capture methodological developments across the review period.

Search Strategy

The search strategy was developed around four principal concepts: forest fires, fire or burned-area mapping, remote sensing and Earth observation, and mapping technologies or analytical methods. A combination of controlled and free-text keywords was used where supported by the individual databases. The principal search terms included forest fire, wildfire, forest wildfire, wildland fire, fire mapping, burned area mapping, burnt area mapping, fire detection, remote sensing, satellite, Earth observation, MODIS, Landsat, Sentinel, SAR, machine learning, and deep learning.

A general Boolean search expression was formulated as follows:

("forest fire" OR wildfire OR "forest wildfire" OR "wildland fire") AND ("fire mapping" OR "burned area mapping" OR "burnt area mapping" OR "fire detection") AND ("remote sensing" OR satellite OR "Earth observation") AND (MODIS OR Landsat OR Sentinel OR SAR OR "machine learning" OR "deep learning")

The search expression was adapted to the syntax and indexing requirements of each database. Where possible, searches were conducted within titles, abstracts, and author keywords to improve the relevance of retrieved records. Additional targeted searches were performed for specific combinations of datasets and techniques, including MODIS burned-area mapping, Landsat forest-fire mapping, Sentinel-2 burned-area mapping, Sentinel-1/SAR wildfire mapping,

Normalized Burn Ratio (NBR), burn-severity mapping, change detection, machine-learning classification, and deep-learning-based segmentation.

The search strategy was designed to capture both established and emerging approaches. Consequently, studies based on spectral indices and thresholding were considered alongside supervised and unsupervised classification, object-based image analysis, ensemble learning, convolutional neural networks (CNNs), U-Net architectures, transfer learning, and more recent transformer-based approaches. The search was restricted to the period January 2016 through 2026 in accordance with the predefined scope of the review.

Eligibility Criteria

Eligibility criteria were established before the screening process to ensure that the studies included in the review directly addressed the research objectives. Studies were considered eligible when they satisfied the predefined inclusion criteria.

Inclusion Criteria

Studies were included when they met the following criteria:

1. Study phenomenon: The study investigated forest fires, wildfires, burned areas, fire-affected forests, or vegetation affected by fire.
2. Data source: The study used satellite remote sensing, aerial imagery, GIS, or other Earth-observation data capable of supporting spatial fire mapping.
3. Mapping objective: The study addressed the detection, delineation, classification, mapping, or characterization of fire-affected areas or burned areas.
4. Analytical method: The study applied an identifiable image-processing, spectral-index, and change-detection, statistical, machine-learning, deep-learning, or multi-sensor approach.
5. Outcome: The study reported spatial, temporal, methodological, or accuracy-related findings relevant to forest-fire mapping.
6. Publication type: Peer-reviewed journal articles and relevant conference publications were considered. Authoritative technical publications were considered where they provided sufficient methodological information and directly contributed to understanding fire-mapping techniques.
7. Language: Publications available in English were included.
8. Publication period: Studies published from 2021 to 2026 were eligible.

9. Methodological detail: The publication provided sufficient information about its data sources, processing procedures, mapping methodology, or validation approach to permit meaningful synthesis.

Exclusion Criteria

Studies were excluded when they met one or more of the following criteria:

1. Studies focused primarily on firefighting operations, emergency response, human health effects, or socioeconomic impacts without a relevant remote-sensing mapping component.
2. Studies addressing laboratory-based fire behaviour or experimental combustion without a spatial Earth-observation component.
3. Studies dealing solely with atmospheric emissions or smoke transport when no burned-area or active-fire mapping component was included.
4. Duplicate records retrieved from multiple databases.
5. Publications for which the full text could not be obtained or which lacked sufficient methodological information for assessment.
6. Publications outside the predefined 2021–2026 publication period.
7. Studies that substantially duplicated another publication without providing a distinct dataset, methodology, application, or analytical contribution.

The eligibility criteria were intended to maintain a clear distinction between studies that map fire occurrence or fire-affected areas and studies that address broader wildfire-related topics without a spatial mapping objective.

Study Selection and Screening Process

The study-selection process was performed in several sequential stages. First, all records identified through the electronic database searches and supplementary citation searches were compiled into a single reference database. Duplicate records were identified and removed before formal screening. The remaining records were subjected to title and abstract screening to determine their apparent relevance to the review objectives.

During the title and abstract screening stage, publications were retained when they potentially addressed forest-fire detection, burned-area mapping, fire-affected vegetation mapping, or related remote-sensing methodologies. Records that clearly failed to meet the inclusion criteria were excluded at this stage. Studies for which eligibility could not be determined from the title and abstract were retained for full-text assessment.

Full-text articles were subsequently assessed against the predefined inclusion and exclusion criteria. Reasons for excluding studies at the full-text stage were recorded to improve

transparency and reproducibility. Common reasons for exclusion included an absence of a relevant mapping component, inappropriate study objectives, insufficient methodological information, publication outside the specified period, or duplication of another included study.

Data Extraction and Data Items

A structured data-extraction framework was developed to ensure consistent collection of information from all included studies. The study screening process, including title and abstract screening and full-text assessment, was independently conducted by the two authors. Any disagreements regarding study eligibility were resolved through discussion and consensus between the authors. Data were extracted systematically and organized according to publication characteristics, geographical and environmental context, remote-sensing datasets, preprocessing procedures, mapping techniques, validation approaches, and principal findings.

The following information was extracted from each eligible publication:

- Publication characteristics: author(s), year of publication, journal or conference, and study type;
- Geographical characteristics: country or region, geographic extent, and study location;
- Environmental characteristics: vegetation type, forest characteristics, fire regime, and relevant environmental conditions;
- Remote-sensing data: satellite or sensor platform, spectral bands, spatial resolution, temporal resolution, revisit characteristics, and acquisition period;
- Spectral indices and predictors: NBR, differenced NBR (dNBR), Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Burned Area Index (BAI), and other spectral or textural variables;
- Main findings: methodological performance, principal advantages and limitations, transferability, and key conclusions relevant to forest-fire mapping.

Particular attention was given to differences in sensor characteristics and methodological design because these factors can substantially influence mapping performance. Information regarding spatial resolution, temporal frequency, spectral configuration, cloud contamination, topographic conditions, vegetation structure, fire size, and time elapsed between fire occurrence and image acquisition was therefore extracted where reported.

Data Synthesis

Because the included studies were expected to differ substantially in geographical setting, fire characteristics, sensor platforms, spatial and temporal resolutions, algorithms, reference datasets, and accuracy-assessment procedures, the evidence was synthesized primarily through a structured narrative and thematic approach rather than a statistical meta-analysis.

The synthesis was organized around major methodological themes, including: (i) remote-sensing datasets and sensor characteristics; (ii) active-fire and burned-area mapping; (iii) spectral indices and change-detection techniques; (iv) machine-learning methods; (v) deep-learning approaches;

(vi) multi-sensor and multi-temporal data integration; and (vii) emerging technologies and research directions.

Comparisons between studies were interpreted in the context of their methodological and environmental differences. Reported accuracy values were not treated as directly interchangeable when they were derived from different reference datasets, spatial resolutions, sampling strategies, study areas, or evaluation metrics. Instead, the synthesis emphasized patterns in methodological development, commonly reported strengths and limitations, and factors associated with improved or reduced mapping performance.

The synthesis also considered the evolution of forest-fire mapping from conventional spectral-index and threshold-based approaches toward machine learning, deep learning, multi-sensor fusion, and increasingly automated processing environments. This thematic organization enabled the review to identify established practices, methodological advances, persistent challenges, and areas requiring further research within the 2016–2026 literature.

Quality and Risk-of-Bias Considerations

The methodological quality of the included studies was considered in relation to the transparency of their data sources, preprocessing procedures, mapping methodology, reference data, and validation strategy. Particular consideration was given to whether studies provided sufficient information to reproduce the mapping workflow and whether their validation data were independent and appropriate for the spatial and thematic resolution of the mapped products.

Studies were also examined for potential sources of methodological bias, including inadequate reference sampling, spatial mismatch between prediction and reference data, insufficient validation samples, class imbalance, dependence on the same imagery for model development and validation, and the use of accuracy measures that did not adequately represent burned-area mapping performance.

The assessment did not exclude studies solely because they used different methodological approaches. Instead, quality-related observations were incorporated into the synthesis to distinguish between findings supported by robust validation procedures and findings that should be interpreted with greater caution. This approach was particularly important because differences in validation design can produce substantial variation in reported mapping accuracy even when similar remote-sensing datasets and algorithms are used.

Results

Distribution of research papers

The initial database search identified 202 articles across five academic sources (Fig. 2): 82 from ScienceDirect, 54 from SpringerLink, 39 from MDPI, 25 from Google Scholar, and 2 from Taylor & Francis. After rigorous screening of titles, abstracts, and full texts against the

predefined inclusion criteria, 51 studies met the eligibility requirements and were included in the systematic review. These comprised 6 studies retrieved from Google Scholar, 16 from MDPI, 13 from ScienceDirect, and 16 from SpringerLink. No studies retrieved from Taylor & Francis met the methodological and thematic inclusion criteria.

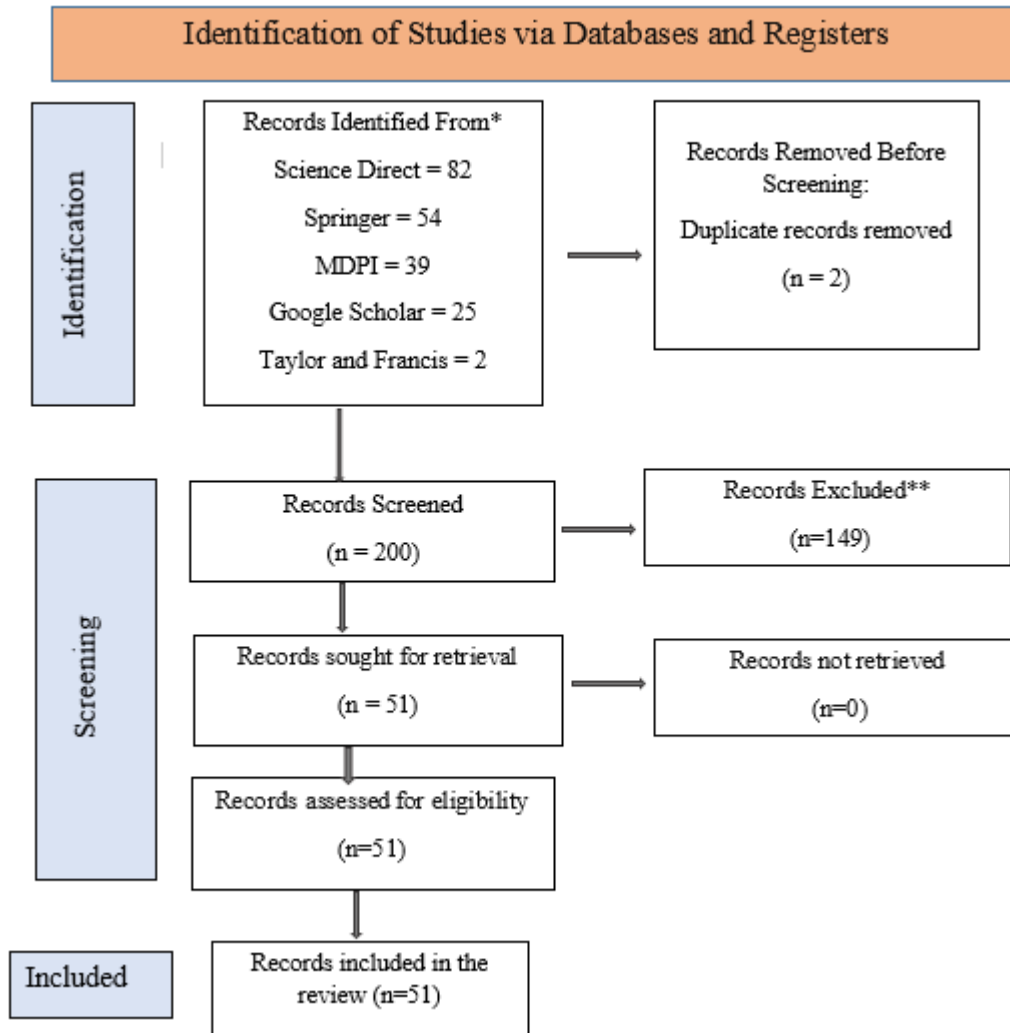


Fig 2: PRISMA flow diagram utilized in the study

Distribution of reviewed papers based on year

The annual distribution of the selected publications, illustrated in (Fig. 3), demonstrates a fluctuating but overall increasing trend in research on forest fire mapping using GIS, remote sensing, and machine learning. Publication output increased from 3 studies in 2021 to 10 in

2022, declined to 5 in 2023, and subsequently rose to 13 studies in both 2024 and 2025. In 2026, 7 publications were recorded. Overall, the distribution indicates growing research interest in the integration of GIS, remote sensing, and machine learning for forest fire mapping.

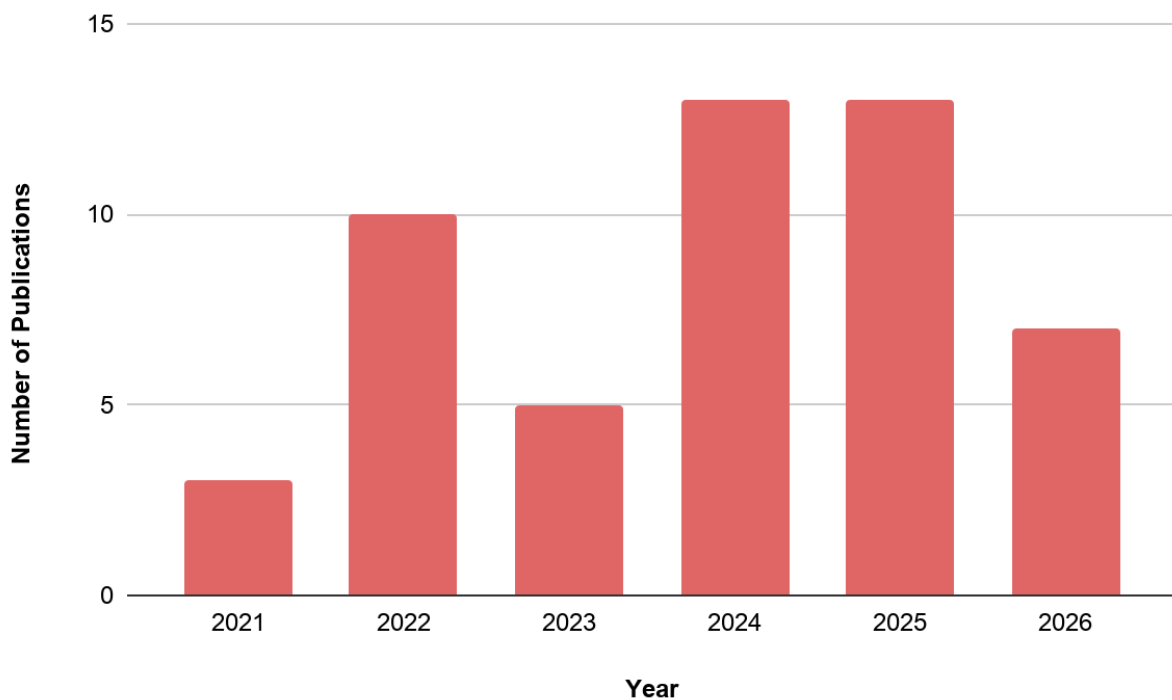


Fig. 3 Distribution of the selected publications per year

Distribution of reviewed papers by country

The geographical distribution of the selected studies is relatively diverse (Table 1). China, India, and Türkiye had the highest number of publications, with six each, followed by Canada and Pakistan, with three each. Morocco, Algeria, the United States, Germany, and Ecuador each contributed two publications, while the remaining countries contributed one study each. The global distribution, illustrated in Fig. 4, demonstrates widespread research interest in forest fire

mapping using GIS, remote sensing, and machine learning. The higher concentration of publications in countries such as China, India, Türkiye, Pakistan, and Canada may reflect their greater research activity and, potentially, the prevalence and impact of forest fires in these regions.

Table 1 Research papers by country

Country	Frequency	Country	Frequency
Syria	1	Thailand	1
Malaysia	1	America	2
Peru	1	Vietnam	1
China	6	Canada	3
Kazakhstan	1	Turkey	6
Morocco	2	Portugal	1
Greece	1	Indonesia	1
Brazil	1	Hungary	1
Ecuador	2	Iran	1
India	6	Bosnia and Herzegovina	1
South Korea	1	France	1
Germany	2	Bangladesh	1
Algeria	2	Chile	1
Pakistan	3		

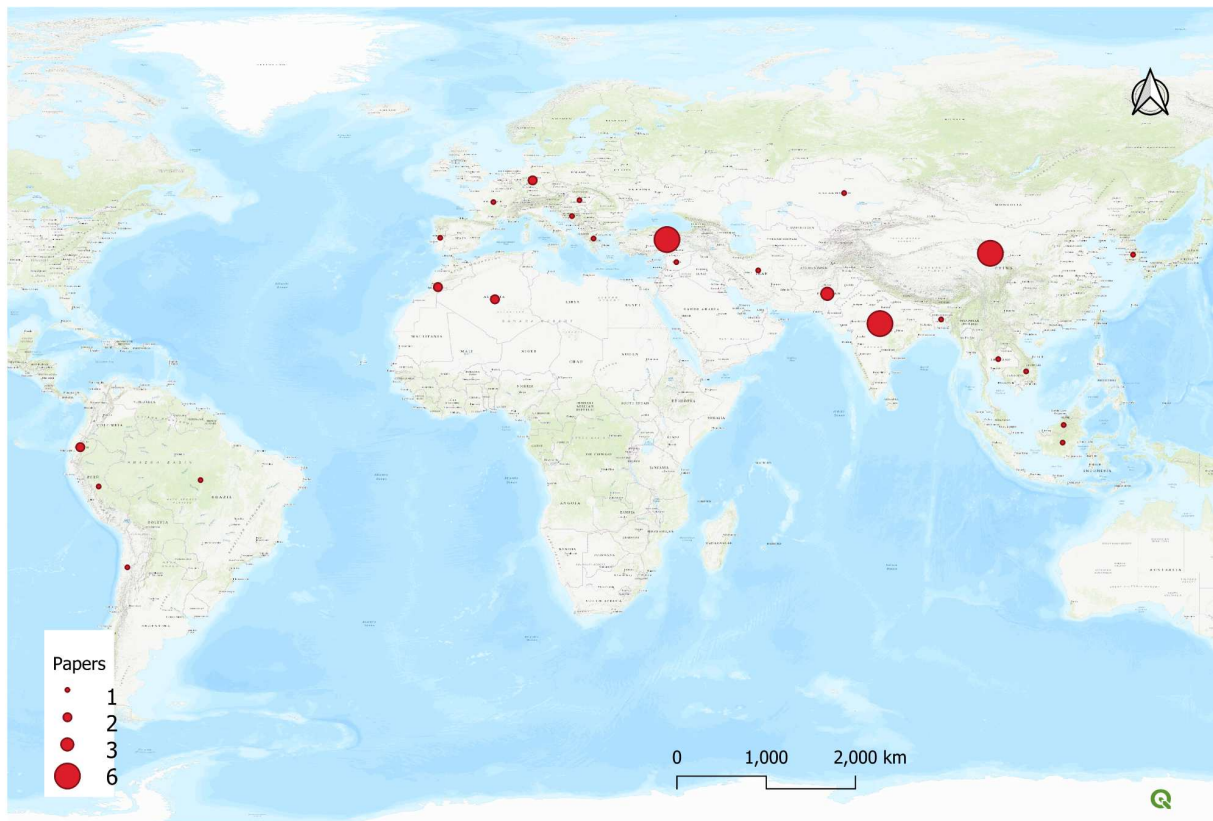


Fig. 4 Research paper collection at country level

Distribution of reviewed papers by continent

The continental distribution of the reviewed literature, summarized in Table 2, highlights the geographical focus of forest fire mapping research. Asia accounted for the largest proportion of studies, with 62.7% ($n = 32$), followed by America with 15.6% ($n = 8$), Europe with 13.7% ($n = 7$), and Africa with 7.8% ($n = 4$). This distribution indicates a strong concentration of research in Asia, which may reflect both the region's research activity and the prevalence and impacts of forest fires.

Table 2 Research papers by continent

Continent	Number
Africa	4
America	8
Asia	32

Europe	7
--------	---

Summary of the studies reviewed

The final set of 51 studies included in this systematic review, comprehensively summarized in Table 3, represents a diverse body of research applying GIS, remote sensing, and machine learning to forest fire mapping. The table provides details on the retrieval source, full reference, study title, year of publication, and the GIS, remote sensing, and machine learning techniques employed. As shown in Table 3, machine learning approaches were more frequently used than traditional GIS-based methods, indicating a broader methodological shift from conventional, manually intensive approaches towards more advanced and data-driven techniques for forest fire mapping.

Retrieved from	Reference	Title	Year	GIS and Machine Learning Models Used
Google Scholar	[23]	Forest fire susceptibility modeling in the Eastern Mediterranean: A machine learning assessment	2026	Random Forest, Support Vector Machine, Multilayer Perception, K-Nearest Neighbor
Google Scholar	[24]	Hotspots Forest Fire Susceptibility Mapping for Land Use or Land Cover using Remote Sensing and Geographical Information Systems (GIS)	2022	Analytical Hierarchical Process (AHP)
Google Scholar	[25]	Integration of the AHP Method and GIS Techniques for Mapping Areas Susceptible to Forest Fires in the Southern Amazon Region (Peru)	2024	Analytical Hierarchical Process (AHP)
Google Scholar	[26]	Comparative study of machine learning methods for mapping forest fire areas using Sentinel-1B and 2A imagery	2024	Support Vector Machine (SVM), Random Forest (RF), and Neural Network (NN)
Google Scholar	[27]	Mapping fire hazard potential in Kazakhstan: a machine learning and remote sensing perspective	2025	Maximum Entropy (MaxEnt) model
Google Scholar	[28]	Using Machine Learning Coupled with Remote Sensing for Fire Susceptibility Mapping. Case Study Tetouan Province, Northern Morocco	2022	XGBoost (XGB), Random Forest (RF), and Support Vector Machine (SVM)
MDPI	[29]	Employing Copernicus Land Service and Sentinel-2 Satellite Mission Data to Assess the Spatial Dynamics and Distribution of the Extreme Forest Fires of 2023 in Greece	2023	
MDPI	[30]	Characterizing Spatial Patterns of Amazon Rainforest Wildfires and Driving Factors by Using Remote Sensing and GIS Geospatial Technologies	2022	Kernel Density Estimation (KDE), Geographically Weighted Poisson Regression (GWPR)
MDPI	[31]	Assessment of Forest Fire Severity for a Management Conceptual Model: Case Study in Vilcabamba, Ecuador	2024	Analytical Hierarchical Process (AHP), Logistic Regression
MDPI	[32]	Forest Fire Assessment Using Remote Sensing to Support the Development of an Action Plan Proposal in Ecuador	2022	Principal Component Analysis
MDPI	[33]	Forest Fire Susceptibility Zonation in Eastern India Using Statistical and	2023	Analytical Hierarchical Process (AHP)

		Weighted Modelling Approaches		
MDPI	[34]	Application of Remote Sensing and Explainable Artificial Intelligence (XAI) for Wildfire Occurrence Mapping in the Mountainous Region of Southwest China	2024	Random Forest, Logistic Regression, Extreme Gradient Boosting Model
MDPI	[35]	Forest Fire Risk Prediction in South Korea Using Google Earth Engine: Comparison of Machine Learning Models	2025	Random forest, Extreme Gradient Boosting model , and artificial neural network
MDPI	[36]	BIPE: A Bi-Layer Predictive Ensemble Framework for Forest Fire Susceptibility Mapping in Germany	2024	Bi-Layer Predictive Ensemble
MDPI	[37]	Wildfire Risk Assessment in Liangshan Prefecture, China Based on An Integration Machine Learning Algorithm	2022	Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting
MDPI	[38]	Remote Sensing and Machine Learning for Accurate Fire Severity Mapping in Northern Algeria	2024	Support Vector Machine, Convolutional Neural Networks (CNN)
MDPI	[39]	Integrated Spatial Analysis of Forest Fire Susceptibility in the Indian Western Himalayas (IWH) Using Remote Sensing and GIS-Based Fuzzy AHP Approach	2023	Analytical Hierarchical Process (AHP)
MDPI	[40]	Integrating Geographic Information System and Logistic Regression for Forest Fire Susceptibility Mapping in Chom Thong District, Chiang Mai Province, Thailand	2026	Logistic Regression
MDPI	[41]	Forest Fire Prediction: A Spatial Machine Learning and Neural Network Approach	2024	Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Convolutional Neural Network (CNN)
MDPI	[42]	A New Approach Based on TensorFlow Deep Neural Networks with ADAM Optimizer and GIS for Spatial Prediction of Forest Fire Danger in Tropical Areas	2023	Random Forest, Support Vector Machine, Logistic Regression, TensorFlow deep neural networks
MDPI	[43]	A Forest Fire Susceptibility Modeling Approach Based on Light Gradient Boosting Machine Algorithm	2022	Random Forest, Logistic Regression, Light Gradient Boosting Model
MDPI	[44]	Forest Fire Occurrence Prediction in China Based on Machine Learning Methods	2022	Artificial Neural Network, radial basis function network, Support-Vector Machine, Random Forest
Science Direct	[45]	Geospatial deep learning and SHAP-based explainable AI for wildfire susceptibility and exposure mapping in Western Canada	2026	Long short-term memory (LSTM) and bidirectional LSTM (BiLSTM) models,
Science Direct	[46]	Advanced forest fire risk mapping: Combining Sentinel-2 MSI data with hybrid machine learning in Similipal Biosphere Reserve	2025	Random Forest
Science Direct	[47]	Machine learning based wildfire susceptibility mapping using remotely sensed fire data and GIS: A case study of Adana and Mersin provinces, Turkey	2022	Random Forest (RF), Gradient Boosting (GB), eXtreme Gradient Boosting (XGB), and AdaBoost (AB)
Science Direct	[48]	A deep learning ensemble model for wildfire susceptibility mapping	2021	Deep Learning(ENSEMBLE MODEL)
Science Direct	[49]	Fire risk mapping using machine learning method and remote sensing in the	2025	Maximum Entropy (MaxEnt) model

		Mediterranean region		
Science Direct	[50]	A machine learning-based wildfire susceptibility mapping framework for China's three-north shelterbelt region	2026	Random Forest (RF), Gradient-Boosting Decision Tree (GBDT), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Logistic Regression (LR)
Science Direct	[51]	Assessing Chilgoza Pine (Pinus gerardiana) forest fire severity: Remote sensing analysis, correlations, and predictive modeling for enhanced management strategies	2024	Random Forest (RF), Extreme Gradient Boosting , and logistic regression
Science Direct	[52]	Data driven forest fire susceptibility mapping in Bangladesh	2025	Artificial Neural Network (ANN), Classification and Regression Trees (CART), Categorical Boosting (CatBoost), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Gradient Boosting Decision Tree (GBDT), Random Forest (RF), Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost)
Science Direct	[53]	Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area	2021	Frequency Ratio-Multilayer Perceptron (FR-MLP), Frequency Ratio-Logistic Regression (FRLR), Frequency Ratio-Classification and Regression Tree (FR-CART), Frequency Ratio-Support Vector Machine (FR-SVM), and Frequency Ratio-Random Forest (FR-RF)
Science Direct	[54]	Wildfire susceptibility mapping with multiple machine learning algorithms utilizing forest inventory and FIRMS data: A case study in Arsin, Trabzon, Türkiye	2024	Random Forest (RF), Artificial Neural Network (ANN), Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), and Deep Neural Network (DNN)
Science Direct	[55]	Assessing wildfire susceptibility and driving variables in Portugal using machine learning approach	2025	Random Forest
Science Direct	[56]	Assessment of forest fire vulnerability prediction in Indonesia: Seasonal variability analysis using machine learning techniques	2025	Random forest (RF) and eXtreme Gradient Boosting (XGB)
Science Direct	[57]	Artificial intelligence-driven forest fire land susceptibility mapping: A remote sensing and machine learning approach	2026	Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting, and Gradient Boosting Machine (GBM)
Springer	[58]	Multi-factor Fire Susceptibility Index (FSI) in Hungary: a data-driven approach using remotely sensed data for peri-urban and forested landscapes	2026	Google Earth Engine
Springer	[59]	Machine learning wildfire susceptibility mapping for Germany	2025	Random Forest
Springer	[60]	Assessing wildfire extents in Siberian forests using machine learning	2025	XGBoost, Random Forest, K-Nearest Neighbors, Logistic Regression, and Decision Tree
Springer	[61]	Forest fire mapping: a comparison between GIS-based random forest and Bayesian	2023	GIS-based Bayesian and Random Forest (RF)

		models		
Springer	[62]	Advancing wildfire monitoring: remote sensing techniques and applications in the Sana River Basin, Bosnia and Herzegovina	2025	Google Earth Engine
Springer	[63]	GIS-based forest fire risk determination for Milas district, Turkey	2022	Analytical Hierarchical Process (AHP)
Springer	[64]	An integrated remote sensing and AHP framework for forest fire vulnerability assessment in Gironde, France	2025	Analytical Hierarchical Process (AHP)
Springer	[65]	A Synergistic Approach Using Machine Learning and Deep Learning for Forest Fire Susceptibility in Himalayan Forests	2025	Random Forest, Gradient Boosting Model
Springer	[66]	Harnessing geospatial intelligence for wildfire risk mapping using ML and DL techniques	2026	XGBoost, CatBoost, LightGBM, and AdaBoost
Springer	[67]	Forest fire risk mapping using analytical hierarchy process (AHP) and earth observation datasets: a case study in the mountainous terrain of Northeast India	2021	Analytical Hierarchical Process (AHP)
Springer	[68]	Remote sensing for assessing the impact of forest fire severity on ecological and socio-economic activities in Kozan District, Turkey	2024	Spectral Indices
Springer	[69]	Wildfire assessment using machine learning algorithms in different regions	2024	Logistic Regression (LR) and Random Forest (RF)
Springer	[70]	Machine learning-based forest fire vulnerability assessment in subtropical chir pine forests of Pakistan	2025	Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost)
Springer	[71]	Integrated approach for the assessment of forest fire risk and burn severity mapping using GIS, AHP method, and Google Earth Engine in Western Algeria	2022	Analytical Hierarchical Process (AHP)
Springer	[72]	Integrated risk mapping for forest fire management using the analytical hierarchy process and ordered weighted average: a case study in southern Turkey	2024	Analytical Hierarchical Process (AHP)
Springer	[73]	Assessment of forest fire severity and land surface temperature using Google Earth Engine: a case study of Gujarat State, India	2024	Random Forest

Sensors and Data Sources used For Forest Fire Mapping

In response to the first research question concerning the remote sensing datasets and sensors commonly used for forest fire mapping, Table 4 summarizes their frequency of use across the reviewed studies. MODIS was the most frequently used dataset, appearing in 27 studies, followed by Sentinel-2 in 14 studies. VIIRS and Landsat 8 were each used in 6 studies, while FIRMS and Landsat 8/9 were each used in 5 studies. Landsat 9 was used in 3 studies, Landsat 5 in 2 studies, and Landsat 7 and PlanetScope in 1 study each.

Table 4 Data Sources Commonly Used

Data Source	# of times used
MODIS	27
VIIRS	6
Sentinel 2	14
Landsat 8	6
Landsat 8/9	5
Landsat 9	3
Landsat 5	2
Landsat 7	1
FIRMS	5
PlanetScope	1

Table 3 Final studies included in the systematic review

GIS and Machine Learning Techniques Commonly Used

To address the second research question, which examined the commonly used GIS and machine learning techniques, all 51 included publications were systematically screened. Machine learning approaches were predominant, with Random Forest used in 28 studies, Extreme Gradient Boosting (XGBoost) in 20, Support Vector Machine (SVM) in 13, and Logistic Regression in 12. Artificial Neural Networks (ANN) were used in 7 studies, Decision Trees in 4, and

Convolutional Neural Networks (CNN) in 3. AdaBoost, Maximum Entropy, Ensemble Models, Principal Component Analysis (PCA), Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM) were each reported in 2 studies, while Bi-layer Predictive Ensemble was used in 1 study.

Among GIS-based approaches, the Analytical Hierarchy Process (AHP) was applied in 14 studies, whereas the GIS-based Bayesian model was used in 1 study.

Predictor Variables and Spectral Indices

The systematic evaluation conducted for the third research question examined the predictor variables commonly used in forest fire mapping. These variables were grouped into five main categories: human-related, climatic and weather, topographic, vegetation and fuel-related, and spectral indices.

Human-related variables included distance to roads (26 studies), distance to settlements (17), distance to rivers (13), and population density (11). Climatic and weather variables comprised temperature (39 studies), precipitation (32), wind speed (24), soil moisture (6), and humidity (7). Topographic variables included slope (39 studies), aspect (38), elevation (32), and altitude (5). Land use/land cover (LULC), representing vegetation and fuel-related characteristics, was used in 22 studies.

Among the spectral indices, the Normalized Difference Vegetation Index (NDVI) was the most frequently used, appearing in 43 studies, followed by the Normalized Burn Ratio (NBR) in 8 studies. The Normalized Difference Moisture Index (NDMI) and Normalized Difference Water Index (NDWI) were each used in 5 studies, while differenced NBR (dNBR) was used in 4 studies and the Soil-Adjusted Vegetation Index (SAVI) in 1 study. Overall, NDVI, temperature, slope, aspect, precipitation, elevation, and distance to roads were among the most frequently incorporated predictors in forest fire mapping studies.

Limitations and Future Research Direction

Finally, the limitations and future research directions reported across the reviewed publications were systematically analyzed. The main limitations included challenges related to spatial resolution (10 studies), data quality (6), data availability (8), and model-related limitations (9). These findings highlight the importance of improving the quality, accessibility, and spatial and temporal resolution of data, as well as enhancing model performance.

Regarding future directions, several studies recommended integrating generated forest fire risk maps with seasonal risk indices and conducting continuous monitoring of fire dynamics. Other recommendations included extending research to larger geographical areas and across multiple

time series, incorporating deep learning algorithms, and conducting periodic assessments to capture changes in fire patterns and risk over time. These directions could strengthen the accuracy, transferability, and temporal relevance of future forest fire mapping studies.

Discussion

This systematic review demonstrates the growing importance of remote sensing, geographic information systems (GIS), and machine learning in forest fire mapping and risk assessment. The findings indicate a clear transition from conventional and largely manual approaches toward more advanced, data-driven techniques that integrate remotely sensed environmental information with geospatial and machine learning methods. The increasing application of these technologies reflects their capacity to process large volumes of spatial and temporal data, identify patterns associated with fire occurrence, and support the development of forest fire susceptibility and risk maps.

The geographical distribution of the reviewed literature revealed that research activity was concentrated in Asia, particularly in China, India, Türkiye, and Pakistan. These countries accounted for a substantial proportion of the reviewed publications. However, the high number of publications should not be interpreted solely as evidence of a higher frequency of forest fires, as publication output may also be influenced by research capacity, availability of funding, accessibility of remote sensing data, technological infrastructure, and national research priorities. Nevertheless, the concentration of research in these countries highlights the importance placed on forest fire monitoring and risk assessment in regions where wildfire is an important environmental concern. In contrast, only four of the 51 reviewed studies focused on Africa. This relatively limited representation suggests a significant geographical gap in the existing literature. Given the ecological, climatic, and socioeconomic importance of forests across Africa, greater research attention is needed to strengthen the application of GIS, remote sensing, and machine learning for forest fire monitoring and risk assessment across the continent.

The analysis of remote sensing datasets showed that MODIS and Sentinel-2 were among the most frequently used data sources. The frequent application of these datasets reflects their usefulness for forest fire mapping due to their ability to provide spatially and temporally relevant information on vegetation conditions, surface characteristics, and fire-related changes. The widespread use of MODIS, in particular, demonstrates the importance of datasets that provide frequent observations for monitoring fire dynamics over large geographical areas. Sentinel-2 was also frequently used, indicating the value of higher-resolution multispectral imagery for characterising vegetation and landscape conditions associated with fire occurrence. However, the frequent use of a particular dataset does not necessarily mean that it is universally superior.

Dataset selection should be determined by the specific objectives of the study, spatial scale, temporal requirements, geographical context, and the characteristics of the variables being modelled.

Machine learning techniques were the dominant analytical approaches identified in the review. Random Forest was the most frequently applied model, appearing in 28 studies, followed by XGBoost (20), Support Vector Machine (13), and Logistic Regression (12). The widespread application of these models demonstrates the growing role of machine learning in identifying complex and potentially nonlinear relationships between forest fire occurrence and environmental, climatic, topographic, and human-related factors. Random Forest and XGBoost are particularly useful for handling multiple predictor variables and complex interactions, while SVM and Logistic Regression provide alternative approaches for classification and probability-based modelling. The diversity of models used across the reviewed studies also indicates that there is no single modelling approach applicable to all forest fire mapping contexts.

The findings further suggest a gradual shift from traditional GIS-based approaches toward integrated GIS and machine learning frameworks. Although conventional approaches such as analytical and knowledge-based methods remain relevant, the increasing use of machine learning demonstrates the growing emphasis on automated and predictive approaches. Google Earth Engine was also frequently used across the reviewed studies, reflecting the increasing importance of cloud-based geospatial platforms. Such platforms provide access to large remote sensing archives and computational resources, allowing researchers to process extensive spatial and temporal datasets without relying exclusively on conventional desktop-based software. This development has the potential to improve the efficiency and scalability of forest fire mapping, particularly in regions where access to high-performance computing infrastructure may be limited.

The review also identified several predictor variables that are consistently incorporated into forest fire mapping models. Distance to roads, distance to settlements, slope, aspect, elevation, and NDVI were among the most frequently used variables. The frequent inclusion of distance to roads and settlements highlights the importance of human-related factors in explaining spatial patterns of fire occurrence. Roads and settlements may influence fire risk through increased human accessibility and activities, although their effects can vary according to local land-use practices and socioeconomic conditions. Similarly, the frequent use of topographic variables such as slope, aspect, and elevation demonstrates the importance of landscape characteristics in influencing fire behaviour, vegetation distribution, moisture conditions, and solar exposure. NDVI was the most frequently used spectral index, reflecting its usefulness in representing vegetation characteristics and conditions that may influence fire susceptibility.

An important finding of the review concerns the influence of spatial resolution on forest fire mapping. Several studies identified spatial resolution as a limitation, suggesting that the selection

of appropriate data resolution is critical for producing reliable fire risk maps. A coarse spatial resolution may fail to capture small-scale variations in vegetation, human activity, topography, and land use, whereas very high-resolution datasets may increase computational requirements and data-processing complexity. Consequently, researchers should carefully match the spatial resolution of the input datasets to the scale of the study area and the objectives of the analysis. Consideration should also be given to temporal resolution, particularly when monitoring rapidly changing fire conditions.

Finally, the review highlights the importance of careful model selection and validation. The use of increasingly sophisticated machine learning algorithms does not automatically guarantee more accurate or reliable forest fire maps. Model performance can be affected by the quality and representativeness of training data, predictor selection, class imbalance, spatial and temporal sampling, and model parameterisation. Poorly designed training and validation procedures may introduce bias or lead to overestimation of model performance. Therefore, future studies should adopt robust validation strategies, carefully assess predictor variables, address potential data imbalance, and evaluate model transferability across different locations and time periods. Comparative assessment of multiple algorithms may also provide a stronger basis for selecting appropriate models for specific environmental and geographical contexts.

Conclusion and Recommendations

This systematic review demonstrates the increasing importance of remote sensing, GIS, and machine learning in forest fire mapping. MODIS and Sentinel-2 were the most frequently used remote sensing datasets, while Random Forest, XGBoost, and Support Vector Machine were among the most commonly applied machine learning techniques. NDVI, temperature, slope, aspect, elevation, and proximity to roads and settlements were frequently identified as important predictor variables. However, limitations related to spatial resolution, data quality, data availability, and model performance remain significant challenges.

Based on these findings, future research should focus on improving the spatial and temporal resolution and quality of remotely sensed data, particularly in underrepresented regions such as Africa. Researchers should consider integrating multiple remote sensing datasets and environmental variables to improve mapping accuracy. The application of advanced deep learning techniques should also be explored, alongside robust model validation to minimise bias and improve transferability across different geographical areas. Furthermore, periodic monitoring and the integration of forest fire risk maps with seasonal fire-risk indices are recommended to better capture changes in fire patterns over time and support effective forest fire management and decision-making.

STATEMENTS

Acknowledgements

The authors would like to thank the Mount Mulanje Conservation Trust (MMCT) for providing institutional support. We also acknowledge the contributions of colleagues who provided informal feedback during the preparation of this manuscript.

Declarations

Ethics approval and consent to participate

Not applicable. This study is a systematic review of previously published literature and does not involve direct human or animal participants, primary data collection, or any interventions requiring ethical approval.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

References

- [1] Giglio, L., Schroeder, W., & Justice, C. O. (2016). The Collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment*, 178, 31–41. <https://doi.org/10.1016/j.rse.2016.02.054>
- [2] Chuvieco, E., Mouillot, F., van der Werf, G. R., San Miguel, J., Tanase, M., Koutsias, N., García, M., Yebra, M., Padilla, M., Gitas, I., Heil, A., Hawbaker, T. J., & Giglio, L. (2019). Historical background and current developments for mapping burned area from satellite Earth observation. *Remote Sensing of Environment*, 225, 45–64. <https://doi.org/10.1016/j.rse.2019.02.013>
- [3] Guiop-Servan, R. E., Cotrina-Sanchez, A., Puerta-Culqui, J., Oliva-Cruz, M., & Barboza, E. (2025). Remote sensing for wildfire mapping: A comprehensive review of advances, platforms, and algorithms. *Fire*, 8(8), 316. <https://doi.org/10.3390/fire8080316>
- [4] Nelson, D. M., He, Y., & Moore, G. W. K. (2024). Trends and applications in wildfire burned area mapping: Remote sensing data, cloud geoprocessing platforms, and emerging algorithms. *Geomatica*, 76(1), 100008. <https://doi.org/10.1016/j.geomat.2024.100008>
- [5] Giglio, L., Boschetti, L., Roy, D. P., Humber, M. L., & Justice, C. O. (2018). The Collection 6 MODIS burned area mapping algorithm and product. *Remote Sensing of Environment*, 217, 72–85. <https://doi.org/10.1016/j.rse.2018.08.005>

- [6] Boschetti, L., Roy, D. P., Giglio, L., Huang, H., Zubkova, M., & Humber, M. L. (2019). Global validation of the Collection 6 MODIS burned area product. *Remote Sensing of Environment*, 235, 111490. <https://doi.org/10.1016/j.rse.2019.111490>
- [7] Humber, M. L., Boschetti, L., Giglio, L., & Justice, C. O. (2018). Spatial and temporal intercomparison of four global burned area products. *International Journal of Digital Earth*, 12(4), 460–484. <https://doi.org/10.1080/17538947.2018.1433727>
- [8] Humber, M. L., Boschetti, L., & Giglio, L. (2020). Assessing the shape accuracy of coarse resolution burned area identifications. *IEEE Transactions on Geoscience and Remote Sensing*, 58(3), 1516–1526. <https://doi.org/10.1109/TGRS.2019.2943901>
- [9] Roteta, E., Bastarrika, A., Padilla, M., Storm, T., & Chuvieco, E. (2019). Development of a Sentinel-2 burned area algorithm: Generation of a small fire database for sub-Saharan Africa. *Remote Sensing of Environment*, 222, 1–17. <https://doi.org/10.1016/j.rse.2018.12.011>
- [10] Roy, D. P., Huang, H., Boschetti, L., Giglio, L., Yan, L., Zhang, H., & Li, Z. (2019). Landsat-8 and Sentinel-2 burned area mapping—A combined sensor multi-temporal change detection approach. *Remote Sensing of Environment*, 231, 111254. <https://doi.org/10.1016/j.rse.2019.111254>
- [11] Martins, V. S., Roy, D. P., Huang, H., Boschetti, L., Zhang, H. K., & Yan, L. (2022). Deep learning high resolution burned area mapping by transfer learning from Landsat-8 to PlanetScope. *Remote Sensing of Environment*, 280, 113203. <https://doi.org/10.1016/j.rse.2022.113203>
- [12] Zhang, Q., Ge, L., Zhang, R., Metternicht, G. I., Du, Z., Kuang, J., & Xu, M. (2021). Deep-learning-based burned area mapping using the synergy of Sentinel-1 & Sentinel-2 data. *Remote Sensing of Environment*, 264, 112575. <https://doi.org/10.1016/j.rse.2021.112575>
- [13] Zhang, X., et al. (2022). Remote sensing of forest burnt area, burn severity, and post-fire recovery: A review. *Remote Sensing*, 14(19), 4714. <https://doi.org/10.3390/rs14194714>
- [14] Zhang, Q., et al. (2026). Improving wildfire burned area mapping from Sentinel-2 imagery using a context-aware Transformer U-Net (FTSUNet). *Results in Engineering*, 32, 111771. <https://doi.org/10.1016/j.rineng.2026.111771>
- [15] Fang, H., Yang, C., Guo, S., Zhang, P., Tang, P., & Du, P. (2026). Mapping burned areas by unsupervised change detection combining automatic multi-index driven label generation and ensemble learning. *International Journal of Applied Earth Observation and Geoinformation*, 149, 105283.
- [16] Knopp, L., Wieland, M., Rättich, M., & Martinis, S. (2020). A deep learning approach for burned area segmentation with Sentinel-2 data. *Remote Sensing*, 12(15), 2422. <https://doi.org/10.3390/rs12152422>
- [17] Atasever, Ü. H., & Tercan, E. (2024). Deep learning-based burned forest areas mapping via Sentinel-2 imagery: A comparative study. *Environmental Science and Pollution Research*, 31(4), 5304–5318. <https://doi.org/10.1007/s11356-023-31575-5>
- [18] Seydi, S. T., & Sadegh, M. (2025). DLSR-FireCNet: A deep learning framework for burned area mapping based on decision level super-resolution. *Remote Sensing Applications: Society and Environment*, 37, 101513. <https://doi.org/10.1016/j.rsase.2025.101513>

- [19] Boschetti, L., Stehman, S. V., & Roy, D. P. (2016). A stratified random sampling design in space and time for regional to global scale burned area product validation. *Remote Sensing of Environment*, 186, 465–478. <https://doi.org/10.1016/j.rse.2016.09.016>
- [20] Hall, J. V., Argueta, F., & Giglio, L. (2021). Validation of MCD64A1 and FireCCI51 cropland burned area mapping in Ukraine. *International Journal of Applied Earth Observation and Geoinformation*, 102, 102443. <https://doi.org/10.1016/j.jag.2021.102443>
- [21] Chen, R., Rui, X., Zhang, J., & Song, W. (2026). FireCluster: A multi-source satellite active fire data clustering algorithm for comprehensive wildfire event identification. *Science of Remote Sensing*, 13, 100423. <https://doi.org/10.1016/j.srs.2026.100423>
- [22] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* [Internet]. 2021;372:n71. Available from: <https://doi.org/10.1136/bmj.n71>
- [23] Richi, S., Maya, R., & Ghribi, M. (2026). Forest fire susceptibility modeling in the Eastern Mediterranean: A machine learning assessment. *DYSONA-Applied Science*, 7(1), 88-97 <http://dx.doi.org/10.30493/DAS.2025.525949>
- [24] Ya'acob, N., Jamil, I.A., Aziz, N.F., Yusof, A.L., Kassim, M., & Naim, N.F. (2022). Hotspots Forest Fire Susceptibility Mapping for Land Use or Land Cover using Remote Sensing and Geographical Information Systems (GIS). *IOP Conference Series: Earth and Environmental Science*, 1064. [doi:10.1088/1755-1315/1064/1/012029](https://doi.org/10.1088/1755-1315/1064/1/012029)
- [25] Vergara, A.J., Valqui-Reina, V.S., Cieza-Tarrillo, D., Munoz-Astecker, L.D., Ocaña, C.L., Cubas, J., Auquiñivin-Silva, E.A. (2024). Integration of the AHP method and GIS techniques for mapping areas susceptible to forest fires in the southern Amazon region (Peru). *International Journal of Design & Nature and Ecodynamics*, Vol. 19, No. 3, pp. 769-778. <https://doi.org/10.18280/ijdne.190307>
- [26] Chen X, Zhang Y, Wang S, Zhao Z, Liu C and Wen J (2024) Comparative study of machine learning methods for mapping forest fire areas using Sentinel-1B and 2A imagery. *Front. Remote Sens.* 5:1446641. <https://doi.org/10.3389/frsen.2024.1446641>
- [27] Chepashev D, Nurakynov S, Sharma D, Sydyk N, Kabdulova G. (2025) Mapping fire hazard potential in Kazakhstan: a machine learning and remote sensing perspective. *International Journal of Wildland Fire* 34, WF24232. <https://doi.org/10.1071/WF24232>
- [28] Seddouki, M., Benayad, M., Aamir, Z., Tahiri, M., Maanan, M., and Rhinane, H.: USING MACHINE LEARNING COUPLED WITH REMOTE SENSING FOR FOREST FIRE SUSCEPTIBILITY MAPPING. CASE STUDY TETOUAN PROVINCE, NORTHERN MOROCCO, *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLVIII-4/W6-2022, 333–342, <https://doi.org/10.5194/isprs-archives-XLVIII-4-W6-2022-333-2023>.
- [29] Dosiou, A.; Athinelis, I.; Katris, E.; Vassalou, M.; Kyrkos, A.; Krassakis, P.; Parcharidis, I. Employing Copernicus Land Service and Sentinel-2 Satellite Mission Data to Assess the Spatial Dynamics and Distribution of the Extreme Forest Fires of 2023 in Greece. *Fire* 2024, 7, 20. <https://doi.org/10.3390/fire7010020>

- [30] Ma, C.; Pu, R.; Downs, J.; Jin, H. Characterizing Spatial Patterns of Amazon Rainforest Wildfires and Driving Factors by Using Remote Sensing and GIS Geospatial Technologies. *Geosciences* 2022, 12, 237. <https://doi.org/10.3390/geosciences12060237>
- [31] González, F.; MoranteCarballo, F.; González, A.; BravoMontero, L.; Benavidez-Silva, C.; Tedim, F. Assessment of Forest Fire Severity for a Management Conceptual Model: Case Study in Vilcabamba, Ecuador. *Forests* 2024, 15, 2210. <https://doi.org/10.3390/f15122210>
- [32] Morante-Carballo, F.; Bravo-Montero, L.; Carrión-Mero, P.; Velastegui-Montoya, A.; Berrezueta, E. Forest Fire Assessment Using Remote Sensing to Support the Development of an Action Plan Proposal in Ecuador. *Remote Sens.* 2022, 14, 1783. <https://doi.org/10.3390/rs14081783>
- [33] Das, J.; Mahato, S.; Joshi, P.K.; Liou, Y.-A. Forest Fire Susceptibility Zonation in Eastern India Using Statistical and Weighted Modelling Approaches. *Remote Sens.* 2023, 15, 1340. <https://doi.org/10.3390/rs15051340>
- [34] Liu, J.; Wang, Y.; Lu, Y.; Zhao, P.; Wang, S.; Sun, Y.; Luo, Y. Application of Remote Sensing and Explainable Artificial Intelligence (XAI) for Wildfire Occurrence Mapping in the Mountainous Region of Southwest China. *Remote Sens.* 2024, 16, 3602. <https://doi.org/10.3390/rs16193602>
- [35] Choi, J.; Yun, Y.; Chae, H. Forest Fire Risk Prediction in South Korea Using Google Earth Engine: Comparison of Machine Learning Models. *Land* 2025, 14, 1155. <https://doi.org/10.3390/land14061155>
- [36] Hu, L.; Hochschild, V.; Neidhardt, H.; Schultz, M.; Khosravani, P.; Shokati, H. BIPE: A Bi-Layer Predictive Ensemble Framework for Forest Fire Susceptibility Mapping in Germany. *Remote Sens.* 2025, 17, 7. <https://doi.org/10.3390/rs17010007>
- [37] Xie, L.; Zhang, R.; Zhan, J.; Li, S.; Shama, A.; Zhan, R.; Wang, T.; Lv, J.; Bao, X.; Wu, R. Wildfire Risk Assessment in Liangshan Prefecture, China Based on An Integration Machine Learning Algorithm. *Remote Sens.* 2022, 14, 4592. <https://doi.org/10.3390/rs14184592>
- [38] Zikiou, N.; Rushmeier, H.; Capel, M.I.; Kandakji, T.; Rios, N.; Lahdir, M. Remote Sensing and Machine Learning for Accurate Fire Severity Mapping in Northern Algeria. *Remote Sens.* 2024, 16, 1517. <https://doi.org/10.3390/rs16091517>
- [39] Pragma; Kumar, M.; Tiwari, A.; Majid, S.I.; Bhadwal, S.; Sahu, N.; Verma, N.K.; Tripathi, D.K.; Avtar, R. Integrated Spatial Analysis of Forest Fire Susceptibility in the Indian Western Himalayas (IWH) Using Remote Sensing and GIS-Based Fuzzy AHP Approach. *Remote Sens.* 2023, 15, 4701. <https://doi.org/10.3390/rs15194701>
- [40] Samphutthanont, R.; Suppawimut, W. Integrating Geographic Information System and Logistic Regression for Forest Fire Susceptibility Mapping in Chom Thong District, Chiang Mai Province, Thailand. *Geographies* 2026, 6, 75. <https://doi.org/10.3390/geographies6030075>
- [41] Sharma, S.; Khanal, P. Forest Fire Prediction: A Spatial Machine Learning and Neural Network Approach. *Fire* 2024, 7, 205. <https://doi.org/10.3390/fire7060205>
- [42] Truong, T.X.; Nhu, V.-H.; Phuong, D.T.N.; Nghi, L.T.; Hung, N.N.; Hoa, P.V.; Bui, D.T. A New Approach Based on TensorFlow Deep Neural Networks with ADAM Optimizer and GIS for Spatial Prediction of Forest Fire Danger in Tropical Areas. *Remote Sens.* 2023, 15, 3458. <https://doi.org/10.3390/rs15143458>

- [43] Sun, Y.; Zhang, F.; Lin, H.; Xu, S. A Forest Fire Susceptibility Modeling Approach Based on Light Gradient Boosting Machine Algorithm. *Remote Sens.* 2022, 14, 4362. <https://doi.org/10.3390/rs14174362>
- [44] Pang, Y.; Li, Y.; Feng, Z.; Feng, Z.; Zhao, Z.; Chen, S.; Zhang, H. Forest Fire Occurrence Prediction in China Based on Machine Learning Methods. *Remote Sens.* 2022, 14, 5546. <https://doi.org/10.3390/rs14215546>
- [45] Muhammad S. Khan, Aitazaz A. Farooque, Tatiana Al-Mughrabi, Raheleh Malekian, Xander Wang, Travis J. Esau, Qamar Uz Zaman, Geospatial deep learning and SHAP-based explainable AI for wildfire susceptibility and exposure mapping in Western Canada, *Ecological Informatics*, Volume 98, 2026, 103996, ISSN 1574-9541, <https://doi.org/10.1016/j.ecoinf.2026.103996>.
- [46] Bilel Zerouali, Celso Augusto Guimarães Santos, Saleh Qaysi, Richarde Marques da Silva, Nassir Alarifi, Nadjem Bailek, Manoranjan Mishra, Paolo Porto, Youssef M. Youssef, Advanced forest fire risk mapping: Combining Sentinel-2 MSI data with hybrid machine learning in Similipal Biosphere Reserve, *Forest Ecology and Management*, Volume 594, 2025, 122931, ISSN 0378-1127, <https://doi.org/10.1016/j.foreco.2025.122931>.
- [47] Muzaffer Can Iban, Alihsan Sekertekin, Machine learning based wildfire susceptibility mapping using remotely sensed fire data and GIS: A case study of Adana and Mersin provinces, Turkey, *Ecological Informatics*, Volume 69, 2022, 101647, ISSN 1574-9541, <https://doi.org/10.1016/j.ecoinf.2022.101647>.
- [48] Alexandra Bjånes, Rodrigo De La Fuente, Pablo Mena, A deep learning ensemble model for wildfire susceptibility mapping, *Ecological Informatics*, Volume 65, 2021, 101397, ISSN 1574-9541, <https://doi.org/10.1016/j.ecoinf.2021.101397>.
- [49] Fatih Sivrikaya, Döndü Demirel, Fire risk mapping using machine learning method and remote sensing in the Mediterranean region, *Advances in Space Research*, Volume 75, Issue 7, 2025, Pages 5402-5419, ISSN 0273-1177, <https://doi.org/10.1016/j.asr.2025.01.050>.
- [50] Kaida Yan, Fengjun Zhao, Lifu Shu, Yongqiang Liu, Mingyu Wang, Liqing Si, Weike Li, Xiaoxiao Li, Shiyuan Zhang, Siwei Li, Jinglu Wang, A machine learning-based wildfire susceptibility mapping framework for China's three-north shelterbelt region, *Ecological Informatics*, Volume 93, 2026, 103539, ISSN 1574-9541, <https://doi.org/10.1016/j.ecoinf.2025.103539>.
- [51] Kaleem Mehmood, Shoaib Ahmad Anees, Mi Luo, Muhammad Akram, Muhammad Zubair, Khalid Ali Khan, Waseem Razzaq Khan, Assessing Chilgoza Pine (*Pinus gerardiana*) forest fire severity: Remote sensing analysis, correlations, and predictive modeling for enhanced management strategies, *Trees, Forests and People*, Volume 16, 2024, 100521, ISSN 2666-7193, <https://doi.org/10.1016/j.tfp.2024.100521>.
- [52] Mafrid Haydar, Al Hossain Rafi, Halima Sadia, Md Tanvir Hossain, Data driven forest fire susceptibility mapping in Bangladesh, *Ecological Indicators*, Volume 166, 2024, 112264, ISSN 1470-160X, <https://doi.org/10.1016/j.ecolind.2024.112264>.
- [53] Meriame Mohajane, Romulus Costache, Firoozeh Karimi, Quoc Bao Pham, Ali Essahlaoui, Hoang Nguyen, Giovanni Laneve, Fatiha Oudija, Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area, *Ecological Indicators*, Volume 129, 2021, 107869, ISSN 1470-160X, <https://doi.org/10.1016/j.ecolind.2021.107869>.

- [54] Sude Gül Yel, Derya Mumcu Küçükler, Esra Tunç Görmüş, Wildfire susceptibility mapping with multiple machine learning algorithms utilizing forest inventory and FIRMS data: A case study in Arsin, Trabzon, Türkiye, *International Journal of Applied Earth Observation and Geoinformation*, Volume 146, 2026, 105091, ISSN 1569-8432, <https://doi.org/10.1016/j.jag.2026.105091>.
- [55] Vicente Paulo Santana Neto, Adelia de Jesus Nobre Nunes, Fillipe Tamiozzo Pereira Torres, José Marinaldo Gleriani, Diogo Nepomuceno Cosenza, Assessing wildfire susceptibility and driving variables in Portugal using machine learning approach, *Journal for Nature Conservation*, Volume 86, 2025, 126956, ISSN 1617-1381, <https://doi.org/10.1016/j.jnc.2025.126956>.
- [56] Wulan Salle Karurung, Kangjae Lee, Wonhee Lee, Assessment of forest fire vulnerability prediction in Indonesia: Seasonal variability analysis using machine learning techniques, *International Journal of Applied Earth Observation and Geoinformation*, Volume 138, 2025, 104435, ISSN 1569-8432, <https://doi.org/10.1016/j.jag.2025.104435>.
- [57] Xulong Duan, Muhammad Haseeb, Zainab Tahir, Syed Amer Mahmood, Aqil Tariq, Artificial intelligence-driven forest fire land susceptibility mapping: A remote sensing and machine learning approach, *Land Use Policy*, Volume 170, 2026, 108171, ISSN 0264-8377, <https://doi.org/10.1016/j.landusepol.2026.108171>.
- [58] Agustiyara, A., Timár, G. & Székely, B. Multi-factor Fire Susceptibility Index (FSI) in Hungary: a data-driven approach using remotely sensed data for peri-urban and forested landscapes. *Model. Earth Syst. Environ.* **12**, 144 (2026). <http://doi.org/10.1007/s40808-026-02785-w>
- [59] Thies, B. Machine learning wildfire susceptibility mapping for Germany. *Nat Hazards* **121**, 12517–12530 (2025). <https://doi.org/10.1007/s11069-025-07292-2>
- [60] Malashin, I.P., Masich, I., Nelyub, V. *et al.* Assessing wildfire extents in Siberian forests using machine learning. *Sci Rep* **15**, 32834 (2025) doi.org/10.1038/s41598-025-17465-5
- [61] Noroozi, F., Ghanbarian, G., Safaeian, R. *et al.* Forest fire mapping: a comparison between GIS-based random forest and Bayesian models. *Nat Hazards* **120**, 6569–6592 (2024). doi.org/10.1007/s11069-024-06457-9
- [62] Sabljic, L., Peric, Z.M., Bajić, D. *et al.* Advancing wildfire monitoring: remote sensing techniques and applications in the Sana River Basin, Bosnia and Herzegovina. *Nat Hazards* **121**, 18321–18360 (2025). doi.org/10.1007/s11069-025-07518-3
- [63] Cetin, M., Isik Pekkan, Ö., Ozenen Kavlak, M. *et al.* GIS-based forest fire risk determination for Milas district, Turkey. *Nat Hazards* **119**, 2299–2320 (2023). doi.org/10.1007/s11069-022-05601-7
- [64] Khelali, M., Bensekhria, A., Bouhata, R. *et al.* An integrated remote sensing and AHP framework for forest fire vulnerability assessment in Gironde, France. *Nat Hazards* **122**, 626 (2026). doi.org/10.1007/s11069-026-08402-4
- [65] Shome, P., Prakash, A.J., Behera, M.D. *et al.* A Synergistic Approach Using Machine Learning and Deep Learning for Forest Fire Susceptibility in Himalayan Forests. *J Indian Soc Remote Sens* **54**, 4713–4728 (2026). <https://doi.org/10.1007/s12524-025-02157-4>

- [66] Vibhandik, P., Sawant, S., Mishra, V. *et al.* Harnessing geospatial intelligence for wildfire risk mapping using ML and DL techniques. *Discov Appl Sci* **8**, 258 (2026). <https://doi.org/10.1007/s42452-026-08288-8>
- [67] Lamat, R., Kumar, M., Kundu, A. *et al.* Forest fire risk mapping using analytical hierarchy process (AHP) and earth observation datasets: a case study in the mountainous terrain of Northeast India. *SN Appl. Sci.* **3**, 425 (2021). <https://doi.org/10.1007/s42452-021-04391-0>
- [68] Ibrahim, S., Kose, M., Adamu, B. *et al.* Remote sensing for assessing the impact of forest fire severity on ecological and socio-economic activities in Kozan District, Turkey. *J Environ Stud Sci* **15**, 342–354 (2025). <https://doi.org/10.1007/s13412-024-00951-z>
- [69] Moghim, S., Mehrabi, M. Wildfire assessment using machine learning algorithms in different regions. *fire ecol* **20**, 104 (2024) <https://doi.org/10.1186/s42408-024-00335-2>
- [70] Muhammad, S., Nizami, S.M., Jiang, Q.o. *et al.* Machine learning-based forest fire vulnerability assessment in subtropical chir pine forests of Pakistan. *fire ecol* **21**, 72 (2025). <https://doi.org/10.1186/s42408-025-00408-w>
- [71] Fekir, Y., Hamadouche, M.A. & Anteur, D. Integrated approach for the assessment of forest fire risk and burn severity mapping using GIS, AHP method, and Google Earth Engine in Western Algeria. *Euro-Mediterr J Environ Integr* **7**, 531–544 (2022). <https://doi.org/10.1007/s41207-022-00338-y>
- [72] Özcan, Z., Caglayan, İ., Kabak, Ö. *et al.* Integrated risk mapping for forest fire management using the analytical hierarchy process and ordered weighted average: a case study in southern Turkey. *Nat Hazards* **121**, 959–1001 (2025). <https://doi.org/10.1007/s11069-024-06810-y>
- [73] Jodhani, K.H., Patel, H., Soni, U. *et al.* Assessment of forest fire severity and land surface temperature using Google Earth Engine: a case study of Gujarat State, India. *fire ecol* **20**, 23 (2024). <https://doi.org/10.1186/s42408-024-00254-2>

