

Review

A Comprehensive Survey of Satellite-Based Wildfire Indicators and Spatiotemporal Modeling Approaches: Past, Present, and Future

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Abstract

Wildfires pose increasing environmental and socio-economic risks, particularly in climate-sensitive and tropical regions, necessitating reliable satellite-based monitoring and predictive frameworks. This study presents a comprehensive survey of satellite-derived wildfire indicators and spatiotemporal modeling approaches, covering their historical development, current methodologies, and emerging research directions. We review major active fire and hotspot datasets derived from MODIS, VIIRS, and related platforms, along with key environmental drivers such as vegetation indices, meteorological variables, and land-surface with a specific case study for the Indonesian region. Modeling approaches are synthesized from classical statistical regression and time-series analysis to contemporary machine learning and deep learning architectures, including convolutional neural networks, recurrent neural networks, and transformer-based models. The analysis highlights the transition toward multi-source data integration and spatiotemporal deep learning frameworks capable of capturing complex wildfire dynamics. Finally, we identify future research challenges, including hybrid physical–AI modeling, uncertainty quantification, and scalable real-time wildfire intelligence systems. This survey provides a structured reference for researchers and practitioners seeking to advance satellite-based wildfire monitoring and prediction.

Keywords: satellite remote sensing; wildfire indicators; hotspot detection; spatiotemporal modeling; deep learning; MODIS; VIIRS; wildfire prediction; environmental drivers



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1. Introduction

Wildfires rank among the most catastrophic natural disasters, exerting extensive impacts on socioeconomic systems, human health, air quality, and the global carbon balance [1–4]. Beyond the immediate destruction of vegetation and infrastructure, wildfires drive substantial emissions of greenhouse gases and toxic air pollutants, including carbon dioxide (CO₂), nitrogen dioxide (NO₂), methane (CH₄), ozone (O₃), particulate matter (PM), and mercury [5–8]. These emissions contribute not only to regional and global climate forcing but also to secondary atmospheric processes, such as photochemical ozone formation

and aerosol–cloud interactions, prolonging air-quality degradation and amplifying health risks well beyond the active fire period.

Since the late 2000s, wildfire activity has been recognized as a major global environmental and socio-ecological hazard driven by the interaction of climate variability, vegetation dynamics, land-use change, and human ignition sources. Early syntheses framed fire as a key Earth-system process [9], while Amazonian studies showed how climate change and land-use pressure amplify fire risk in tropical forests [10]. Through the 2010s, changing fire regimes became more evident globally: assessments projected increasing fire-season severity under climate change [11], while tropical episodes like the 2013 Sumatran peat fires and 2015 Indonesian fire crisis revealed the strong sensitivity of peatland and forest fires to drought, El Niño conditions, and land degradation [12,13]. In Europe, Mediterranean pine forests exhibited extreme fire-severity patterns, exemplified by meteorologically driven events such as the 2017 Split wildfire in Croatia [14,15]. Collectively, these pre-2019 cases show that severe wildfire activity was already geographically widespread and shaped by interacting climatic and anthropogenic factors.

More recent record-breaking fire seasons underscore the growing global scale and complexity of wildfire risk. The 2019–2020 Australian Black Summer fires caused major ecological damage and injected smoke into the stratosphere across the Pacific [16,17], while the 2023 Canadian wildfire season burned roughly 15 million hectares with severe smoke impacts across Canada and the northeastern United States [18,19]. In the Amazon and Central Africa, drought, land-use change, and forest degradation continue to heighten fire vulnerability [20–22], and similar intensification appears in Southeast Asia, where Indonesia saw about 1.16 million hectares burned in 2023 amid El Niño-driven drought and peatland-clearing pressures [23]. Within the Society for Risk Analysis’s wildfire risk framework, risk comprises likelihood, intensity, and impacts [24]. Though fire regimes vary across ecosystems, these cases together demonstrate that contemporary wildfire risk from the late 2000s onward has been shaped by coupled climatic and human drivers—many trackable through satellite observation at global scale.

Wildfire occurrence emerges from nonlinear interactions among human activities, meteorological conditions, and climate variability that jointly shape ignition, spread, and persistence [25–27]. Human influence dominates many fire-prone regions, but through different pathways: agricultural burning and pastoralism in Sub-Saharan Africa, land-use change and forest degradation in the Congo Basin [22], deforestation-linked burning in the Amazon [20], and lightning combined with drought and aridity in boreal Canada and Russia [18]. In the Mediterranean, land abandonment, fuel accumulation, and recurrent heat extremes have lengthened fire seasons, while in Indonesia most fires occur in non-forest land covers such as degraded peatlands, shrublands, and agricultural areas, including industrial oil palm concessions, with major hotspot concentrations in South and Central Kalimantan and South Sumatra [23,28]. These ignitions are further amplified by prolonged dry spells, high temperatures, low humidity, reduced soil moisture, and large-scale climate variability such as El Niño, especially in peat-rich landscapes [13,29–32]. Long-term satellite observations also show that recurrent fire has been a persistent driver of forest-cover loss in Indonesia [33,34]. Because these processes are multiscale and spatially heterogeneous, satellite-based indicators are essential for monitoring wildfire occurrence, intensity, and dynamics [25,27]. Among them, fire hotspots are widely used as thermal anomalies associated with active flaming or smouldering combustion, detected by AVHRR, MODIS, and VIIRS through contextual algorithms that distinguish fire signals from surrounding background conditions [35–37].

Across fire-prone regions globally, hotspot occurrence reflects the interaction of anthropogenic ignition, fuel availability, and environmental conditions, although the specific drivers differ by biome and socioeconomic context. In tropical Southeast Asia and the Amazon, land-clearing practices on drained peatlands and degraded agricultural landscapes generate persistent hotspot clusters [13,23]. Meteorological factors, including low rainfall, high temperatures, reduced humidity, and favourable wind regimes, further promote hotspot formation, while climate variability—particularly the El Niño–Southern Oscillation—amplifies hotspot activity by inducing extended droughts [32]. In peat-rich environments, subsurface smouldering can persist for weeks to months, generating long-lived hotspot signals closely linked to greenhouse-gas emissions, transboundary haze, and prolonged air-quality degradation [13,38]. In boreal regions, hotspot activity is tightly coupled to drought indices and large-scale atmospheric circulation, as illustrated by the exceptional Canadian 2023 season [18], while in Mediterranean landscapes, wind patterns and vegetation moisture content are major modulating factors. Consequently, hotspot datasets have become central to wildfire monitoring systems, fire-risk assessment, and the development of data-driven prediction approaches [39,40].

Weather variables such as wind speed, relative humidity, temperature, solar radiation, rainfall, and vapour pressure deficit are commonly combined with fuel-moisture estimates and drought indicators, including the Keetch–Byram Drought Index, to derive core fire-danger indices such as the Ignition Component, Spread Component, Burning Index, and Energy Release Component [41]. Similar operational frameworks include the Canadian Forest Fire Weather Index (FWI) System, the McArthur Forest Fire Danger Index (FFDI) in Australia, and the U.S. National Fire Danger Rating System (NFDRS). Among these, the Canadian FWI System is especially valued for its simple computational structure and its fuel-moisture codes, which make it broadly applicable for daily fire-danger estimation across diverse environments [42]. The FFDI has long been used in Australia as an operational indicator of fire weather and fire danger, particularly for estimating the potential for ignition, fire spread, and suppression difficulty [43]. In general, these systems provide an important advantage by translating complex weather–fuel interactions into interpretable indicators that can support early warning and fire-management decisions [44]. Although Indonesia does not operationally apply the National Fire Danger Rating System, this conceptual framework aligns closely with satellite-based wildfire hotspot analysis, in which hotspots detected by sensors such as MODIS and VIIRS serve as proxies for ignition likelihood and active fire occurrence.

Satellite-derived hotspot products provide near-real-time information on active combustion, including fire location, timing, and radiative intensity across large areas [35,36]. Integrated with remote sensing and GIS, these data support wildfire surveillance, spatial modeling, susceptibility mapping, fire-front tracking, and burned-area assessment [9,45–47]. Hotspot observations are also frequently integrated with meteorological variables, vegetation indices, fuel-condition metrics, and drought-related indicators to characterize fire susceptibility and to analyze spatiotemporal wildfire dynamics. This multi-variable framework has been operationalized in recent remote-sensing-based wildfire monitoring studies by jointly exploiting satellite-derived fire information and indicators of drought, vegetation status, and fire severity [48], as well as in wildfire susceptibility mapping through the combination of active-fire detections with climatic, vegetation, fire-weather, and drought-related predictors [49]. Comparable multi-source strategies have likewise been employed to evaluate forest-fire vulnerability by using MODIS fire products in conjunction with topographic, climatic, vegetation, and anthropogenic variables [50]. Similar principles underpin operational fire-danger systems such as CFDRS, the McArthur system, and EFFIS [27,30].

Deep-learning models—including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and hybrid CNN–LSTM configurations—have demonstrated strong capability in short-term hotspot forecasting by jointly learning temporal dependencies and spatial structures embedded within large satellite-derived datasets [26,27,51]. More recently, Transformer-based frameworks have emerged as a promising frontier for wildfire prediction because of their capacity to capture long-range dependencies and high-dimensional spatiotemporal interactions in large, multimodal Earth-observation datasets [52,53]. These advances reflect a broader transition from descriptive hotspot monitoring toward predictive, data-driven wildfire-intelligence systems capable of supporting proactive fire management.

2. Wildfire Indicators and Hotspot Data Sources

2.1. Conceptual Framework of Wildfire Indicators

2.1.1. Definition of Wildfire Indicators

Wildfire indicators are best understood as proxy-based measures used to represent fire occurrence, drivers, behaviour, and impacts across the fire life cycle, from pre-fire conditions to post-fire consequences [9,11,54,55]. Because many fire processes cannot be observed directly at large scales, these indicators rely on measurable signals captured by satellite and related data sources [55]. For example, active-fire products detect thermal anomalies associated with combustion rather than flames themselves [35,36], while burned-area datasets delineate fire-affected extent and can be further linked to vegetation loss, carbon emissions, land degradation, and ecosystem recovery [32,56,57]. These indicators make large-scale wildfire monitoring possible where field observations are limited, although their interpretation remains constrained by sensor resolution, revisit frequency, and the physical signals being measured [55,58,59].

Conceptually, wildfire indicators can be organized according to different phases of the fire cycle, as illustrated in Figure 1. Pre-fire indicators characterize environmental conditions that increase fire likelihood, such as fuel availability, vegetation condition, and drought severity [55,60]. Active-fire indicators describe the fire event itself, including its spatial location, timing, frequency, and radiative intensity [35,36,55]. Post-fire indicators capture the consequences of wildfire, such as burned area, vegetation mortality, atmospheric emissions, and impacts on air quality and human health [32,35,61]. This phased framework facilitates the integration of wildfire indicators into broader analyses of fire regimes, hazard assessment, and climate–fire–ecosystem interactions, and is consistent with recent reviews that explicitly distinguish pre-, active-, and post-wildfire domains in wildfire observation and management [55,60].

2.1.2. Event-Based vs. Impact-Based Indicators

A fundamental conceptual distinction in wildfire research lies between event-based and impact-based indicators, which reflect wildfire as both a physical event and a driver of environmental and societal change. Event-based indicators describe when and where fires occur and capture their immediate physical properties, including satellite-detected active fires (hotspots), fire frequency, fire duration, fire progression, and Fire Radiative Power (FRP), which together represent the spatiotemporal dynamics and energetic characteristics of burning [35,36,55]. By contrast, impact-based indicators describe the consequences of fire, including burned area, burn severity, vegetation loss, post-fire recovery, emissions, smoke exposure, air-quality degradation, and public-health impacts [61,62]. These two classes are not interchangeable because fire occurrence does not necessarily correspond to the scale of ecological or societal damage. Accordingly, recent studies increasingly emphasize integrating both perspectives, including in Indonesian wildfire research where

hotspots, burned area, and carbon emissions are treated as complementary indicators of wildfire processes and impacts [63]. Table S1 summarizes representative event-based and impact-based indicators together with their principal analytical implications and outcomes.

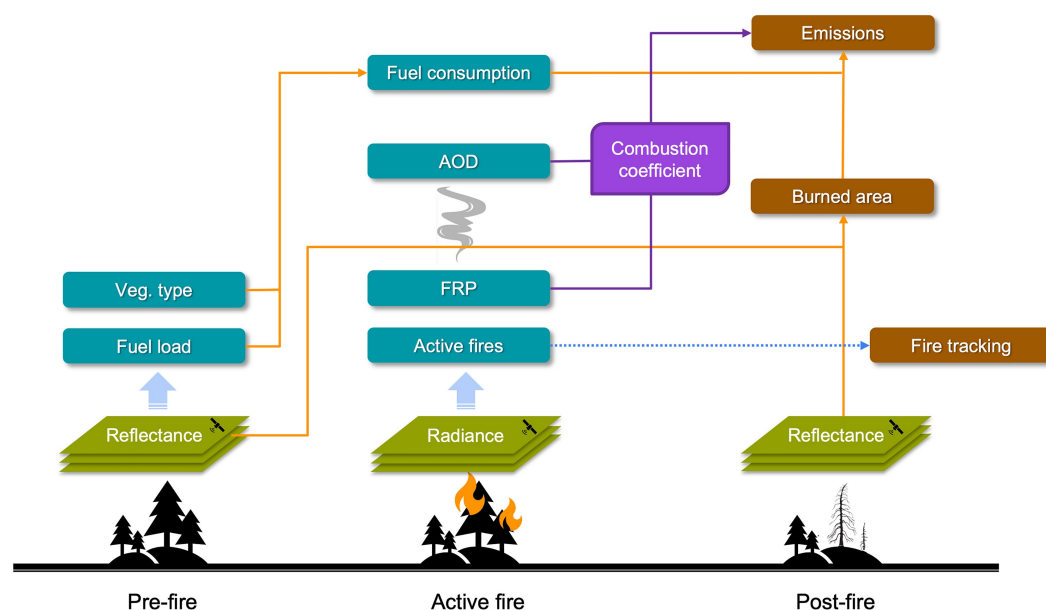


Figure 1. Conceptual organization of wildfire indicators across the fire cycle, including pre-fire, active-fire, and post-fire phases. Adapted from Chen et al. [55], which illustrates how remote sensing supports wildfire monitoring from fuel and vegetation conditions before ignition to active-fire detection, burned-area mapping, emissions estimation, and fire tracking.

2.1.3. Spatial and Temporal Scales

The interpretation and analytical value of wildfire indicators are inherently dependent on spatial and temporal scales, because indicators that are informative at one scale may become incomplete or misleading when applied at another. Spatially, wildfire indicators are used across local, regional, and global scales, each serving different purposes. At the local scale, high-resolution indicators derived from field observations or very high-resolution remote sensing support detailed assessments of fire behaviour, fuel conditions, burn severity, and ecological response [64,65]. At the regional scale, aggregated indicators such as fire frequency, hotspot density, and seasonal burned area are widely used to characterize fire regimes and their relationships with climate variability, vegetation types, and land-use patterns; in Indonesia, regional satellite products have also proven valuable for tracking fire dynamics across provinces and islands [66]. At the global scale, wildfire indicators are essential for estimating total burned area, atmospheric emissions, and climate feedbacks, but these applications rely on coarser-resolution data and are therefore more uncertain in detecting small fires, fragmented burn scars, and heterogeneous landscapes [32,46,67]. Temporal scale is equally important: sub-daily to daily indicators capture ignition timing and short-term fire dynamics for near-real-time monitoring [36], seasonal indicators support analysis of fire seasonality, and interannual to decadal indicators are used to assess long-term trends, regime shifts, and climate-change influences on fire activity [11,68]. Long-term interpretation, however, requires stable indicator definitions and consistent observation systems, because apparent trends may also reflect changes in sensors, algorithms, or detection thresholds rather than genuine changes in wildfire regimes [46,67].

These scale dependencies have direct implications for wildfire analysis and modeling, because mismatches between the indicator, the research question, and the observation system can bias inference and reduce predictive reliability. This issue is particularly important in Indonesia, where coarse global products such as MODIS active-fire or burned-area

data are often applied to peatlands or plantation areas that are patchy, low-temperature, and frequently obscured by smoke. Recent studies show that detection performance can differ substantially between peatland and non-peatland fires, and that sensor characteristics and hotspot clustering strongly affect monitoring accuracy [69]. More generally, coarse-resolution burned-area datasets may substantially underestimate small fires and fire-related landscape change in heterogeneous environments where sub-pixel burning is common [67]. Consequently, selecting a wildfire indicator requires a clear framework that matches the indicator to the research objective, the scale of analysis, and the limitations of the observation system. In this sense, scale is not merely a technical property of the data, but a key factor in determining whether an indicator is appropriate for a given ecological or management application.

2.2. Active Fire (Hotspot) Indicators and Satellite-Based Hotspot Data Sources

Active fire, or hotspot, indicators are widely used for wildfire monitoring because they detect fires during active burning and provide near-real-time information on fire occurrence and intensity, unlike burned-area products that describe conditions after the event [35,36]. Their detection is based on thermal anomalies in the mid- and thermal-infrared spectrum, where burning pixels show much higher radiance than surrounding surfaces; operational algorithms therefore use contextual tests against neighbouring pixels to distinguish active combustion from other hot surfaces and reduce false detections [36,70]. Because these detections represent sub-pixel burning rather than total fire extent, hotspot data are mainly used to derive indicators such as fire occurrence, fire frequency, and (FRP), which are valuable for characterizing fire regimes and their links to climate and land use [9,47].

FRP is a physically meaningful active-fire indicator because it quantifies the instantaneous rate at which radiant energy is released during combustion. Derived from mid-infrared radiance measurements, FRP is approximately proportional to the rate of biomass burning and is therefore widely used as a proxy for active-fire intensity [70]. When integrated over the duration of a fire, FRP yields Fire Radiative Energy (FRE), which can be linked to fuel consumption and, through emission factors, to atmospheric emissions [70–72]. This makes FRP-based analysis distinct from burned-area-based approaches: burned area describes the final extent affected by fire, whereas FRP captures the rate of energy release during active burning. Accordingly, burned-area-based inventories estimate emissions from burned area, fuel load, combustion completeness, and emission factors, while FRP-based approaches provide a more direct pathway from active combustion to emissions through FRE and fuel consumption [32,73,74]. As illustrated in Figure 2, this framework positions FRP as a conceptual bridge between event-based indicators of active burning and impact-based indicators of environmental consequences.

2.2.1. MODIS and VIIRS Active Fire Products

The two principal polar-orbiting satellite systems used for global active-fire monitoring are MODIS and VIIRS. MODIS, carried by NASA's Terra and Aqua satellites launched in 1999 and 2002, provides one of the longest internally consistent active-fire records currently available, through the MOD14 and MYD14 products. This continuity from 2000 to the present is particularly valuable for long-term fire climatology, interannual variability analysis, and trend detection, because the combined Terra–Aqua system supplies multiple daily observations while maintaining a stable archive over more than two decades [35,36,75,76]. For long-term studies, the product version used should be specified, because differences between Collection 6 and Collection 6.1 can affect comparability when time series are combined without careful adjustment [76,77]. Although Collection 6.1 keeps the general structure of the Collection 6 active-fire product, updated calibration in the red and

near-infrared bands used for cloud masking and false-alarm removal can produce small differences in fire classification, hotspot counts, and derived temporal statistics if Collection 6 and Collection 6.1 records are combined without adjustment [76,77].

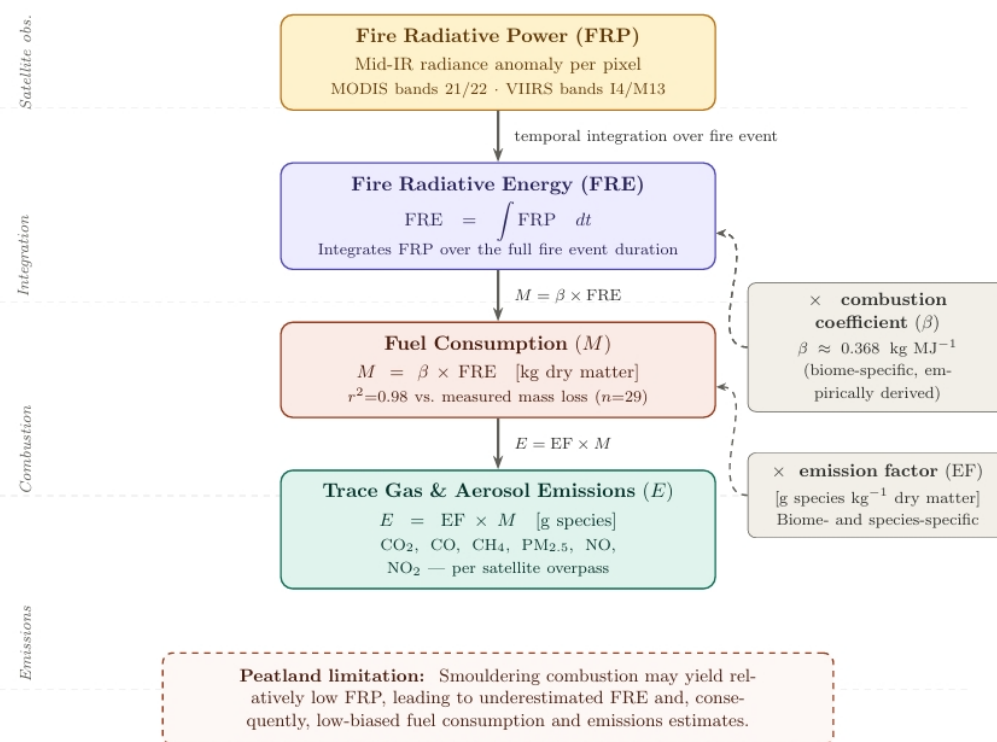


Figure 2. Conceptual FRP-based emissions framework linking FRP, FRE, fuel consumption, and trace-gas and aerosol emissions.

VIIRS extends the MODIS record by providing finer spatial resolution and better sensitivity for active-fire detection. Active-fire products are now generated from both Suomi-NPP and NOAA-20, which together improve revisit frequency compared with a single satellite. The VIIRS 750 m product reduces pixel area by about 44%, while the 375 m product reduces it by about 86%, or roughly four times smaller than the 750 m product [37,78]. As a result, the 375 m product is generally preferred for detecting small or scattered fires and for mapping fire perimeters, while the 750 m product remains important for FRP retrieval and additional fire characterization due to its wider radiometric range for intense fire pixels [37,78]. Table S2 summarizes the main VIIRS channels used in active-fire detection, along with their uses and limitations.

MODIS and VIIRS should be understood as complementary rather than as one replacing the other. MODIS remains essential for long-term fire climatology, interannual variability, and trend analysis because it offers a longer and more consistent historical record. VIIRS, in contrast, provides finer spatial detail and is therefore better suited to detecting small or scattered fires that coarser products may miss. However, better sensor capability does not remove the basic limitations of satellite active-fire detection, including cloud and smoke interference, atmospheric effects, mixed surface backgrounds, viewing angle, and weak thermal signals. These limitations matter most in Indonesia, used here as the central case study, because its recurring wildfire activity over the past two decades has been strongly shaped by drought, land-use change, peatland degradation, and low-temperature smouldering combustion. Indonesian studies using VIIRS-derived hotspots show that, although VIIRS improves fire-activity detection compared with coarser products, the resulting hotspot records still need clustering, validation, and contextual review before

they can reliably support peatland fire management in the field [69,76]. VIIRS therefore represents a major advance in active-fire monitoring, but it does not fully resolve the detection challenges posed by Indonesia's humid tropical peatland environments.

2.2.2. Comparison Between MODIS and VIIRS Active Fire Products

Direct ground-based validation of near-real-time satellite fire detections is often limited by restricted access, high operational costs, and safety risks, particularly in remote or hazardous fire-prone regions [79,80]. As a result, comparison between satellite products is widely used as a practical validation approach [81–83]. Within this framework, comparing MODIS and VIIRS is especially important because the two products differ not only in spatial resolution, but also in temporal depth, sensitivity to small fires, and suitability for different analytical purposes.

Previous studies showed that the VNP14IMG product outperforms MODIS by about 10–35% in detecting fires smaller than 50 ha [84,85]. A comparative assessment in Turkey likewise reported that MODIS detection accuracies ranged from 0.6% to 16.6%, while VIIRS S-NPP achieved higher accuracies of 1.3% to 25.6% across five land-cover classes [86]. In both products, detection rates increased with fire size, showing a persistent limitation in reliably detecting very small fires (<10 ha). Recent work in Borneo supports this pattern, showing that MODIS and VIIRS both differ substantially from finer-resolution Sentinel-2 active-fire records, with VIIRS generally providing a closer match to small-fire spatial patterns than MODIS, although omission errors remain notable for both products in fragmented tropical landscapes [87].

MODIS and VIIRS should be treated as complementary rather than interchangeable active-fire data sources. MODIS is better suited for long-term analysis because the Terra–Aqua record extends back to 2000, supporting fire climatology, interannual variability analysis, and model development using multi-decadal fire histories [76]. VIIRS, in contrast, is more effective for detecting small, scattered, or spatially uneven fires because of its finer spatial resolution and higher detection sensitivity, as shown in the development and assessment of the VIIRS 375 m active-fire product [37]. This difference is not only technical but also practical: MODIS-based hotspot records may underrepresent small or weak fires, which can affect prediction models, emissions estimates, and fine-scale fire-risk mapping if sensor differences are not taken into account. This is consistent with studies documenting the strengths and weaknesses of MODIS hotspots for global fire occurrence analysis [84], as well as studies showing the value of VIIRS for direct burned-area mapping [85]. Regional assessments outside Indonesia further show that MODIS and VIIRS can differ in monitoring performance depending on ecosystem conditions, fire size, and observation constraints, as reported for Turkey [86] and Sub-Saharan Africa [88].

In tropical peatland settings such as Indonesia, the MODIS–VIIRS distinction requires added caution because fires in Sumatra and Kalimantan are often fragmented, obscured by smoke or cloud, and linked to low-temperature smouldering combustion. Indonesian studies suggest that VIIRS improves active-fire monitoring relative to coarser products, but hotspot records still need contextual interpretation, clustering, and validation to support peatland fire management in practice [69]. Together with the regional patterns observed in Turkey and Sub-Saharan Africa, this illustrates that sensor performance is shaped by local fire behaviour and land-cover conditions as much as by sensor design. Accordingly, MODIS and VIIRS are best used as complementary products, with the choice guided by the study objective, required temporal depth, expected fire type, and ecosystem context. Table 1 summarizes their main strengths, weaknesses, and implications for fire analysis and modeling.

Table 1. Comparison of MODIS and VIIRS active fire products.

Aspect	MODIS	VIIRS	Refs
Nominal active-fire resolution	1 km	375 m active-fire product, with 750 m support for FRP	[85,86]
Temporal depth	2000–present	2012–present; revisit improved with NOAA-20 after 2018	[35,78]
Main strength	Long-term consistency for climatology, trend analysis, and historical model training	Better sensitivity to small and fragmented fires; finer spatial localization	[86,87]
Main weakness	Greater omission of small, weakly radiative, or fragmented fires	Shorter historical record; still affected by smoke, cloud, and low-temperature combustion	[87,89]
Best suited for	Long-term regional/global fire history and multi-decadal analysis	Local/regional monitoring, small-fire analysis, and finer hotspot characterization	[86,87]
Known tropical/peatland issue	Sub-pixel smouldering and persistent haze/cloud can suppress detections	Better than MODIS in principle, but peatland smoke, smouldering, and obscuration still limit completeness	[31,79,87]
Implication for modeling	May provide systematically incomplete targets for small-fire regimes	Better for capturing recent fine-scale activity, but shorter archive constrains long-horizon hindcasting	[78,88,90]

2.2.3. Uncertainties and Limitations of Hotspot Data

Satellite-derived hotspot indicators face two main uncertainties: commission errors, where non-fire thermal anomalies are misclassified as fires, and omission errors, where real fires go undetected. These are common across sensors and regions. Global assessments show that MODIS hotspots are effective in characterizing fire occurrence, but they can miss small, short-lived or weak events under poor observation conditions [84]. Validation with higher-resolution sensors indicates that omission and commission errors depend on fire size, background surface, viewing geometry, cloud cover, smoke, and sensor resolution [82,85]. Regional studies further show that MODIS and VIIRS performance varies between ecosystems, including monitoring of wildfires in Turkey [86] and monitoring of burned areas in Sub-Saharan Africa [88]. In this broader context, Indonesia is a critical tropical peatland case, where persistent cloud and smoke, fragmented fires, and low-temperature smouldering amplify uncertainty. VIIRS-based analysis in Indonesia showed that spatially structured false positives can be reduced with geo-feature masks [91], while Sentinel-2 validation over Borneo found omission rates of 45.1% for MODIS and 34.2% for VIIRS during the 2019 fires [87]. If uncorrected, these errors bias hotspot-based estimates of fire occurrence and propagate into burned-area, fuel-consumption, emissions, and fire-frequency products such as GFED and GFAS [32,87]. Mitigation therefore requires combining confidence-based screening [35,92], land-cover or geo-feature masking [91], and multi-sensor validation using higher-resolution imagery, geostationary observations, independent active-fire detections, and burned-area products [39,87,89,93–95].

3. Variables for Forest Fire

Forest fire occurrence and development are shaped by interactions among biophysical conditions, atmospheric processes, and terrain. To capture these drivers, this study uses a multi-source environmental framework combining remote sensing, meteorological, topographic, and vegetation datasets. Focusing on natural driving mechanisms, the variables are grouped into three main categories: fuel (vegetation), topography, and meteorology, which together represent the key controls on fire ignition, spread, and persistence. Table 2 summarizes the environmental variables used to identify forest fires.

Table 2. Summary of environmental variables commonly used in forest fire modeling.

Variable Category	Indicator	Typical Unit	Variable Type	Role in Forest Fire Dynamics	Refs
Meteorological	Air temperature	°C or K	Continuous	Controls fuel drying rate and combustion efficiency	[30,48]
	Relative humidity	%	Continuous	Regulates fuel moisture and ignition likelihood	[48,95]
	Dew point temperature	°C	Continuous	Serves as a proxy for atmospheric moisture availability	[48,95,96]
	Wind speed	m s ^{−1}	Continuous	Influences fire spread rate, direction, and intensity	[95,97]
	Precipitation	mm	Continuous	Suppresses fire occurrence by increasing fuel moisture	[30,48,98]
	Drought indices (SPI and SPEI)	Dimensionless	Continuous	Represent antecedent moisture deficits and climatic stress	[48,99,100]
Fuel/Vegetation	Vegetation or land-cover type	–	Categorical	Determines fuel availability and combustibility	[9,48,101]
	Fuel class or combustibility level	Ordinal	Categorical (ordinal)	Differentiates fire susceptibility among vegetation types	[102,103]
	Biomass density (proxy)	kg m ^{−2} or index	Continuous	Influences fire intensity and duration	[9,103]
	Vegetation moisture condition (proxy)	% or index	Continuous	Regulates ignition probability and fire persistence	[48,104,105]
Topographic	Elevation	m	Continuous	Represents large-scale climatic gradients	[106,107]
	Slope	degrees (°)	Continuous	Controls fire spread velocity, particularly in upslope terrain	[97,108]
	Aspect	degrees (0–360°)	Circular/Continuous	Governs solar radiation exposure and fuel dryness	[106,109]
	Topographic relief	m	Continuous	Captures local terrain variability and surface roughness	[110,111]
	Slope length (proxy)	m	Continuous	Reflects potential fire propagation distance along inclined terrain	[108,112]

3.1. Vegetation Variables

Vegetation data are a key component of forest and land fire studies because they describe fuel conditions that influence fire ignition, spread, persistence, and intensity, especially during seasonal drought. Vegetation condition is commonly represented using the Normalized Difference Vegetation Index (NDVI), where lower values generally indicate sparse, stressed, or dry vegetation with higher susceptibility to burning. In fire impact assessment, NDVI can also be compared before and after a fire event; the differenced NDVI (dNDVI), calculated as the change between pre-fire and post-fire NDVI values, is used to indicate vegetation loss or degradation caused by burning. This logic has been applied in remote-sensing wildfire studies such as Sabljic et al. [48], which used dNDVI together with dNBR to assess vegetation condition, burn severity, and wildfire impacts across different land-use types. In Indonesia, vegetation information from land-cover data and spectral indices has also been identified as an important predictor of fire vulnerability, particularly across fire-prone regions such as Kalimantan, Sumatra, and Papua [40]. In peatland ecosystems, vegetation type and condition are especially important because conversion from intact peat swamp forest to drained land uses, including plantations and shrublands, can increase flammability by reducing canopy cover, lowering fuel moisture, and exposing organic soils [14]. Remote-sensing analyses further show that post-fire vegetation degradation can be captured through NDVI reductions and land-cover transitions from forest to shrubland or plantation classes [113]. The key vegetation-related

variables, indicators, and their roles in regulating forest and land fire occurrence are summarized in Table 3.

Table 3. Vegetation types, data indicators, flammability, and fire mechanisms in Indonesian forest and land fire contexts.

Vegetation Type	Key Vegetation Data/Indicators	Fuel and Flammability Characteristics	Dominant Fire Mechanism	Influence of Dry Season	Refs
Peatlands	Land-cover class, NDVI/EVI, canopy cover, peatland condition, water-table proxies	Very high flammability when drained; large organic fuel load with low moisture retention	Persistent subsurface smouldering and surface fires	Prolonged dry seasons and El Niño events lower water tables, enabling sustained peat combustion	[38,114]
Oil palm plantations	Land cover, canopy structure, understory density, vegetation indices	High flammability due to exposed litter, dry understory grasses, and homogeneous fuels	Frequent surface fires	Fine fuels dry rapidly during drought, increasing ignition probability	[115,116]
Secondary forests	Canopy cover, NDVI, forest fragmentation metrics	Moderate–high flammability due to reduced canopy shading and increased fine fuels	Recurrent low- to moderate-intensity surface fires	Accelerated fuel drying during dry seasons enhances fire spread	[117,118]
Shrubland/bushland	Shrub density, vegetation greenness (NDVI), and land-cover continuity	High flammability with continuous fine fuels	Fire–vegetation feedback cycles	Continuous dry fuels sustain repeated burning under seasonal drought	[119]
Grassland/savanna	Grass cover, biomass indices, phenological metrics	Very high flammability dominated by fine fuels	Fast-spreading surface fires	Extreme fine-fuel drying during dry seasons leads to rapid fire spread	[10,12]
Cropland/mixed agriculture	Crop residue cover, phenology, fallow stage indicators	Moderate–high flammability, strongly influenced by management	Human-ignited surface fires	Seasonal drought coincides with residue burning and land preparation	[120,121]
Mangroves (degraded)	Canopy loss, vegetation stress indices, land-cover change	Low–moderate flammability under normal conditions	Limited surface fires	Fire occurs mainly under severe drought and extensive degradation	[122,123]

3.2. Topographic Variables

Topography influences wildfire not as a direct ignition source, but by conditioning where fuels accumulate, how dry they become, and how fire spreads once ignition occurs [124]. For this reason, variables such as elevation, slope, aspect, slope length, and topographic relief are more informative for explaining spatial variation in fire behaviour and burn severity than for predicting ignition alone. Elevation represents broad climatic gradients that shape vegetation type and fuel moisture, with burn severity in some regions peaking at mid-elevations before declining at higher altitudes [125,126]. Slope primarily affects fire spread by accelerating upslope preheating and flame transfer, although this effect may weaken on extremely steep terrain [108,127]. Aspect modifies solar exposure and surface dryness, thereby influencing fuel flammability and local fire intensity [109,128].

To capture terrain heterogeneity, slope length and topographic relief are employed as proxies: slope length reflects potential fire travel distance along inclined terrain, often operationalized through the slope length and steepness factor,

$$LS = \left(\frac{A}{22.13} \right)^m \cdot (10.8 \sin \theta + 0.03)^n \quad (1)$$

where A is upslope contributing area per unit contour width, θ is slope angle, and m is a slope-length exponent [129–131]. Relief represents local elevation variability and surface roughness, which strongly modulate fire severity patterns [132].

3.3. Meteorological Variables

Meteorological conditions are among the most important short-term controls on wild-fire activity because they regulate fuel dryness, combustion conditions, and the likelihood that ignitions develop into spreading fires. Their main analytical value lies in capturing

temporal variability: unlike topography or many land-surface variables, meteorological conditions change rapidly and therefore help explain why fire activity can escalate sharply over short periods. This role is reflected in operational fire-danger systems such as the Fire Weather Index (FWI), which converts daily atmospheric conditions into indicators of fuel flammability and potential fire intensity [44,95]. Beyond ground-based station observations, satellite-derived, reanalysis, and gridded meteorological products are increasingly used to characterize both drought conditions preceding wildfire events and fire-weather conditions during wildfire occurrence. Products such as Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), ERA5, ERA5-Land, and MODIS-derived drought or vegetation-stress indicators provide spatially continuous information on precipitation, temperature, humidity, evapotranspiration, runoff anomalies, and vegetation stress, which is particularly valuable in regions where meteorological stations are sparse, unevenly distributed, or discontinuous. Recent drought-monitoring studies, for example, have used CHIRPS precipitation to derive the Standardized Precipitation Index (SPI), ERA5-Land runoff anomalies to support hydrological drought assessment, and MODIS-derived Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI) to characterize vegetation stress [133,134]. In wildfire-specific applications, Sabljic et al. used CHIRPS and ERA5 to identify meteorological preconditions, compute the Standardized Precipitation-Evapotranspiration Index (SPEI), and derive ERA5-based temperature and relative-humidity inputs for the Angstrom fire-danger index [48]. Similar multi-source approaches have been applied in Central Chile to evaluate extreme drought conditions preceding wildfire occurrence [135], and in Greece to combine fire-weather and remotely sensed vegetation indicators for wildfire prediction [136]. Empirical studies likewise show that extreme fire events are commonly associated with periods of anomalously high meteorological stress, often linked to broader circulation patterns that intensify fire spread and behaviour [137]. In Indonesia, this temporal control is especially important because fire activity responds strongly to rainfall deficits and drought conditions, with fire outbreaks and higher intensity often coinciding with periods of elevated fire-weather stress [138].

3.4. Human Activity Variables

Vegetation, topography, and meteorology help explain whether fire can spread, but human activity variables are often needed to explain where ignitions are likely to occur. In global wildfire studies, these variables are not represented by a single universal mechanism; rather, their relevance depends on the dominant socio-ecological setting of each region. In the United States, for example, human-started wildfires have been shown to expand the spatial and seasonal fire niche, while road networks influence the distribution of human-caused ignitions [125,139]. At broader scales, the expansion of the wildland–urban interface has increased the importance of settlement patterns, infrastructure, and human exposure in wildfire-risk analysis [140]. In Mediterranean and Eurasian contexts, accessibility, land use, and settlement-related variables have also been incorporated into regional fire-risk assessments, including wildland–urban interface modeling in Türkiye and susceptibility mapping in China and Pakistan [49,50,141]. In tropical forest regions such as the Amazon, human activity variables are more closely linked to deforestation, land-use transition, agricultural expansion, and frontier development, which interact with climate stress to increase fire activity [10,142]. These examples show that human activity variables are not merely auxiliary predictors, but context-dependent indicators of ignition probability, land-management pressure, and potential exposure.

In the Indonesian context, these variables are also important because many forest and land fires are associated with land clearing, agricultural activities, plantation development,

accessibility, and socioeconomic conditions [23,40,143,144]. Additional factors such as land-use change, concession boundaries, fire history, settlement proximity, and local response capacity can further improve wildfire modeling because they help capture where ignition is socially and operationally more likely [23,66,86,87,143,145]. Accordingly, Table S3 presents the key human activity variables recommended for Indonesian wildfire modeling frameworks, along with their data sources, spatial resolution, fire mechanism, operationalization, and supporting references.

4. Forest Fire Models

Forest fire modeling should be interpreted in relation to both the wildfire indicators introduced in Section 2 and the predictor groups discussed in Section 3. Different modeling families are not equally suited to all wildfire data types. Event-based indicators such as hotspot occurrence, fire counts, and FRP often favour models designed for classification, count prediction, or short-term spatiotemporal forecasting, whereas impact-based indicators such as burned area, emissions, and post-fire effects may require models that better capture spatial extent, cumulative effects, or longer temporal dependencies. Likewise, model suitability depends on the dominant predictor structure: meteorological variables often drive short-term temporal prediction, topographic and land-surface variables provide relatively stable spatial controls, and human-activity indicators are particularly important in anthropogenic fire regimes. Accordingly, modeling choices should be evaluated not only by algorithmic complexity, but by their fit to the indicator type, predictor structure, spatial–temporal scale, and research objective.

4.1. Early Approaches to Forest Fire Modeling

These early methods were most appropriate when wildfire indicators were relatively simple, such as hotspot presence, fire counts, or aggregated fire density, and when the main objective was spatial diagnosis or interpretable driver attribution rather than high-dimensional prediction. In this context, classical methods can be grouped into three broad categories: pattern-detection approaches, which identify clustering or hotspot concentration; regression-based approaches, which relate fire occurrence to explanatory variables; and semi-parametric extensions, which relax the linearity assumptions of classical regression. This functional grouping is more informative than treating each method separately because these approaches differ not only in formulation, but also in what question they are able to answer, how much data they require, and how well they generalize across wildfire settings [14,99–114,116–119].

Pattern-detection methods, including Moran's I , Getis–Ord G_i^* , and kernel density estimation (KDE), were especially useful when the main objective was to describe the spatial structure of fire observations rather than to build predictive models. Moran's I provides a global measure of spatial autocorrelation and is therefore appropriate for testing whether fire occurrence is spatially clustered at the study-wide level [99,100]. Moran's I is defined as

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad (2)$$

where x_i represents fire occurrence or fire intensity at location i , $\bar{x}$ is the global mean, w_{ij} denotes the spatial weight between locations i and j , N is the number of spatial units, and W is the sum of all spatial weights.

Getis–Ord G_i^* complements this by identifying where statistically significant local hotspots occur [103–105]. KDE, by contrast, produces a smooth intensity surface from dis-

crete fire detections and is often easier to interpret visually in GIS-based applications [106]. However, these methods are not interchangeable. The G_i^* statistic for location i is given by

$$G_i^* = \frac{\sum_j w_{ij} x_j - \bar{x} \sum_j w_{ij}}{s \sqrt{\frac{N \sum_j w_{ij}^2 - \left(\sum_j w_{ij} \right)^2}{N-1}}} \quad (3)$$

where x_j denotes fire counts or FRP at location j , and $\bar{x}$ and s are the global mean and standard deviation, respectively. Moran's I and G_i^* provide inferential evidence of spatial dependence, whereas KDE is mainly descriptive and highly sensitive to bandwidth choice. KDE is useful for exploration mapping and decision support, but less rigorous when statistical significance is required. Accordingly, if the objective is to determine whether fire events exhibit statistically significant spatial clustering and to identify the locations of such clustering, spatial statistical methods are more appropriate than density-smoothing approaches. By contrast, when the objective is to obtain an exploratory visualization of the spatial concentration of fire detections over time, KDE may be adequate.

Regression-based methods became more appropriate when wildfire research moved from spatial description toward explanatory modeling. Logistic regression is well suited for binary fire occurrence problems, especially when the available predictors are limited in number and the study requires interpretable coefficients for attribution analysis [111,112]. The model estimates fire occurrence probability as

$$\Pr(Y_i = 1 \mid \mathbf{x}_i) = p_i = \frac{1}{1 + \exp\left(-(\beta_0 + \boldsymbol{\beta}^\top \mathbf{x}_i)\right)} \quad (4)$$

Poisson regression extends this framework to count data and is therefore appropriate when fire events are aggregated over grid cells or administrative units. Yet its usefulness depends on the equidispersion assumption, which is often violated in wildfire applications. In this framework, the expected number of fires in spatial unit i is modelled as

$$Y_i \sim \text{Poisson}(\lambda_i), \quad \log(\lambda_i) = \beta_0 + \boldsymbol{\beta}^\top \mathbf{x}_i \quad (5)$$

where λ_i represents the mean fire count and the logarithmic link function ensures non-negative predictions. Negative binomial and zero-inflated variants address this limitation by accommodating overdispersion and excess zeros, making them more appropriate for sparse and heterogeneous fire-count datasets [113,114]. Compared with spatial statistics, these regression models require richer covariate information and stronger distributional assumptions, but they offer a clearer route to inference on fire drivers. Their main weakness is structural rigidity: linear predictors in logistic or count models can oversimplify threshold effects, nonlinear climatic responses, and interactions among fuel, weather, and human pressures. Thus, these models are most suitable when sample size is moderate, the predictor set is well defined, and interpretability is prioritized over flexibility.

Generalized Additive Models (GAMs) emerged as an important intermediate step between classical regression and more flexible machine-learning approaches because they preserve much of the interpretability of generalized linear models while allowing nonlinear covariate effects to be estimated through smooth functions [14,116–119]. In wildfire applications, this is particularly valuable because the effects of rainfall deficits, vegetation state, temperature, and anthropogenic pressure are rarely linear across space or time. Relative to logistic or negative binomial regression, GAMs are better suited to settings where nonlinear

environmental gradients are expected but where full black-box machine learning would reduce interpretability too much. However, this added flexibility also increases data demand, model complexity, and the risk of overfitting if smoothing is poorly controlled. GAMs therefore occupy a middle ground: they generalize better than strictly linear statistical models in nonlinear fire systems but remain less scalable and less expressive than later tree-based or deep-learning methods when interactions become very high-dimensional.

Taken together (Table 4), these early approaches should not be viewed as a simple historical sequence in which newer methods replaced older ones. Rather, they addressed different wildfire-analysis scenarios. Spatial statistics were most effective for diagnosing clustering and hotspot persistence, KDE for exploratory intensity mapping, regression models for driver attribution and parsimonious prediction, and GAMs for interpretable nonlinear modeling. Their main differences lie in analytical purpose: spatial statistics prioritize spatial dependence, KDE prioritizes visualization, regression prioritizes inference, and GAMs prioritize interpretable flexibility.

Table 4. Comparative approaching methods in wildfire modeling.

Method	Main Purpose	Best Used When	Data Demand	Interpretability	Scalability	Main Strengths	Main Limitations	Refs
Moran's I	Detect global spatial autocorrelation	Need to test whether fires are clustered overall	Low	High	High	Simple global diagnosis of clustering	Does not localize hotspots; not predictive	[105,110]
Getis-Ord (G_i^*)	Detect local hotspots/ cold spots	Need statistically significant hotspot zones	Low-moderate	High	Moderate-high	Identifies local priority areas	Sensitive to spatial weights; not explanatory	[105,110]
KDE	Smooth fire-event density surface	Need exploration hotspot visualization	Low	High	High	Easy to visualize; useful in GIS	Descriptive only; bandwidth sensitive; no formal inference	[63,105]
Logistic regression	Model fire presence/ absence	Binary outcome with interpretable predictors	Moderate	Very high	High	Clear coefficient interpretation; efficient baseline	Assumes linear log-odds; weak for nonlinear interactions	[111,116,146]
Poisson regression	Model fire counts	Count outcome with near-equidispersion	Moderate	High	High	Natural count model	Often violated by overdispersion	[39,111]
Negative binomial/ zero-inflated models	Model overdispersed or sparse fire counts	Many zeros or heterogeneous count intensity	Moderate	High	High	Better fit for realistic fire counts	Still limited in nonlinear structure	[39]
GAM	Model nonlinear but interpretable relationships	Nonlinear covariate effects expected	Moderate-high	Moderate-high	Moderate	Flexible smooth effects with retained interpretability	More complex; less transparent than GLM; interaction structure still limited	[14,111,112]

Under the same wildfire-analysis scenario, the suitability of early methods differs substantially. If the objective is to determine whether fire events are spatially clustered, Moran's I is more appropriate than KDE because it provides formal statistical evidence of autocorrelation. If the objective is to identify localized priority zones for intervention, Getis-Ord G_i^* is preferable because it reveals statistically significant hotspots. If the objective is to explain fire occurrence using climatic and anthropogenic predictors, regression-based models are more suitable than purely spatial diagnostics. When those predictor-response relationships are expected to be nonlinear, GAMs provide a better balance between interpretability and flexibility than conventional logistic or count regression. This comparison shows that these methods are not direct substitutes, but tools optimized for different analyt-

ical purposes. This comparison also clarifies why later machine-learning approaches gained prominence: they were not introduced because the earlier methods were unusable, but because wildfire systems often involve nonlinear, interacting, and scale-dependent processes that exceed the assumptions of classical models [14,112,118]. Still, early approaches remain valuable as baselines, diagnostic tools, and interpretable reference models in contemporary wildfire research.

4.2. Supervised Machine Learning Methods

These supervised methods became particularly useful when hotspot occurrence, fire susceptibility, or burned-area outcomes were modelled using mixed predictor sets that combined meteorological, vegetation, topographic, and anthropogenic variables. However, machine-learning families should not be viewed simply as increasingly complex alternatives, but as different trade-offs in interpretability, data requirements, computational cost, and generalization. The key question, therefore, is not only what each method does, but under which conditions it is most suitable [12].

Among the most widely applied supervised approaches in wildfire studies are Decision Trees (DTs), Random Forests (RFs), Support Vector Machines (SVMs), and Gradient Boosting models. These methods address broadly similar predictive tasks, including wildfire susceptibility mapping, hotspot classification, fire occurrence prediction, and burned-area estimation, yet they differ substantially in their suitability across scenarios.

Decision Trees are the most interpretable of the four and are particularly useful when the objective is to identify explicit rule-based thresholds, such as combinations of temperature, rainfall deficit, vegetation condition, or proximity to roads associated with elevated fire risk. The recursive partitioning process divides the feature space into regions with homogeneous fire behaviour by selecting splits that minimize node impurity, commonly measured using Gini impurity or entropy:

$$G(t) = 1 - \sum_{k=1}^K p_k^2 \quad (6)$$

$$H(t) = - \sum_{k=1}^K p_k \log(p_k) \quad (7)$$

For continuous fire-related targets, such as burned area or Fire Radiative Power (FRP), regression trees minimize the Mean Squared Error (MSE):

$$\text{MSE}(t) = \frac{1}{N_t} \sum_{i \in t} (y_i - \bar{y}_t)^2 \quad (8)$$

Because a tree partitions the predictor space into successively more homogeneous regions, it allows a transparent representation of decision logic that is often attractive for operational and policy-oriented contexts. Nevertheless, this interpretability comes at the expense of predictive stability. Single trees are highly sensitive to sample variation, prone to overfitting, and generally less robust in heterogeneous fire regimes where wildfire drivers vary across ecosystems, climates, and human-use settings [123].

Random Forests were adopted in part to address these weaknesses. By aggregating many decorrelated trees trained on bootstrap samples and random predictor subsets, RF substantially improves predictive robustness while retaining the ability to model nonlinear relationships and higher-order interactions. This makes RF especially suitable for wildfire datasets derived from remote sensing and geospatial sources, where predictors are often high-dimensional, collinear, and partly noisy. The RF predictor is expressed as

$$\hat{f}(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^B T_b(\mathbf{x}) \quad (9)$$

where $T_b(x)$ denotes the prediction of the b -th tree. Under the same wildfire prediction setting, RF is often more suitable than a single Decision Tree when the objective is stable predictive performance across heterogeneous predictors rather than direct rule-based interpretation. This advantage has been noted in wildfire machine-learning studies, where RF has been widely used for fire occurrence, susceptibility, vulnerability, and hotspot prediction tasks [27]. Indonesia-focused studies have also used RF-based or tree-ensemble approaches to model wildfire hotspots and fire vulnerability using climatic, vegetation, land-cover, topographic, and accessibility-related variables [39,40]. Similar applications in China and Pakistan further show that RF and related tree-based ensemble models are useful for integrating heterogeneous environmental and human-related predictors in wildfire susceptibility and vulnerability assessment [49,50]. By aggregating many decorrelated trees, RF reduces the variance and instability that can arise from individual tree predictions and can capture nonlinear relationships and interactions among predictors. However, its ensemble structure reduces interpretability relative to a single Decision Tree and may increase computational cost for very large spatiotemporal or high-resolution datasets [124–127].

Support Vector Machines (SVMs) occupy a different position in this methodological landscape. Whereas tree-based methods partition the feature space recursively, SVMs maximize the margin between classes and can represent nonlinear boundaries through kernel functions. In wildfire studies, this makes them particularly attractive when the classification boundary is complex, the predictor space is high-dimensional, and the sample size is not especially large. Under the same scenario, SVMs are often more appropriate than RF when the dataset is moderately sized and the signal distinguishing fire and non-fire conditions is subtle, because margin-based learning can yield strong classification performance even when separability is difficult to achieve in the original feature space. However, SVMs scale less efficiently than many tree-based ensembles, especially for large spatio-temporal wildfire datasets, and their performance depends strongly on kernel choice and hyperparameter tuning. This makes them less convenient for large operational systems or highly heterogeneous multi-source datasets, where RF and boosting methods often offer better scalability and easier integration with tabular environmental predictors [128,129].

Gradient Boosting models, including optimized implementations such as XGBoost, extend tree-based learning in another direction by sequentially fitting weak learners to correct the residual errors of previous iterations. In wildfire modeling, this sequential error-correction framework often yields stronger predictive performance than RF when the underlying fire–environment relationships are highly nonlinear and include complex interactions or subtle local structure. Accordingly, under the same susceptibility-mapping or fire-occurrence forecasting task, Gradient Boosting is often preferable when maximizing predictive accuracy is the primary objective and when sufficient data, tuning effort, and computational resources are available. The additive model formulation is given by

$$F_m(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \eta h_m(\mathbf{x}) \quad (10)$$

where $h_m(\mathbf{x})$ is typically a shallow decision tree and η is the learning rate. Residuals are computed as the negative gradient of the loss function:

$$r_{im} = - \left[\frac{\partial L(y_i, F(\mathbf{x}_i))}{\partial F(\mathbf{x}_i)} \right]_{F=F_{m-1}} \quad (11)$$

Compared with RF, boosting methods typically provide finer predictive discrimination and greater flexibility, but they are also more sensitive to hyperparameter settings and can overfit if regularization is inadequate, particularly in spatially autocorrelated fire datasets. Thus, while RF is often the safer default for robust wildfire prediction, Gradient Boosting is more advantageous in performance-oriented settings where careful model optimization is feasible [130–132].

Viewed comparatively, these methods differ mainly in the modeling priorities they support rather than in their basic applicability to wildfire prediction. Decision Trees are most useful when transparent threshold-based reasoning is needed; RF perform better for robust nonlinear prediction with many correlated predictors; SVMs are effective for high-dimensional classification with limited to moderate sample sizes but are less scalable; and Gradient Boosting is often preferred when predictive accuracy is the main goal and intensive tuning is acceptable. These methods should therefore be seen as complementary rather than universally superior, with suitability depending on the balance between interpretability, computational cost, predictive power, and data structure [10,12,121–132]. Table 5 shows the comparative characteristics of supervised machine learning methods in wildfire modeling.

Table 5. Comparative characteristics of supervised machine learning methods in wildfire modeling.

Method	Typical Wildfire Use	Best Suited When	Data Demand	Interpretability	Scalability	Main Strengths	Main Limitations	Refs
Decision Tree	Fire occurrence classification, rule-based susceptibility mapping	Explicit thresholds and transparent decision rules are needed	Low to moderate	Very high	High	Easy to interpret; useful for extracting fire-risk rules	High variance; unstable; prone to overfitting	[27,40]
Random Forest	Susceptibility mapping, hotspot classification, burned-area prediction	Predictive robustness is needed for nonlinear, high-dimensional, and correlated predictors	Moderate to high	Moderate	Moderate to high	Robust; handles nonlinearities and multicollinearity well; variable importance available	Less transparent than single trees; computationally heavier	[27,39,40,114]
Support Vector Machine	Fire/non-fire classification, high-dimensional wildfire detection	Sample size is limited to moderate and class separation is complex	Moderate	Moderate to low	Low to moderate	Strong classification performance in complex feature spaces	Sensitive to kernel and hyperparameters; limited scalability	[27,40]
Gradient Boosting/XGBoost	Fire occurrence prediction, risk forecasting, susceptibility modeling	Highest predictive accuracy is prioritized and tuning resources are available	Moderate to high	Low to moderate	Moderate	Strong predictive performance; captures complex nonlinear interactions	Sensitive to tuning; may overfit; less interpretable	[27,40,51]

4.3. Unsupervised Learning and Dimensionality Reduction for Wildfire and Hotspot Analysis

Unsupervised learning and dimensionality reduction play an important role in wildfire and hotspot analysis when labeled data are unavailable or limited. Rather than predicting fire occurrence directly, they are mainly used to reveal latent patterns, identify fire regimes or anomalies, and reduce redundancy in multivariate datasets from remote sensing, meteorology, and geospatial sources. Their main value lies in pattern discovery and data simplification: clustering methods group similar fire events or landscapes, while dimensionality reduction methods compress complex predictor spaces while retaining dominant variability [15,137,138,143–145].

Among the most commonly used unsupervised approaches in wildfire studies are K-means clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Principal Component Analysis (PCA). Although these methods are often

grouped under unsupervised analysis, they serve different analytical purposes and should not be treated as interchangeable. In wildfire and hotspot studies, K-means has been used to partition hotspot records or fire-prone areas into broad groups, including applications for identifying fire-prone areas from hotspot data in West Kalimantan and for clustering hotspot-location data [147,148]. DBSCAN is more appropriate when the objective is to identify spatially dense fire or hotspot clusters while distinguishing isolated detections as noise, as shown in wildfire-risk mapping based on DBSCAN clustering and in density-based clustering of vegetation fire points [149,150]. PCA, by contrast, is not a clustering method but a dimensionality-reduction technique; in forest-fire studies, it has been used to reduce correlated spatial, environmental, and GIS-based predictors into a smaller set of components for fire-risk zonation [151]. Accordingly, the critical question is not simply whether unsupervised methods are useful in wildfire research, but under which data conditions and analytical goals one method is preferable to another [15,137,138,143–145].

K-means clustering is most suitable when wildfire or hotspot data can be represented as a small number of relatively homogeneous groups, such as broad fire-risk classes or recurring environmental regimes. Its main advantages are simplicity, computational efficiency, and scalability to large satellite datasets. However, because K-means works best for clusters that are roughly spherical, similar in size, and clearly separated, it may be less suitable for wildfire data that are spatially irregular, fragmented, or noisy. Thus, K-means is useful for broad stratification of fire conditions, but less appropriate when cluster shape, density variation, or noise detection is important [137].

DBSCAN addresses several limitations of K-means and is often more suitable for spatial hotspot analysis in heterogeneous wildfire landscapes. It does not require the number of clusters to be specified in advance, can detect clusters of irregular shape, and can explicitly identify noise, which is useful for separating true fire clusters from isolated or potentially spurious detections. However, DBSCAN is sensitive to parameter selection and may perform less consistently when cluster density varies strongly across regions or seasons [138].

PCA plays a different role from K-means and DBSCAN, serving as a complementary preprocessing method rather than a clustering tool. In wildfire studies with many correlated predictors, PCA helps reduce dimensionality, multicollinearity, and computational burden by transforming the variables into a smaller set of orthogonal components. This can improve downstream clustering or supervised models, although it comes at the cost of reduced interpretability, since principal components are less directly linked to wildfire processes than the original variables [15,143–145].

Taken together, these methods differ most clearly in analytical purpose, data assumptions, and inferential utility. K-means is computationally efficient and useful for broad fire-regime stratification, but it is constrained by its assumption of compact, predefined clusters. DBSCAN is more flexible for spatially irregular hotspot patterns and is better able to isolate noise, but it is more sensitive to parameterization and varying density structures. PCA does not identify groups directly, yet it is often essential when wildfire datasets contain many correlated predictors that would otherwise reduce the stability or interpretability of later analyses. These differences also imply different data demands and generalization behaviour. K-means and PCA scale efficiently to large remote-sensing datasets, whereas DBSCAN may become more computationally demanding depending on dataset size and neighborhood search structure. In interpretability terms, K-means clusters are often more straightforward to communicate operationally, DBSCAN outputs are more realistic spatially but parameter dependent, and PCA offers strong compression at the cost of direct physical meaning. Consequently, these approaches should be viewed as complementary rather than competing tools: K-means for coarse regime partitioning,

DBSCAN for density-based hotspot delineation and noise filtering, and PCA for dimension reduction and preprocessing in multivariate wildfire workflows [15,137,138,143–145]. This comparison highlights that unsupervised learning is not merely a substitute for supervised modeling when labels are unavailable. Instead, it serves distinct functions such as regime discovery, anomaly filtering, and predictor simplification, and remains useful even when labeled data exist. These methods are often most effective as part of broader workflows, helping structure, clean, and prepare wildfire data for further analysis. Table 6 summarizes their comparative characteristics in forest fire and hotspot analysis.

Table 6. Comparative characteristics of unsupervised learning and dimensionality reduction methods in forest fire and hotspot analysis.

Method	Typical Wildfire Use	Best Suited When	Data Demand	Interpretability	Scalability	Main Strengths	Main Limitations	Refs
K-means clustering	Fire-regime stratification, broad fire-risk class partitioning	Data form compact, roughly spherical, and similarly sized clusters	Low to moderate	Moderate to high	High	Simple; computationally efficient; scales well to large satellite datasets	Requires predefined cluster number; poor fit for irregular or noisy spatial patterns	[137]
DBSCAN	Spatial hotspot delineation, noise filtering in fire detection datasets	Clusters are irregularly shaped and noise separation is needed	Moderate	Moderate	Moderate	No predefined cluster number needed; detects irregular shapes; isolates noise	Sensitive to parameter selection; less consistent under varying density structures	[138]
PCA	Dimensionality reduction and preprocessing of multivariate wildfire predictor sets	Many correlated predictors reduce model stability or interpretability	Moderate to high	Low to moderate	High	Reduces multicollinearity and computational burden; retains dominant variability	Components lack direct physical meaning; interpretability reduced	[15,143–145]

4.4. Deep Learning Architectures for Hotspot and Wildfire Modeling

Deep learning has become increasingly important in wildfire and hotspot modeling because many fire-related problems involve nonlinear, high-dimensional, spatial, temporal, and multimodal relationships that are difficult to represent using conventional statistical or shallow machine-learning methods. Its applications now extend across several wildfire tasks, including active-fire and smoke detection, burned-area segmentation, burn-severity mapping, hotspot forecasting, next-day fire-spread prediction, fire-risk assessment, and decision-support systems [51,60,152,153]. This breadth reflects the diversity of wildfire data sources, including satellite imagery, gridded meteorological fields, vegetation indices, topographic layers, hotspot sequences, burned-area products, and human-activity variables. Therefore, deep-learning architectures should not be viewed simply as progressively more advanced models, but as different representational strategies suited to different wildfire questions, data structures, and operational constraints.

A useful synthesis is to distinguish deep-learning architectures according to the wildfire structure they are designed to learn. Recurrent architectures, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs), are primarily suited to sequential prediction problems, such as hotspot forecasting, fire occurrence time series, drought–fire lag effects, and delayed vegetation responses. In these settings, the main objective is to learn temporal persistence and antecedent conditions from variables such as rainfall deficit, fire-weather indices, vegetation stress, and past fire activity. However, standard RNNs are rarely preferred for long wildfire sequences because their recurrent memory is limited by vanishing-gradient problems, whereas LSTMs and GRUs use gating mechanisms to retain or discard information over longer time horizons. LSTMs are generally more suitable when long-range

climatic memory and delayed fuel-moisture effects are important, while GRUs may be preferable when similar temporal performance is desired with fewer parameters and lower computational cost.

Convolutional Neural Networks (CNNs) address a different class of wildfire problems by extracting local and multiscale spatial patterns from gridded or image-based data. They are widely used for active-fire detection, smoke recognition, burned-area mapping, burn-scar segmentation, and spatial fire-risk classification from satellite, aerial, or UAV imagery [60,152]. CNN-based segmentation models, including U-Net-like and related encoder–decoder architectures, are particularly useful when the objective is to delineate burned pixels or fire-affected regions rather than predict a single fire occurrence label. For example, deep-learning-based burned-area mapping studies have used post-fire Sentinel-2 imagery to automate fire-damage delineation, while recent Indonesian burned-area studies have also applied neural-network-based ensemble approaches for remote-sensing classification [97,98,154]. These applications show that CNNs are strongest when fire information is expressed as spatial texture, spectral contrast, fire perimeter, smoke plume, or burn-scar geometry.

For explicitly spatiotemporal wildfire problems, hybrid architectures have become increasingly important. CNN–RNN, ConvLSTM, and related recurrent-convolutional models combine spatial feature extraction with temporal dependency learning, making them relevant for fire-spread prediction, sequential burned-area evolution, and next-day fire expansion. Benchmark datasets for next-day wildfire spread prediction demonstrate the need to combine gridded fire history with meteorology, vegetation, topography, drought, and human-related variables in a spatially aligned prediction framework [155]. In this context, deep learning is not only used to classify whether fire occurs, but also to estimate how fire extent may evolve across space and time, which is more directly relevant for suppression planning, evacuation support, and operational risk assessment [153].

Graph Neural Networks (GNNs) provide another extension by representing wildfire systems as irregular relational structures rather than regular image grids. This is useful when fire dynamics are shaped by non-Euclidean relationships such as landscape connectivity, adjacency among spatial units, road networks, human-access pathways, fuel continuity, or long-range climatic teleconnections. Recent graph-based wildfire studies show that GNNs can be used to model spatial dependence, interregional fire relationships, and burned-area forecasting in ways that are difficult for purely convolutional models to capture [156,157]. Their main advantage is the ability to encode relational structure directly, but their performance depends strongly on how the graph is constructed, whether edges represent physical adjacency, climatic similarity, human connectivity, or learned relationships.

Transformer-based models represent a further shift toward attention-based dependency learning. Instead of relying primarily on recurrence or local convolution, Transformers use attention mechanisms to identify relevant interactions across long temporal windows, spatial locations, or multimodal feature sets. This makes them attractive for large-scale wildfire forecasting, fire-spread modeling, and remote-sensing segmentation where long-range dependencies, delayed climate signals, and spatially distributed drivers are important [52,53]. Recent wildfire studies have also explored Transformer-based frameworks for integrating remote-sensing, meteorological, and decision-support information, while comparative studies indicate that CNNs and Transformers may emphasize different aspects of spatial context and interpretability in wildfire spread prediction [52,53]. Nevertheless, Transformers usually require larger datasets, stronger regularization, and greater computational resources than recurrent or convolutional models, so they may not always

be the most practical choice for smaller regional studies or operational systems with limited training data.

Collectively, the application of deep learning in wildfire science is moving from single-task image classification toward integrated spatiotemporal and multimodal modeling. CNNs remain central for spatial detection and segmentation; recurrent models are useful for temporal forecasting; hybrid CNN–RNN models are appropriate for fire-spread evolution, GNNs are promising for relational and teleconnection-aware modeling, and Transformers are increasingly used for long-range context integration. The choice of architecture should therefore be guided by the target variable, data structure, spatial and temporal resolution, available training data, interpretability requirements, and operational constraints. Table 7 summarizes the comparative characteristics of deep-learning architectures in forest fire and hotspot analysis.

Table 7. Comparative characteristics of deep learning in wildfire and hotspot analysis.

Family	Primary Structure Modeled	Best Suited When	Data Demand	Interpretability	Scalability	Main Strengths	Main Limitations	Refs
RNN	Short- to moderate-range temporal sequences	Temporal dependence is important, but sequence complexity is limited	Moderate	Moderate	High	Simple recurrent baseline; useful for early sequential modeling	Weak long-range memory; susceptible to vanishing or exploding gradients	[51]
LSTM	Long-range temporal dependencies	Forecasting depends on accumulated climatic or ecological memory	Moderate to high	Moderate	Moderate	Strong temporal memory; widely validated in wildfire forecasting	Requires more parameters and is computationally heavier than GRU	[51,158]
GRU	Efficient temporal dependency modeling	Tasks are similar to those addressed by LSTM, but faster training and lower complexity are required	Moderate	Moderate	High	Provides a good balance between predictive accuracy and computational efficiency	Has a slightly less expressive memory structure than LSTM	[51,158]
CNN	Local and multiscale spatial structures on regular grids	Raster imagery, burn-scar mapping, hotspot detection, or spatial risk mapping is dominant	Moderate to high	Moderate	High	Excellent spatial feature extraction; effective for remote-sensing inputs	Does not inherently model temporal evolution	[51,97]
GNN	Irregular spatial or relational connectivity	Wildfire interactions follow graph-like or non-Euclidean structures	High	Low to moderate	Moderate	Models spatial and relational connectivity beyond regular grids	Graph construction is complex and introduces greater modeling overhead	[51]
Transformer	Long-range temporal or spatial dependencies through attention	Broad contextual information and long-range dependencies are central, with ample training data available	High to very high	Low to moderate	Moderate	Strong long-context modeling with flexible attention mechanisms	Data-intensive, computationally expensive, and less operationally transparent	[51–53]

Taken together, these deep-learning families differ mainly in the type of wildfire structure they are designed to capture. RNNs, LSTMs, and GRUs focus on temporal sequences; CNNs on local spatial patterns; GNNs on irregular relational structure; and Transformers on long-range dependencies and attention-based context integration. Their suitability therefore depends on the wildfire problem itself. This also explains why recent wildfire studies increasingly use hybrid or multimodal architectures, since real wildfire systems rarely involve only one type of structure [159,160].

4.5. Spatiotemporal Modeling Paradigms

Wildfire dynamics are inherently spatiotemporal, since fire activity evolves through the interaction of local environmental conditions, spatial connectivity, and temporal persistence. Models that consider only temporal dependence may capture seasonality or recurrence

but ignore spatial propagation, whereas models that consider only spatial structure may identify fire-prone locations without representing temporal evolution. For this reason, recent wildfire research has increasingly framed prediction as a spatiotemporal learning problem, in which the objective is not merely to estimate whether fire will occur, but to model how fire conditions emerge, persist, and propagate across space and time. Their practical value is greatest when the target indicator evolves continuously across both space and time, as in hotspot forecasting, spread modeling, and short-horizon fire-risk prediction. Within this broader shift, the literature has converged on several distinct spatiotemporal modeling paradigms that differ in how spatial and temporal information are represented, fused, and propagated through the learning architecture [161].

In general, spatiotemporal wildfire modeling can be grouped into three paradigms: separated spatial–temporal modeling, coupled spatiotemporal modeling, and spatially enhanced coupled modeling. Although all aim to model wildfire dynamics across space and time, they differ in how tightly spatial and temporal dependencies are integrated.

Separated spatial–temporal modeling is the most modular paradigm, first extracting spatial features with CNNs or graph-based operators and then passing them to a temporal model such as an RNN, LSTM, or GRU; this makes it simple, flexible, and efficient, but less effective for capturing fine-grained spatiotemporal interactions. Coupled spatiotemporal modeling addresses this limitation by preserving spatial structure over time and operating directly on tensors or graphs, which better supports wildfire spread, hotspot migration, and short-term spatial risk forecasting, although with greater computational and training complexity. Spatially enhanced coupled modeling further strengthens spatial representation before or during prediction, making it especially useful under strong spatial heterogeneity, but at the cost of higher data demand, lower interpretability, and greater computational burden. Overall, these paradigms differ mainly in priority: separated models favor modularity and scalability, coupled models better capture evolving spatial structure, and spatially enhanced coupled models offer the richest representation when predictive performance under complex spatial variability is the main objective.

This same comparative logic also helps contextualize the candidate architectures that have recently been benchmarked in wildfire studies. Recurrent models such as GRU and LSTM remain useful when temporal dependency is dominant or when spatial information has already been summarized in earlier processing stages. By contrast, architectures such as U-Net, Attention U-Net, UNETR, and SwinUNETR are more relevant when spatial encoding or spatially structured prediction is central, particularly in image-like or grid-based wildfire applications [162]. However, the significance of these benchmarks lies less in the superiority of any single architecture than in what they reveal about modeling needs: as wildfire prediction moves toward probabilistic risk estimation and spread forecasting, models increasingly require both multiscale spatial representation and temporal dependency learning. Consequently, the key issue for the literature is no longer whether to use spatial or temporal models separately, but how best to integrate them for the specific wildfire process, spatial domain, and forecasting horizon of interest. Table 8 shows the comparative characteristics of spatial–temporal modeling paradigms in forest fire analysis.

Across these modeling families, no single approach is universally superior; suitability depends on the structure of the wildfire indicator, the predictor set, and the modeling objective. Classical statistical models remain valuable when inference and interpretability are prioritized, especially for well-defined hotspot or fire-count problems. Machine-learning models are often more effective for nonlinear tabular prediction using mixed environmental and anthropogenic predictors, while deep-learning and spatiotemporal architectures become most advantageous when wildfire data are strongly spatial, temporal, or multimodal. In general, gains in representational power are accompanied by lower transparency, greater

tuning complexity, and higher data and computational requirements. For this reason, model comparison in wildfire research should focus less on identifying a universally best algorithm and more on matching each modeling family to the relevant indicator type, predictor structure, and operational context.

Table 8. Comparative characteristics of spatiotemporal modeling paradigms in wildfire analysis.

Paradigm	Core Idea	Best Suited When	Data Demand	Interpretability	Scalability	Main Strengths	Main Limitations	Refs
Separated spatial-temporal modeling	Spatial features are extracted first, then passed to a temporal model	Modularity and implementation simplicity are prioritized	Moderate	Moderate to high	High	Flexible design; easier to train and adapt; lower computational burden	May lose fine spatial structure; weaker cross-spatiotemporal interaction learning	[51,158]
Coupled spatiotemporal modeling	Spatial and temporal dependencies are learned jointly within structured tensors or graphs	Fire propagation and neighbourhood interaction are central	High	Moderate	Moderate	Preserves evolving spatial structure; better for localized dynamics	More complex; higher computational cost; more difficult to optimize	[51,52]
Spatially enhanced coupled modeling	Stronger spatial feature extraction is integrated into coupled spatiotemporal prediction	High-resolution heterogeneity and predictive performance are prioritized	High to very high	Low to moderate	Moderate to low	Richest representation of wildfire dynamics; strong predictive potential	Highest data and tuning demand; lowest transparency; computationally expensive	[51–53]

5. Research Challenges and Future Directions

Despite major advances in wildfire indicator development, significant research challenges remain. Persistent uncertainties in hotspot detection, burned area mapping, and emission estimation continue to limit the precision of wildfire impact assessments, particularly in regions characterized by small, low-intensity, or obscured fires. Differences in sensor resolution, overpass timing, and algorithm design complicate cross-dataset comparisons and introduce structural uncertainty into long-term trend analyses. Addressing these challenges requires improved sensor capabilities, harmonized multi-sensor datasets, and transparent uncertainty quantification.

5.1. Practical Considerations and Persistent Challenges in Wildfire Modeling

Although wildfire modeling has advanced rapidly, several persistent challenges still limit both scientific reliability and operational usefulness. These challenges arise not only from model architecture, but also from the quality, compatibility, and representativeness of the underlying wildfire observations [27,51]. Active-fire products support near-real-time monitoring, yet remain affected by sensor resolution, overpass timing, cloud cover, and omission of small or low-intensity fires [59], while burned-area products vary across sensors, ecosystems, and retrieval methods [163]. These limitations are especially severe in tropical landscapes, where fragmented land cover, persistent smoke, and low-temperature combustion reduce detection accuracy [69,164]. Emissions estimation remains particularly difficult because hotspot counts alone are insufficient: emissions also depend on FRP, fire duration, fuel consumption, and combustion completeness, especially in peat systems where long-smouldering fires may remain partly undetected despite substantial carbon release [1,70,119,165,166].

A second major challenge is model transferability across space and time. Domain shift reduces performance when models are applied to regions with different climates, vegetation structures, ignition regimes, and land-use systems [27,51], while scale mismatch can produce statistically convenient but physically misleading relationships when

datasets with different spatial and temporal resolutions are combined without careful alignment [51,55]. These problems arise across many wildfire systems: models trained in temperate forests may not transfer well to Mediterranean landscapes, tropical peatlands, savanna fire regimes, or rapidly expanding wildland–urban interface regions because each setting is shaped by different combinations of fuel structure, climate stress, human ignition, and land-management practices [10,15,30,140,142,145]. In tropical Southeast Asia, for example, peat combustion, drainage, land-use change, and anthropogenic ignition create fire dynamics that differ from those in many temperate and Mediterranean systems [40,63,117,167,168]. In addition, non-stationarity caused by climate change is altering fire weather, drought behaviour, and extreme-event frequency, weakening the stability of historical fire climate relationships and reducing the long-term reliability of static predictive models [26,54]. Together, these issues show that progress in wildfire modeling depends not only on improving accuracy, but also on better harmonization, validation, transferability assessment, and operational feasibility; Table S4 summarizes the main practical challenges, representative studies, and proposed solution paths [27,51].

5.2. *Specific Integration Paths for Next-Generation Wildfire Modeling*

Future wildfire modeling should focus on integration strategies that directly address persistent limitations rather than on increasingly complex architectures alone. A first priority is adaptation to non-stationarity through rolling retraining, recalibration, temporally structured validation, and monitoring of predictor drift as climate change alters fire weather, drought behaviour, and extreme-event frequency [26,30,54]. A second priority is explicit treatment of domain shift through multi-region pretraining combined with local recalibration, because models trained in one fire system may not transfer reliably to regions with different fuels, ignition regimes, climate controls, and land-management practices [27,51]. This issue is relevant across multiple fire-prone environments, including Mediterranean landscapes affected by wind- and drought-driven fire behaviour [15], tropical forest frontiers where land-use transition and agricultural expansion shape fire activity [10,142], savanna systems where rainfall, fire season, and management influence fire intensity [124], wildland–urban interface regions where exposure and human ignition pressure are central [140], and tropical peatlands where drainage, smouldering combustion, and land-use change complicate fire detection and prediction [117,164]. A third priority is multimodal integration, particularly when combining active-fire, burned-area, FRP, duration, and fuel-related information helps close observational gaps in event characterization and emissions estimation [59,70,166].

At the same time, next-generation systems should place greater emphasis on uncertainty quantification, explainability, scalable computing, and operational usability. Because both wildfire observations and predictive models contain uncertainty, future studies should move beyond point prediction toward calibrated probabilities, prediction intervals, sensitivity analysis, and comparison across alternative fire products [55,59,89,115,163,164]. Explainability is equally important for operational uptake, since decision-makers need to know whether predictions are driven mainly by drought, fuels, topography, accessibility, or human pressure [24,27,51,53,105,110]. From an implementation perspective, scalable workflows are essential because the most accurate systems are often computationally demanding, making tiered or cloud-based deployment more realistic for operational use [51,60,169]. Ultimately, wildfire modeling should be designed not only for predictive performance, but also for timely decision support in same-day alerts, weekly suppression planning, seasonal preparedness, emissions assessment, and smoke-related public-health response [2,24,96,158].

6. Discussion

A central lesson from this survey is that wildfire cannot be understood through a single indicator, predictor group, or modeling family. Active-fire detections are essential for near-real-time monitoring but remain sensitive to overpass timing, cloud cover, sensor resolution, and missed small or low-intensity fires [35]. Burned-area products better represent spatial extent and post-fire footprint, whereas FRP-related indicators add information on combustion intensity and energy release [46,55,70]. Their value is therefore strongest when they are matched to the research objective and interpreted as complementary rather than interchangeable indicators [35,46,55,70].

The same principle applies to predictors and models. The relative importance of climate, vegetation, topography, and human activity differs across fire regimes, with weather and drought often dominating in climate-limited systems, while accessibility, land-cover change, concession dynamics, and anthropogenic ignition become more important in human-dominated and tropical peatland settings [23,26,125]. Accordingly, statistical models remain useful for interpretable inference, machine learning is effective for nonlinear tabular prediction, and deep learning is most appropriate when wildfire data are strongly spatial, temporal, or multimodal [27,51]. More complex models should not be treated as automatically superior, because performance depends as much on indicator choice, predictor design, preprocessing, and validation strategy as on algorithmic sophistication [27,51]. In practice, robust wildfire intelligence requires combining complementary indicators, context-appropriate predictors, and modeling frameworks that fit both the data structure and the intended decision task [23,27,40,51,63,170].

7. Conclusions

This survey leads to five main conclusions. First, wildfire activity is best understood as the product of interacting climatic, vegetation, topographic, land-use, and human drivers rather than any single dominant factor. Second, no single wildfire indicator or model family is universally best; their suitability depends on the study objective, data structure, spatial and temporal scale, and fire regime. Third, although the field has advanced rapidly in methodological diversity, comparability across studies remains limited because indicators, preprocessing choices, predictor definitions, and validation strategies are still highly heterogeneous. Fourth, model transferability remains a major unresolved challenge, especially when methods developed in temperate systems are applied to tropical and peatland-dominated regions such as Indonesia. Finally, future progress will depend less on adding ever more complex models and more on improving data harmonization, uncertainty treatment, validation design, and context-aware integration between physical understanding and data-driven approaches.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/earth7040121/s1>, Table S1. Criteria for distinguishing event-based and impact-based wildfire indicators and their implications. Table S2. VIIRS channels used in the active-fire detection framework. Table S3. Human activity variables recommended for inclusion in Indonesian wildfire modeling frameworks, with data sources, spatial resolution, fire mechanism, operationalization, and supporting references. Table S4. Summary of uncertainty types in satellite-derived hotspot data, their physical mechanisms, Indonesia-specific evidence, recommended mitigation strategies, downstream products affected, and key references *. Table S5. Practical challenges in wildfire modeling, representative sources, and possible solution paths.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
API(s)	Application Programming Interface(s)
AVHRR	Advanced Very High-Resolution Radiometer
CFDRS	Canadian Forest Fire Danger Rating System
CH ₄	Methane
CNN	Convolutional Neural Networks
CO ₂	Carbon Dioxide
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DL	Deep Learning
DT	Decision Tree
EFFIS	European Forest Fire Information System
EVI	Enhanced Vegetation Index
FFDI	Forest Fire Danger Index
FIRMS	Fire Information for Resource Management System
FRP	Fire Radiative Power
FWI	Fire Weather Index
GAMs	Generalized Additive Models
GFED	Global Fire Emissions Database
GIS	Geographic Information Systems
GloCAB	Global Cropland Burned Area
GNNs	Graph Neural Networks
GRUs	Gated Recurrent Units
KDE	Kernel Density Estimation
LS	Slope Length and Steepness Factor
LSSVM	Least Squares Support Vector Machine
LSSVM-CA	Least Squares Support Vector Machine-Cellular Automaton
LSTM	Long Short-Term Memory
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer

MSE	Mean Squared Error
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NFDRS	National Fire Danger Rating System
NO ₂	Nitrogen Dioxide
O ₃	Ozone
PCA	Principal Component Analysis
PM	Particulate Matter
RF	Random Forest
RNNs	Recurrent Neural Networks
S-NPP	Suomi National Polar-orbiting Partnership
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SVMs	Support Vector Machines
SwinUNETR	Swin Transformer U-Net with Encoder-Decoder Architecture
UAV	Unmanned Aerial Vehicle
U-Net	U-shaped Convolutional Network
UNETR	U-Net with Transformers
US	United States
VIIRS	Visible Infrared Imaging Radiometer Suite
XGBoost	Extreme Gradient Boosting

References

1. Bowd, E.J.; Blair, D.P.; Lindenmayer, D.B. Prior Disturbance Legacy Effects on Plant Recovery Post-High-Severity Wildfire. *Ecosphere* **2021**, *12*, e03480. [[CrossRef](#)]
2. Holder, A.L.; Ahmed, A.; Vukovich, J.M.; Rao, V. Hazardous Air Pollutant Emissions Estimates from Wildfires in the Wildland Urban Interface. *PNAS Nexus* **2023**, *2*, pgad186. [[CrossRef](#)] [[PubMed](#)]
3. Lopez, A.M.; Avila, C.C.E.; VanderRoest, J.P.; Roth, H.K.; Fendorf, S.; Borch, T. Molecular Insights and Impacts of Wildfire-Induced Soil Chemical Changes. *Nat. Rev. Earth Environ.* **2024**, *5*, 431–446. [[CrossRef](#)]
4. Mena-Rivera, L.; Dean, J.F.; Garnett, M.H.; Holt, A.D.; Pickard, A.E.; Andersen, R.; Graham, E.; Bishop, J.; Spencer, R.G.M.; Evans, C.D.; et al. Wildfires Impact the Thermal Stability and Molecular Composition but Not the Age of Dissolved Organic Carbon Exported by Northern Streams. *J. Geophys. Res. Biogeosci.* **2025**, *130*. [[CrossRef](#)]
5. Pelletier, N.; Millard, K.; Darling, S. Wildfire Likelihood in Canadian Treed Peatlands Based on Remote-Sensing Time-Series of Surface Conditions. *Remote Sens. Environ.* **2023**, *296*, 113747. [[CrossRef](#)]
6. Hua, L.; Shao, G. The Progress of Operational Forest Fire Monitoring with Infrared Remote Sensing. *J. For. Res.* **2017**, *28*, 215–229. [[CrossRef](#)]
7. McNorton, J.R.; Di Giuseppe, F. A Global Fuel Characteristic Model and Dataset for Wildfire Prediction. *Biogeosciences* **2024**, *21*, 279–300. [[CrossRef](#)]
8. Yang, C.-E.; Fu, J.S.; Liu, Y.; Dong, X.; Liu, Y. Projections of Future Wildfires Impacts on Air Pollutants and Air Toxics in a Changing Climate over the Western United States. *Environ. Pollut.* **2022**, *304*, 119213. [[CrossRef](#)] [[PubMed](#)]
9. Bowman, D.M.J.S.; Balch, J.K.; Artaxo, P.; Bond, W.J.; Carlson, J.M.; Cochrane, M.A.; D'Antonio, C.M.; DeFries, R.S.; Doyle, J.C.; Harrison, S.P.; et al. Fire in the Earth System. *Science* **2009**, *324*, 481–484. [[CrossRef](#)] [[PubMed](#)]
10. Cochrane, M.A.; Barber, C.P. Climate Change, Human Land Use and Future Fires in the Amazon. *Glob. Change Biol.* **2009**, *15*, 601–612. [[CrossRef](#)]
11. Flannigan, M.; Cantin, A.S.; de Groot, W.J.; Wotton, M.; Newbery, A.; Gowman, L.M. Global Wildland Fire Season Severity in the 21st Century. *For. Ecol. Manag.* **2013**, *294*, 54–61. [[CrossRef](#)]
12. Gaveau, D.L.A.; Salim, M.A.; Hergoualc'h, K.; Locatelli, B.; Sloan, S.; Wooster, M.; Marlier, M.E.; Molidena, E.; Yaen, H.; DeFries, R.; et al. Major Atmospheric Emissions from Peat Fires in Southeast Asia during Non-Drought Years: Evidence from the 2013 Sumatran Fires. *Sci. Rep.* **2014**, *4*, 6112. [[CrossRef](#)] [[PubMed](#)]
13. Field, R.D.; Van Der Werf, G.R.; Fanin, T.; Fetzer, E.J.; Fuller, R.; Jethva, H.; Levy, R.; Livesey, N.J.; Luo, M.; Torres, O.; et al. Indonesian Fire Activity and Smoke Pollution in 2015 Show Persistent Nonlinear Sensitivity to El Nino-Induced Drought. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 9204–9209. [[CrossRef](#)] [[PubMed](#)]
14. Lecina-Diaz, J.; Alvarez, A.; Retana, J. Extreme Fire Severity Patterns in Topographic, Convective and Wind-Driven Historical Wildfires of Mediterranean Pine Forests. *PLoS ONE* **2014**, *9*, e85127. [[CrossRef](#)] [[PubMed](#)]

15. Cavlina Tomasevic, I.; Cheung, K.K.W.; Vucetic, V.; Fox-Hughes, P.; Horvath, K.; Telisman Prtenjak, M.; Beggs, P.J.; Malecic, B.; Milic, V. The 2017 Split Wildfire in Croatia: Evolution and the Role of Meteorological Conditions. *Nat. Hazards Earth Syst. Sci.* **2022**, *22*, 3143–3165. [CrossRef]
16. Driscoll, D.A.; Macdonald, K.J.; Gibson, R.K.; Doherty, T.S.; Nimmo, D.G.; Nolan, R.H.; Ritchie, E.G.; Williamson, G.J.; Heard, G.W.; Tasker, E.M.; et al. Biodiversity Impacts of the 2019–2020 Australian Megafires. *Nature* **2024**, *635*, 898–905. [CrossRef] [PubMed]
17. Khaykin, S.; Legras, B.; Bucci, S.; Sellitto, P.; Isaksen, I.; Tence, F.; Bekki, S.; Bourassa, A.; Rieger, L.; Zawada, D.; et al. The 2019/20 Australian Wildfires Generated a Persistent Smoke-Charged Vortex Rising up to 35 Km Altitude. *Commun. Earth Environ.* **2020**, *1*, 22. [CrossRef]
18. Jain, P.; Barber, Q.E.; Taylor, S.W.; Whitman, E.; Castellanos Acuna, D.; Boulanger, Y.; Chavardes, R.D.; Chen, J.; Englefield, P.; Flannigan, M.; et al. Drivers and Impacts of the Record-Breaking 2023 Wildfire Season in Canada. *Nat. Commun.* **2024**, *15*, 6764. [CrossRef] [PubMed]
19. Kirchmeier-Young, M.C.; Malinina, E.; Barber, Q.E.; Garcia Perdomo, K.; Curasi, S.R.; Liang, Y.; Jain, P.; Gillett, N.P.; Parisien, M.-A.; Cannon, A.J.; et al. Human Driven Climate Change Increased the Likelihood of the 2023 Record Area Burned in Canada. *npj Clim. Atmos. Sci.* **2024**, *7*, 316. [CrossRef] [PubMed]
20. Lapola, D.M.; Pinho, P.; Barlow, J.; Aragao, L.E.O.C.; Berenguer, E.; Carmenta, R.; Liddy, H.M.; Seixas, H.; Silva, C.V.J.; Silva-Junior, C.H.L.; et al. The Drivers and Impacts of Amazon Forest Degradation. *Science* **2023**, *379*, eabp8622. [CrossRef] [PubMed]
21. Bourgoignie, C.; Beuchle, R.; Branco, A.; Carreiras, J.; Ceccherini, G.; Oom, D.; San-Miguel-Ayanz, J.; Sedano, F. Extensive Fire-Driven Degradation in 2024 Marks Worst Amazon Forest Disturbance in over 2 Decades. *Biogeosciences* **2025**, *22*, 5247–5256. [CrossRef]
22. Wimberly, M.C.; Wanyama, D.; Doughty, R.; Peiro, H.; Crowell, S. Increasing Fire Activity in African Tropical Forests Is Associated With Deforestation and Climate Change. *Geophys. Res. Lett.* **2024**, *51*, e2023GL106240. [CrossRef]
23. United Nations Office for Disaster Risk Reduction. *Wildfires in Indonesia: Risk Drivers, Impacts, and Disaster Risk Reduction*; UNDRR: Geneva, Switzerland, 2024.
24. Miller, C.; Ager, A.A. A Review of Recent Advances in Risk Analysis for Wildfire Management. *Int. J. Wildland Fire* **2013**, *22*, 1–14. [CrossRef]
25. Bowman, D.M.J.S.; Williamson, G.J.; Abatzoglou, J.T.; Kolden, C.A.; Cochrane, M.A.; Smith, A.M.S. Human Exposure and Sensitivity to Globally Extreme Wildfire Events. *Nat. Ecol. Evol.* **2017**, *1*, 0058. [CrossRef] [PubMed]
26. Abatzoglou, J.T.; Williams, A.P.; Barbero, R. Global Emergence of Anthropogenic Climate Change in Fire Weather Indices. *Geophys. Res. Lett.* **2019**, *46*, 326–336. [CrossRef]
27. 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. *Environ. Rev.* **2020**, *28*, 478–505. [CrossRef]
28. PreventionWeb. Indonesia Wildfires, 2023–Forensic Analysis. *PreventionWeb*. 2024. Available online: <https://www.preventionweb.net/resource/indonesia-wildfires-2023-forensic-analysis> (accessed on 15 July 2026).
29. Bhattarai, H.; Val Martin, M.; Sitch, S.; Yung, D.H.Y.; Tai, A.P.K. Global Wildfire Patterns and Drivers under Climate Change. *Biogeosciences* **2025**, *22*, 7591–7610. [CrossRef]
30. Abatzoglou, J.T.; Williams, A.P. Impact of Anthropogenic Climate Change on Wildfire across Western US Forests. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 11770–11775. [CrossRef] [PubMed]
31. Chen, Y.; Morton, D.C.; Andela, N.; van der Werf, G.R.; Giglio, L.; Randerson, J.T. A Pan-Tropical Cascade of Fire Driven by El Nino/Southern Oscillation. *Nat. Clim. Change* **2017**, *7*, 906–911. [CrossRef]
32. van der Werf, G.R.; Randerson, J.T.; Giglio, L.; van Leeuwen, T.T.; Chen, Y.; Rogers, B.M.; Mu, M.; van Marle, M.J.E.; Morton, D.C.; Collatz, G.J.; et al. Global Fire Emissions Estimates during 1997–2016. *Earth Syst. Sci. Data* **2017**, *9*, 697–720. [CrossRef]
33. Global Forest Watch. *Fire and Tree Cover Loss in Indonesia*; World Resources Institute: Washington, DC, USA, 2024.
34. WRI Indonesia. *Forest and Land Fire Dynamics in Indonesia*; WRI Indonesia: Jakarta, Indonesia, 2025.
35. Giglio, L.; Schroeder, W.; Justice, C.O. The Collection 6 MODIS Active Fire Detection Algorithm and Fire Products. *Remote Sens. Environ.* **2016**, *178*, 31–41. [CrossRef] [PubMed]
36. Justice, C.O.; Giglio, L.; Korontzi, S.; Owens, J.; Morisette, J.T.; Roy, D.; Descloitres, J.; Alleaume, S.; Petitcolin, F.; Kaufman, Y. The MODIS Fire Products. *Remote Sens. Environ.* **2002**, *83*, 244–262. [CrossRef]
37. Schroeder, W.; Oliva, P.; Giglio, L.; Csiszar, I.A. The New VIIRS 375 m Active Fire Detection Data Product: Algorithm Description and Initial Assessment. *Remote Sens. Environ.* **2014**, *143*, 85–96. [CrossRef]
38. Page, S.E.; Siegert, F.; Rieley, J.O.; Boehm, H.-D.V.; Jaya, A.; Limin, S. The Amount of Carbon Released from Peat and Forest Fires in Indonesia during 1997. *Nature* **2002**, *420*, 61–65. [CrossRef] [PubMed]
39. Azis, I.; Djuraidah, A.; Aidi, M.; Sopaheluwakan, A. Spatial Prediction of the Number of Wildfire Hotspots Using Negative Binomial Conditional Autoregressive Random Forest. *Glob. J. Environ. Sci. Manag.* **2024**, *11*, 1509–1526. [CrossRef]

40. Karurung, W.S.; Lee, K.; Lee, W. Assessment of Forest Fire Vulnerability Prediction in Indonesia: Seasonal Variability Analysis Using Machine Learning Techniques. *Int. J. Appl. Earth Obs. Geoinf.* **2025**, *138*, 104435. [\[CrossRef\]](#)
41. Jolly, W.; Freeborn, P.; Page, W.; Butler, B. Severe Fire Danger Index: A Forecastable Metric to Inform Firefighter and Community Wildfire Risk Management. *Fire* **2019**, *2*, 47. [\[CrossRef\]](#)
42. Flannigan, M.D.; Stocks, B.J.; Wotton, B.M. Climate Change and Forest Fires. *Sci. Total Environ.* **2000**, *262*, 221–229. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Dowdy, A.J.; Mills, G.A.; Finkele, K.; de Groot, W. Index Sensitivity Analysis Applied to the Canadian Forest Fire Weather Index and the McArthur Forest Fire Danger Index. *Meteorol. Appl.* **2010**, *17*, 298–312. [\[CrossRef\]](#)
44. Zacharakis, I.; Tsihrintzis, V.A. Environmental Forest Fire Danger Rating Systems and Indices around the Globe: A Review. *Land* **2023**, *12*, 194. [\[CrossRef\]](#)
45. Chuvieco, E.; Opazo, S.; Sione, W.; Valle, H.D.; Anaya, J.; Bella, C.D.; Cruz, I.; Manzo, L.; Lopez, G.; Mari, N.; et al. Global Burned-Land Estimation in Latin America Using MODIS Composite Data. *Ecol. Appl.* **2008**, *18*, 64–79. [\[CrossRef\]](#) [\[PubMed\]](#)
46. Giglio, L.; Boschetti, L.; Roy, D.P.; Humber, M.L.; Justice, C.O. The Collection 6 MODIS Burned Area Mapping Algorithm and Product. *Remote Sens. Environ.* **2018**, *217*, 72–85. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Andela, N.; Morton, D.C.; Giglio, L.; Chen, Y.; van der Werf, G.R.; Kasibhatla, P.S.; DeFries, R.S.; Collatz, G.J.; Hantson, S.; Kloster, S.; et al. A Human-Driven Decline in Global Burned Area. *Science* **2017**, *356*, 1356–1362. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Sabljčić, L.; Perić, Z.M.; Bajić, D.; Marković, S.B.; Adžić, D.; Lukić, T. Advancing wildfire monitoring: Remote sensing techniques and applications in the Sana River Basin, Bosnia and Herzegovina. *Nat. Hazards* **2025**, *121*, 18321–18360. [\[CrossRef\]](#)
49. Yan, K.; Zhao, F.; Shu, L.; Liu, Y.; Wang, M.; Si, L.; Li, W.; Li, X.; Zhang, S.; Li, S.; et al. A machine learning-based wildfire susceptibility mapping framework for China's three-north shelterbelt region. *Ecol. Inform.* **2026**, *93*, 103539. [\[CrossRef\]](#)
50. Muhammad, S.; Nizami, S.M.; Jiang, Q.; Mehmood, K.; Hussain, M.; Anees, S.A.; Shahzad, F.; Khan, W.R. Machine learning-based forest fire vulnerability assessment in subtropical chir pine forests of Pakistan. *Fire Ecol.* **2025**, *21*, 72. [\[CrossRef\]](#)
51. Xu, Z.; Li, J.; Cheng, S.; Rui, X.; Zhao, Y.; He, H.; Guan, H.; Sharma, A.; Erxleben, M.; Chang, R.; et al. Deep Learning for Wildfire Risk Prediction: Integrating Remote Sensing and Environmental Data. *ISPRS J. Photogramm. Remote Sens.* **2025**, *227*, 632–677. [\[CrossRef\]](#)
52. Dubey, P.; Dubey, P. Bridging Spatiotemporal Wildfire Prediction and Decision Modeling Using Transformer Networks and Fuzzy Inference Systems. *MethodsX* **2025**, *15*, 103498. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Zhou, Y.; Kong, R.; Xu, Z.; Xu, L.; Cheng, S. Comparative and Interpretative Analysis of CNN and Transformer Models in Predicting Wildfire Spread Using Remote Sensing Data. *J. Geophys. Res. Mach. Learn. Comput.* **2025**, *2*, e2024JH000409. [\[CrossRef\]](#)
54. Jones, M.W.; Abatzoglou, J.T.; Veraverbeke, S.; Andela, N.; Lasslop, G.; Forkel, M.; Smith, A.J.P.; Burton, C.; Betts, R.A.; van der Werf, G.R.; et al. Global and Regional Trends and Drivers of Fire Under Climate Change. *Rev. Geophys.* **2022**, *60*, e2020RG000726. [\[CrossRef\]](#)
55. Chen, Y.; Morton, D.C.; Randerson, J.T. Remote Sensing for Wildfire Monitoring: Insights into Burned Area, Emissions, and Fire Dynamics. *ONE Earth* **2024**, *7*, 1022–1028. [\[CrossRef\]](#)
56. Roy, D.P.; Boschetti, L.; Justice, C.O.; Ju, J. The Collection 5 MODIS Burned Area Product—Global Evaluation by Comparison with the MODIS Active Fire Product. *Remote Sens. Environ.* **2008**, *112*, 3690–3707. [\[CrossRef\]](#)
57. Zhu, C.; Zhu, J.; Zheng, X.; Lu, D.; Li, X. Comparison of Gap Formation and Distribution Pattern Induced by Wind/Snowstorm and Flood in a Temperate Secondary Forest Ecosystem, Northeast China. *Silva Fenn.* **2017**, *51*, 7693. [\[CrossRef\]](#)
58. Sperling, S.; Wooster, M.J.; Malamud, B.D. Influence of Satellite Sensor Pixel Size and Overpass Time on Undercounting of Cerrado/Savannah Landscape-Scale Fire Radiative Power (FRP): An Assessment Using the MODIS Airborne Simulator. *Fire* **2020**, *3*, 11. [\[CrossRef\]](#)
59. Wooster, M.J.; Roberts, G.J.; Giglio, L.; Roy, D.P.; Freeborn, P.H.; Boschetti, L.; Justice, C.; Ichoku, C.; Schroeder, W.; Davies, D.; et al. Satellite Remote Sensing of Active Fires: History and Current Status, Applications and Future Requirements. *Remote Sens. Environ.* **2021**, *267*, 112694. [\[CrossRef\]](#)
60. Boroujeni, S.P.H.; Razi, A.; Khoshdel, S.; Afghah, F.; Coen, J.L.; O'Neill, L.; Fule, P.; Watts, A.; Kokolakis, N.-M.T.; Vamvoudakis, K.G. A Comprehensive Survey of Research towards AI-Enabled Unmanned Aerial Systems in Pre-, Active-, and Post-Wildfire Management. *Inf. Fusion* **2024**, *108*, 102369. [\[CrossRef\]](#)
61. Gould, C.F.; Heft-Neal, S.; Johnson, M.; Aguilera, J.; Burke, M.; Nadeau, K. Health Effects of Wildfire Smoke Exposure. *Annu. Rev. Med.* **2024**, *75*, 277–292. [\[CrossRef\]](#) [\[PubMed\]](#)
62. Kurbanov, E.; Vorobev, O.; Lezhnin, S.; Sha, J.; Wang, J.; Li, X.; Cole, J.; Dergunov, D.; Wang, Y. Remote Sensing of Forest Burnt Area, Burn Severity, and Post-Fire Recovery: A Review. *Remote Sens.* **2022**, *14*, 4714. [\[CrossRef\]](#)
63. Nurdianti, S.; Sopaheluwakan, A.; Septiawan, P.; Ardhana, M.R. Joint Spatio-Temporal Analysis of Various Wildfire and Drought Indicators in Indonesia. *Atmosphere* **2022**, *13*, 1591. [\[CrossRef\]](#)
64. Keeley, J.E. Fire Intensity, Fire Severity and Burn Severity: A Brief Review and Suggested Usage. *Int. J. Wildland Fire* **2009**, *18*, 116–126. [\[CrossRef\]](#)

65. Lentile, L.B.; Holden, Z.A.; Smith, A.M.S.; Falkowski, M.J.; Hudak, A.T.; Morgan, P.; Lewis, S.A.; Gessler, P.E.; Benson, N.C. Remote Sensing Techniques to Assess Active Fire Characteristics and Post-Fire Effects. *Int. J. Wildland Fire* **2006**, *15*, 319–345. [\[CrossRef\]](#)
66. Vetrita, Y.; Albar, I.; Santoso, I.; Prasasti, I.; Kartika, T.; Usman, A.B.; Tosiani, A.; Haryanto, D.; Endrawati; Famurianty, E.; et al. Monthly Mapping of Indonesia's Burned Areas: Implementation, History, Techniques, and Future Directions. *Int. J. Remote Sens.* **2025**, *46*, 636–660. [\[CrossRef\]](#)
67. Fornacca, D.; Ye, Y.; Li, X.; Xiao, W. Including Small Fires in Global Historical Burned Area Products: Promising Results from a Landsat-Based Product. *Fire* **2025**, *8*, 422. [\[CrossRef\]](#)
68. Bowman, D.M.J.S.; Kolden, C.A.; Abatzoglou, J.T.; Johnston, F.H.; van der Werf, G.R.; Flannigan, M. Vegetation Fires in the Anthropocene. *Nat. Rev. Earth Environ.* **2020**, *1*, 500–515. [\[CrossRef\]](#)
69. Indradjad, A.; Dimiyati, M.; Vetrita, Y.; Adiningsih, E.S.; Rokhmatuloh, R. Enhancing Fire Monitoring Method over Peatlands and Non-Peatlands in Indonesia Using Visible Infrared Imaging Radiometer Suite Data. *Fire* **2023**, *7*, 9. [\[CrossRef\]](#)
70. Wooster, M.J.; Roberts, G.; Perry, G.L.W.; Kaufman, Y.J. Retrieval of Biomass Combustion Rates and Totals from Fire Radiative Power Observations: FRP Derivation and Calibration Relationships between Biomass Consumption and Fire Radiative Energy Release. *J. Geophys. Res. Atmos.* **2005**, *110*, D24311. [\[CrossRef\]](#)
71. Wooster, M. Fire Radiative Energy for Quantitative Study of Biomass Burning: Derivation from the BIRD Experimental Satellite and Comparison to MODIS Fire Products. *Remote Sens. Environ.* **2003**, *86*, 83–107. [\[CrossRef\]](#)
72. Mota, B.; Wooster, M.J. A New Top-down Approach for Directly Estimating Biomass Burning Emissions and Fuel Consumption Rates and Totals from Geostationary Satellite Fire Radiative Power (FRP). *Remote Sens. Environ.* **2018**, *206*, 45–62. [\[CrossRef\]](#)
73. French, N.H.F.; Hudak, A.T. Biomass Burning Fuel Consumption and Emissions for Air Quality. In *Landscape Fire, Smoke, and Health: Linking Biomass Burning Emissions to Human Well-Being*; American Geophysical Union: Washington, DC, USA, 2023; pp. 69–88.
74. Kaiser, J.W.; Heil, A.; Andreae, M.O.; Benedetti, A.; Chubarova, N.; Jones, L.; Morcrette, J.-J.; Razinger, M.; Schultz, M.G.; Suttie, M.; et al. Biomass Burning Emissions Estimated with a Global Fire Assimilation System Based on Observed Fire Radiative Power. *Biogeosciences* **2012**, *9*, 527–554. [\[CrossRef\]](#)
75. Giglio, L.; Descloitres, J.; Justice, C.O.; Kaufman, Y.J. An Enhanced Contextual Fire Detection Algorithm for MODIS. *Remote Sens. Environ.* **2003**, *87*, 273–282. [\[CrossRef\]](#)
76. Roman, M.O.; Justice, C.; Paynter, I.; Boucher, P.B.; Devadiga, S.; Endsley, A.; Erb, A.; Friedl, M.; Gao, H.; Giglio, L.; et al. Continuity between NASA MODIS Collection 6.1 and VIIRS Collection 2 Land Products. *Remote Sens. Environ.* **2024**, *302*, 113963. [\[CrossRef\]](#)
77. Giglio, L.; Schroeder, W.; Hall, J.V.; Justice, C.O. *MODIS Collection 6 and Collection 6.1 Active Fire Product User's Guide Version 1.0*; NASA: Washington, DC, USA, 2021.
78. Schroeder, W.; Giglio, L.; Hall, J. *Collection 2 Visible Infrared Imaging Radiometer Suite (VIIRS) 375-m Active Fire Product User's Guide Version 1.2*; NASA: Washington, DC, USA, 2025.
79. Sofan, P.; Bruce, D.; Jones, E.; Marsden, J. Detection and Validation of Tropical Peatland Flaming and Smouldering Using Landsat-8 SWIR and TIRS Bands. *Remote Sens.* **2019**, *11*, 465. [\[CrossRef\]](#)
80. Tanpipat, V.; Honda, K.; Nuchaiya, P. MODIS Hotspot Validation over Thailand. *Remote Sens.* **2009**, *1*, 1043–1054. [\[CrossRef\]](#)
81. Hall, J.V.; Zhang, R.; Schroeder, W.; Huang, C.; Giglio, L. Validation of GOES-16 ABI and MSG SEVIRI Active Fire Products. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *83*, 101928. [\[CrossRef\]](#)
82. Schroeder, W.; Prins, E.; Giglio, L.; Csiszar, I.; Schmidt, C.; Morisette, J.; Morton, D. Validation of GOES and MODIS Active Fire Detection Products Using ASTER and ETM+ Data. *Remote Sens. Environ.* **2008**, *112*, 2711–2726. [\[CrossRef\]](#)
83. Wickramasinghe, C.; Wallace, L.; Reinke, K.; Jones, S. Intercomparison of Himawari-8 AHI-FSA with MODIS and VIIRS Active Fire Products. *Int. J. Digit. Earth* **2020**, *13*, 457–473. [\[CrossRef\]](#)
84. Hantson, S.; Padilla, M.; Corti, D.; Chuvieco, E. Strengths and Weaknesses of MODIS Hotspots to Characterize Global Fire Occurrence. *Remote Sens. Environ.* **2013**, *131*, 152–159. [\[CrossRef\]](#)
85. Oliva, P.; Schroeder, W. Assessment of VIIRS 375m Active Fire Detection Product for Direct Burned Area Mapping. *Remote Sens. Environ.* **2015**, *160*, 144–155. [\[CrossRef\]](#)
86. Coskuner, K. Assessing the Performance of MODIS and VIIRS Active Fire Products in the Monitoring of Wildfires: A Case Study in Turkey. *iForest* **2022**, *15*, 85–94. [\[CrossRef\]](#)
87. Guo, X.; Liu, Y.; Liu, P.; Wang, H.; Wu, W. Monitoring Active Fires in Borneo from Sentinel-2 MSI Images. *GISci. Remote Sens.* **2025**, *62*, 2539551. [\[CrossRef\]](#)
88. Ouattara, B.; Thiel, M.; Sponholz, B.; Paeth, H.; Yebra, M.; Mouillot, F.; Kacic, P.; Hackman, K. Enhancing Burned Area Monitoring with VIIRS Dataset: A Case Study in Sub-Saharan Africa. *Sci. Remote Sens.* **2024**, *10*, 100165. [\[CrossRef\]](#)
89. Grosvenor, M.J.; Ardiyani, V.; Wooster, M.J.; Gillott, S.; Green, D.C.; Lestari, P.; Suri, W. Catastrophic Impact of Extreme 2019 Indonesian Peatland Fires on Urban Air Quality and Health. *Commun. Earth Environ.* **2024**, *5*, 649. [\[CrossRef\]](#) [\[PubMed\]](#)

90. Xia, L.; Ren, C.; Yang, Y.; Li, J.; Fan, W.; Liu, R. Unravelling Spatiotemporal Heterogeneity of Wildfire Carbon Dioxide Emissions in Southeast Asia: Based on a High-Resolution Inventory. *J. Environ. Manag.* **2025**, *385*, 125634. [[CrossRef](#)] [[PubMed](#)]
91. Sofan, P.; Yulianto, F.; Sakti, A.D. Characteristics of False-Positive Active Fires for Biomass Burning Monitoring in Indonesia from VIIRS Data and Local Geo-Features. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 601. [[CrossRef](#)]
92. Davies, D.K.; Ilavajhala, S.; Wong, M.M.; Justice, C.O. Fire Information for Resource Management System: Archiving and Distributing MODIS Active Fire Data. *IEEE Trans. Geosci. Remote Sens.* **2009**, *47*, 72–79. [[CrossRef](#)]
93. Schmidt, A.; Ellsworth, L.M.; Boisen, G.A.; Novita, N.; Malik, A.; Gangga, A.; Albar, I.; Dwi Nurhayati, A.; Putra Ritonga, R.; Asyhari, A.; et al. Fire Frequency, Intensity, and Burn Severity in Kalimantan's Threatened Peatland Areas over Two Decades. *Front. For. Glob. Change* **2024**, *7*, 1221797. [[CrossRef](#)]
94. Miettinen, J.; Hooijer, A.; Vernimmen, R.; Liew, S.C.; Page, S.E. From Carbon Sink to Carbon Source: Extensive Peat Oxidation in Insular Southeast Asia since 1990. *Environ. Res. Lett.* **2017**, *12*, 024014. [[CrossRef](#)]
95. Davies, D. Geostationary Active Fire Detection Data in FIRMS. Available online: <https://www.earthdata.nasa.gov/news/blog/geostationary-active-fire-detection-data-firms> (accessed on 1 April 2026).
96. Moritz, M.A.; Batllori, E.; Bradstock, R.A.; Gill, A.M.; Handmer, J.; Hessburg, P.F.; Leonard, J.; McCaffrey, S.; Odion, D.C.; Schoennagel, T.; et al. Learning to Coexist with Wildfire. *Nature* **2014**, *515*, 58–66. [[CrossRef](#)] [[PubMed](#)]
97. Sudiana, D.; Lestari, A.I.; Rizkinia, M.; Riyanto, I.; Vetrita, Y.; Bayanuddin, A.A.; Putri, F.A.; Kartika, T.; Suhadha, A.G.; Julzarika, A.; et al. Assessing Burned Area Detection in Indonesia Using the Stacking Ensemble Neural Network (SENN): A Comparative Analysis of C- and L-Band Performance. *Computers* **2025**, *14*, 337. [[CrossRef](#)]
98. Pereira, A.A.; Libonati, R.; Rodrigues, J.A.; Nogueira, J.; Santos, F.L.M.; Oom, D.; Sanches, W.; Alvarado, S.T.; Pereira, J.M.C. Multi-Sensor, Active Fire-Supervised, One-Class Burned Area Mapping in the Brazilian Savanna. *Remote Sens.* **2021**, *13*, 4005. [[CrossRef](#)]
99. Van Wagner, C. *Development and Structure of the Canadian Forest Fire Weather Index System*; Canadian Forestry Service: Ottawa, ON, Canada, 1987.
100. Anderson, M.C.; Norman, J.M.; Mecikalski, J.R.; Otkin, J.A.; Kustas, W.P. A Climatological Study of Evapotranspiration and Moisture Stress across the Continental United States Based on Thermal Remote Sensing: 1. Model Formulation. *J. Geophys. Res. Atmos.* **2007**, *112*, D10117. [[CrossRef](#)]
101. Rotherznel, R.C.; Harris, R.W. *A Mathematical Model for Predicting Fire Spread in Wildland Fuels*; U.S. Department of Agriculture: Ogden, UT, USA, 1972.
102. Bishop, D.A.; Williams, A.P.; Seager, R. Increased Fall Precipitation in the Southeastern United States Driven by Higher-Intensity, Frontal Precipitation. *Geophys. Res. Lett.* **2019**, *46*, 8300–8309. [[CrossRef](#)]
103. Vicente-Serrano, S.M.; Begueria, S.; Lopez-Moreno, J.I. A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *J. Clim.* **2010**, *23*, 1696–1718. [[CrossRef](#)]
104. Abatzoglou, J.T.; Dobrowski, S.Z.; Parks, S.A.; Hegewisch, K.C. TerraClimate, a High-Resolution Global Dataset of Monthly Climate and Climatic Water Balance from 1958–2015. *Sci. Data* **2018**, *5*, 170191. [[CrossRef](#)] [[PubMed](#)]
105. Chuvieco, E.; Aguado, I.; Yebra, M.; Nieto, H.; Salas, J.; Martin, M.P.; Vilar, L.; Martinez, J.; Martin, S.; Ibarra, P.; et al. Development of a Framework for Fire Risk Assessment Using Remote Sensing and Geographic Information System Technologies. *Ecol. Modell.* **2010**, *221*, 46–58. [[CrossRef](#)]
106. Scott, J.; Burgan, R. Standard Fire Behavior Fuel Models: A Comprehensive Set for Use with Rothermel's Surface Fire Spread Model. In *The Bark Beetles, Fuels, and Fire Bibliography*; USDA Forest Service: Salt Lake City, UT, USA, 2005.
107. Keane, R.E. Describing Wildland Surface Fuel Loading for Fire Management: A Review of Approaches, Methods and Systems. *Int. J. Wildland Fire* **2013**, *22*, 51–62. [[CrossRef](#)]
108. Chuvieco, E.; Cocero, D.; Aguado, I.; Palacios, A.; Prado, E. Improving Burning Efficiency Estimates through Satellite Assessment of Fuel Moisture Content. *J. Geophys. Res. Atmos.* **2004**, *109*, D14S07. [[CrossRef](#)]
109. Yebra, M.; Dennison, P.E.; Chuvieco, E.; Riano, D.; Zylstra, P.; Hunt, E.R.; Danson, F.M.; Qi, Y.; Jurdao, S. A Global Review of Remote Sensing of Live Fuel Moisture Content for Fire Danger Assessment: Moving towards Operational Products. *Remote Sens. Environ.* **2013**, *136*, 455–468. [[CrossRef](#)]
110. Parisien, M.-A.; Snetsinger, S.; Greenberg, J.A.; Nelson, C.R.; Schoennagel, T.; Dobrowski, S.Z.; Moritz, M.A. Spatial Variability in Wildfire Probability across the Western United States. *Int. J. Wildland Fire* **2012**, *21*, 313–327. [[CrossRef](#)]
111. Moritz, M.A.; Parisien, M.-A.; Batllori, E.; Krawchuk, M.A.; Van Dorn, J.; Ganz, D.J.; Hayhoe, K. Climate Change and Disruptions to Global Fire Activity. *Ecosphere* **2012**, *3*, 1–22. [[CrossRef](#)]
112. Estes, B.L.; Knapp, E.E.; Skinner, C.N.; Miller, J.D.; Preisler, H.K. Factors Influencing Fire Severity under Moderate Burning Conditions in the Klamath Mountains, Northern California, USA. *Ecosphere* **2017**, *8*, e01794. [[CrossRef](#)]
113. Riley, S.; Degloria, S.; Elliot, S.D. A Terrain Ruggedness Index That Quantifies Topographic Heterogeneity. *Int. J. Sci.* **1999**, *5*, 23–27.

114. Zahura, F.T.; Bisht, G.; Li, Z.; McKnight, S.; Chen, X. Impact of Topography and Climate on Post-Fire Vegetation Recovery across Different Burn Severity and Land Cover Types through Random Forest. *Ecol. Inform.* **2024**, *82*, 102757. [\[CrossRef\]](#)
115. Atwood, E.C.; Englhart, S.; Lorenz, E.; Halle, W.; Wiedemann, W.; Siegert, F. Detection and Characterization of Low Temperature Peat Fires during the 2015 Fire Catastrophe in Indonesia Using a New High-Sensitivity Fire Monitoring Satellite Sensor (FireBird). *PLoS ONE* **2016**, *11*, e0159410. [\[CrossRef\]](#) [\[PubMed\]](#)
116. McRae, R. Prediction of Areas Prone to Lightning Ignition. *Int. J. Wildland Fire* **1992**, *2*, 123–130. [\[CrossRef\]](#)
117. Vetrita, Y.; Cochrane, M.A. Fire Frequency and Related Land-Use and Land-Cover Changes in Indonesia's Peatlands. *Remote Sens.* **2019**, *12*, 5. [\[CrossRef\]](#)
118. Putra, E.I.; Ramadhi, A.; Shadiqin, M.F.; Saad, A.; Setianto, E.; Nurhayati, A.D.; Saharjo, B.H.; Cochrane, M.A. Assessing the Severity of Forest Fire in Sungai Buluh Protected Peat Forest, Jambi. *IOP Conf. Ser. Earth Environ. Sci.* **2022**, *959*, 012059. [\[CrossRef\]](#)
119. Turetsky, M.R.; Benscoter, B.; Page, S.; Rein, G.; van der Werf, G.R.; Watts, A. Global Vulnerability of Peatlands to Fire and Carbon Loss. *Nat. Geosci.* **2015**, *8*, 11–14. [\[CrossRef\]](#)
120. Hall, J.V.; Argueta, F.; Zubkova, M.; Chen, Y.; Randerson, J.T.; Giglio, L. GloCAB: Global Cropland Burned Area from Mid-2002 to 2020. *Earth Syst. Sci. Data* **2024**, *16*, 867–885. [\[CrossRef\]](#)
121. da Silva, S.S.; Fearnside, P.M.; de Alencastro Graca, P.M.L.; Brown, I.F.; Alencar, A.; de Melo, A.W.F. Dynamics of Forest Fires in the Southwestern Amazon. *For. Ecol. Manag.* **2018**, *424*, 312–322. [\[CrossRef\]](#)
122. Pausas, J.G.; Ribeiro, E. Fire and Plant Diversity at the Global Scale. *Glob. Ecol. Biogeogr.* **2017**, *26*, 889–897. [\[CrossRef\]](#)
123. Archibald, S.; Lehmann, C.E.R.; Gomez-Dans, J.L.; Bradstock, R.A. Defining Pyromes and Global Syndromes of Fire Regimes. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 6442–6447. [\[CrossRef\]](#) [\[PubMed\]](#)
124. Govender, N.; Trollope, W.S.W.; van Wilgen, B.W. The Effect of Fire Season, Fire Frequency, Rainfall and Management on Fire Intensity in Savanna Vegetation in South Africa. *J. Appl. Ecol.* **2006**, *43*, 748–758. [\[CrossRef\]](#)
125. Balch, J.K.; Bradley, B.A.; Abatzoglou, J.T.; Nagy, R.C.; Fusco, E.J.; Mahood, A.L. Human-Started Wildfires Expand the Fire Niche across the United States. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 2946–2951. [\[CrossRef\]](#) [\[PubMed\]](#)
126. Adame, M.F.; Reef, R.; Santini, N.S.; Najera, E.; Turschwell, M.P.; Hayes, M.A.; Masque, P.; Lovelock, C.E. Mangroves in Arid Regions: Ecology, Threats, and Opportunities. *Estuar. Coast. Shelf Sci.* **2021**, *248*, 106796. [\[CrossRef\]](#)
127. Sippo, J.Z.; Lovelock, C.E.; Santos, I.R.; Sanders, C.J.; Maher, D.T. Mangrove Mortality in a Changing Climate: An Overview. *Estuar. Coast. Shelf Sci.* **2018**, *215*, 241–249. [\[CrossRef\]](#)
128. Dillon, G.K.; Holden, Z.A.; Morgan, P.; Crimmins, M.A.; Heyerdahl, E.K.; Luce, C.H. Both Topography and Climate Affected Forest and Woodland Burn Severity in Two Regions of the Western US, 1984 to 2006. *Ecosphere* **2011**, *2*, 130. [\[CrossRef\]](#)
129. Van, L.N.; Lee, G. Investigating the Relationship Between Topographic Variables and Wildfire Burn Severity. *Geographies* **2025**, *5*, 47. [\[CrossRef\]](#)
130. Alizadeh, M.R.; Abatzoglou, J.T.; Adamowski, J.; Modaresi Rad, A.; AghaKouchak, A.; Pausata, F.S.R.; Sadegh, M. Elevation-Dependent Intensification of Fire Danger in the Western United States. *Nat. Commun.* **2023**, *14*, 1773. [\[CrossRef\]](#) [\[PubMed\]](#)
131. Wang, Y.; Liu, X.; Yan, Q.; Hu, Y. Impacts of Slash Burning on Soil Carbon Pools Vary with Slope Position in a Pine Plantation in Subtropical China. *CATENA* **2019**, *183*, 104212. [\[CrossRef\]](#)
132. Lee, H.-J.; Choi, Y.; Lee, S.-W. Complex Relationships of the Effects of Topographic Characteristics and Susceptible Tree Cover on Burn Severity. *Sustainability* **2018**, *10*, 295. [\[CrossRef\]](#)
133. Sabljčić, L.; Bajić, D.; Marković, S.B.; Adžić, D.; Spalevic, V.; Sestraš, P.; Pavić, D.; Lukić, T. Remote Sensing and GIS Assessment of Drought Dynamics in the Ukrina River Basin, Bosnia and Herzegovina. *Atmosphere* **2026**, *17*, 124. [\[CrossRef\]](#)
134. Sabljčić, L.; Lukić, T.; Marković, S.B.; Bajić, D. Potential of Remote Sensing Techniques for Integrated Spatio-Temporal Monitoring and Analysis of Drought in the Sana River Basin, Bosnia and Herzegovina. *Időjárás* **2024**, *128*, 399–423. [\[CrossRef\]](#)
135. Chávez, R.O.; Castillo-Soto, M.E.; Traipe, K.; Olea, M.; Lastra, J.A.; Quiñones, T. A Probabilistic Multi-Source Remote Sensing Approach to Evaluate Extreme Precursory Drought Conditions of a Wildfire Event in Central Chile. *Front. Environ. Sci.* **2022**, *10*, 865406. [\[CrossRef\]](#)
136. Ntinopoulos, N.; Sakellariou, S.; Christopoulou, O.; Sfougaris, A. Fusion of Remotely-Sensed Fire-Related Indices for Wildfire Prediction through the Contribution of Artificial Intelligence. *Sustainability* **2023**, *15*, 11527. [\[CrossRef\]](#)
137. Desmet, P.; Govers, G. A GIS Procedure for Automatically Calculating the USLE LS Factor on Topographically Complex Landscape Units. *J. Soil Water Conserv.* **1996**, *51*, 427–433. [\[CrossRef\]](#)
138. Moore, I.D.; Grayson, R.B.; Ladson, A.R. Digital Terrain Modelling: A Review of Hydrological, Geomorphological, and Biological Applications. *Hydrol. Process.* **1991**, *5*, 3–30. [\[CrossRef\]](#)
139. Narayanaraj, G.; Wimberly, M.C. Influences of Forest Roads on the Spatial Patterns of Human- and Lightning-Caused Wildfire Ignitions. *Appl. Geogr.* **2012**, *32*, 878–888. [\[CrossRef\]](#)
140. Schug, F.; Bar-Massada, A.; Carlson, A.R.; Cox, H.; Hawbaker, T.J.; Helmers, D.; Hostert, P.; Kaim, D.; Kasraee, N.K.; Martinuzzi, S.; et al. The Global Wildland–Urban Interface. *Nature* **2023**, *621*, 94–99. [\[CrossRef\]](#) [\[PubMed\]](#)

141. Aksoy, E.; Kocer, A.; Yilmaz, I.; Akcal, A.N.; Akpinar, K. Assessing Fire Risk in Wildland–Urban Interface Regions Using a Machine Learning Method and GIS Data: The Example of Istanbul’s European Side. *Fire* **2023**, *6*, 408. [\[CrossRef\]](#)
142. Ribeiro, A.F.S.; Santos, L.; Randerson, J.T.; Uribe, M.R.; Alencar, A.A.C.; Macedo, M.N.; Morton, D.C.; Zscheischler, J.; Silvestrini, R.A.; Rattis, L.; et al. The Time since Land-Use Transition Drives Changes in Fire Activity in the Amazon-Cerrado Region. *Commun. Earth Environ.* **2024**, *5*, 96. [\[CrossRef\]](#)
143. Nearing, M.A. A Single, Continuous Function for Slope Steepness Influence on Soil Loss. *Soil Sci. Soc. Am. J.* **1997**, *61*, 917–919. [\[CrossRef\]](#)
144. Parks, S.A.; Holsinger, L.M.; Voss, M.A.; Loehman, R.A.; Robinson, N.P. Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. *Remote Sens.* **2018**, *10*, 879. [\[CrossRef\]](#)
145. Atalay, H.; Dervisoglu, A.; Sunar, A.F. Exploring Forest Fire Dynamics: Fire Danger Mapping in Antalya Region, Türkiye. *ISPRS Int. J. Geoinf.* **2024**, *13*, 74. [\[CrossRef\]](#)
146. Ikhsan, A.N.; Hadmoko, D.S.; Widayani, P. Spatial Modeling of Forest and Land Fire Susceptibility Using the Information Value Method in Kotawaringin Barat Regency, Indonesia. *Fire* **2023**, *6*, 170. [\[CrossRef\]](#)
147. Khairani, M.; Sutoyo, E. Application of K-Means Clustering Algorithm for Determination of Fire-Prone Areas Utilizing Hotspots in West Kalimantan Province. *Int. J. Adv. Data Inf. Syst.* **2020**, *1*, 9–16. [\[CrossRef\]](#)
148. Karo, I.M.K.; Dewi, S.; Mardiana, M.; Ramadhani, F.; Harliana, P. K-Means and K-Medoids Algorithm Comparison for Clustering Hotspot Location Data. *Ecotipe* **2023**, *10*, 86–94.
149. Anwar, M.T.; Hadikurniawati, W.; Winarno, E.; Supriyanto, A. Wildfire Risk Map Based on DBSCAN Clustering and Cluster Density Evaluation. *Adv. Sustain. Sci. Eng. Technol.* **2019**, *1*, 343561. [\[CrossRef\]](#)
150. Gao, X.; Wang, T.; Xie, K. Density-Based Spatial Clustering of Vegetation Fire Points. *Fire* **2025**, *8*, 431. [\[CrossRef\]](#)
151. Xu, D.; Shao, G.; Dai, L.; Hao, Z.; Tang, L.; Wang, H. Mapping forest fire risk zones with spatial data and principal component analysis. *Sci. China Ser. E Technol. Sci.* **2006**, *49*, 140–149. [\[CrossRef\]](#)
152. Ghali, R.; Akhloufi, M.A.; Mseddi, W.S. Deep learning approaches for wildland fires using satellite remote sensing data: Detection, mapping, and prediction. *Fire* **2023**, *6*, 192. [\[CrossRef\]](#)
153. Andrianarivony, H.S.; Akhloufi, M.A. Machine learning and deep learning for wildfire spread prediction: A review. *Fire* **2024**, *7*, 482. [\[CrossRef\]](#)
154. Seydi, S.T.; Saeidi, V.; Kalantar, B.; Ueda, N.; Halin, A.A. Burnt-Net: Wildfire burned area mapping with single post-fire Sentinel-2 data and deep learning morphological neural network. *Ecol. Indic.* **2022**, *140*, 108999. [\[CrossRef\]](#)
155. Huot, F.; Hu, R.L.; Goyal, N.; Sankar, T.; Ihme, M.; Chen, Y.-F. Next Day Wildfire Spread: A machine learning data set to predict wildfire spreading from remote-sensing data. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 4412513. [\[CrossRef\]](#)
156. Chen, D.; Cheng, S.; Hu, J.; Kasoar, M.; Arcucci, R. Explainable Global Wildfire Prediction Models Using Graph Neural Networks. *Geod. AI* **2026**, 100052. [\[CrossRef\]](#)
157. Zhao, S.; Prapas, I.; Karasante, I.; Xiong, Z.; Papoutsis, I.; Camps-Valls, G.; Zhu, X.X. Causal graph neural networks for robust wildfire forecasting across geographic shifts. *ISPRS J. Photogramm. Remote Sens.* **2026**, *236*, 654–667. [\[CrossRef\]](#)
158. Anderson, L.O.; Burton, C.; dos Reis, J.B.C.; Pessoa, A.C.M.; Bett, P.; Carvalho, N.S.; Junior, C.H.L.S.; Williams, K.; Selaya, G.; Armenteras, D.; et al. An Alert System for Seasonal Fire Probability Forecast for South American Protected Areas. *Clim. Resil. Sustain.* **2022**, *1*, e19. [\[CrossRef\]](#)
159. Burgess, R.; Hansen, M.; Olken, B.A.; Potapov, P.; Sieber, S. The Political Economy of Deforestation in the Tropics. *Q. J. Econ.* **2012**, *127*, 1707–1754. [\[CrossRef\]](#)
160. Edwards, R.B.; Naylor, R.L.; Higgins, M.M.; Falcon, W.P. Causes of Indonesia’s Forest Fires. *World Dev.* **2020**, *127*, 104717. [\[CrossRef\]](#)
161. Sun, D.; Yang, T.; Li, S.; Goldberg, M.; Kalluri, S.; Helfrich, S.; Sjonberg, B.; Zhou, L.; Zhang, Q.; Straka, W.; et al. Hazard or Non-Hazard Flood: Post Analysis for Paddy Rice, Wetland, and Other Potential Non-Hazard Flood Extraction from the VIIRS Flood Products. *ISPRS J. Photogramm. Remote Sens.* **2024**, *209*, 415–431. [\[CrossRef\]](#)
162. Yang, T.; Sun, D.; Li, S.; Kalluri, S.; Zhou, L.; Helfrich, S.; Yuan, M.; Zhang, Q.; Straka, W.; Maggioni, V.; et al. Extracting Wetlands in Coastal Louisiana from the Operational VIIRS and GOES-R Flood Products. *Remote Sens.* **2024**, *16*, 3769. [\[CrossRef\]](#)
163. Boschetti, L.; Roy, D.P.; Giglio, L.; Huang, H.; Zubkova, M.; Humber, M.L. Global Validation of the Collection 6 MODIS Burned Area Product. *Remote Sens. Environ.* **2019**, *235*, 111490. [\[CrossRef\]](#) [\[PubMed\]](#)
164. Sofan, P.; Bruce, D.; Schroeder, W.; Jones, E.; Marsden, J. Assessment of VIIRS 375 m Active Fire Using Tropical Peatland Combustion Algorithm Applied to Landsat-8 over Indonesia’s Peatlands. *Int. J. Digit. Earth* **2020**, *13*, 1695–1716. [\[CrossRef\]](#)
165. van der Werf, G.R.; Randerson, J.T.; van Wees, D.; Chen, Y.; Giglio, L.; Hall, J.; Vernooij, R.; Mu, M.; Binte Shahid, S.; Barsanti, K.C.; et al. Landscape Fire Emissions from the 5th Version of the Global Fire Emissions Database (GFED5). *Sci. Data* **2025**, *12*, 1870. [\[CrossRef\]](#) [\[PubMed\]](#)
166. Lu, X.; Zhang, X.; Li, F.; Cochrane, M.A. Improved Estimation of Fire Particulate Emissions Using a Combination of VIIRS and AHI Data for Indonesia during 2015–2020. *Remote Sens. Environ.* **2022**, *281*, 113238. [\[CrossRef\]](#)

167. Cattau, M.E.; Harrison, M.E.; Shinyo, I.; Tungau, S.; Uriarte, M.; DeFries, R. Sources of Anthropogenic Fire Ignitions on the Peat-Swamp Landscape in Kalimantan, Indonesia. *Glob. Environ. Change* **2016**, *39*, 205–219. [[CrossRef](#)]
168. Santika, T.; Budiharta, S.; Law, E.A.; Dennis, R.A.; Dohong, A.; Struebig, M.J.; Medrilzam; Gunawan, H.; Meijaard, E.; Wilson, K.A. Interannual Climate Variation, Land Type and Village Livelihood Effects on Fires in Kalimantan, Indonesia. *Glob. Environ. Change* **2020**, *64*, 102129. [[CrossRef](#)]
169. Liu, T.; Randerson, J.T.; Chen, Y.; Morton, D.C.; Wiggins, E.B.; Smyth, P.; Foufoula-Georgiou, E.; Nadler, R.; Nevo, O. Systematically Tracking the Hourly Progression of Large Wildfires Using GOES Satellite Observations. *Earth Syst. Sci. Data* **2024**, *16*, 1395–1424. [[CrossRef](#)]
170. Maslanka, W.M.; Wooster, M.J.; Liu, Z.; He, J. Direct Estimation of Wildfire Emissions at High Latitudes from Combined Polar Orbiter FRP and Sentinel-5P CO Data. *EGUsphere* 2025, *preprint*.

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