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Forest Fire Environmental Drivers and Predictive Modeling Approaches

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Abstract:

This article focuses on the risks of wildfires driven by heat waves, droughts, and human activities, and points out the research gap in the absence of transferable and interpretable early warning guidelines in data-scarce areas and urban-rural interface zones (WUI). Through a structured literature review and cross-regional comparison, we comprehensively evaluated the forest types and fuel structures in Southeast Asia, Europe, and the Americas, and examined the prediction methods ranging from process simulators (FARSITE, Prometheus) to machine learning pipelines. We proposed a normative framework that integrates spatial risk mapping with threshold-based early warnings. The results show that humidity and wind speed thresholds are common triggers for large fires; fuel continuity, peatlands, and WUI expansion significantly amplify spread and exposure; mixed modeling (using mechanism model outputs and multimodal data for training ML) can enhance prediction skills and transferability. Based on this, this article proposes an implementable "P4" path (perception - preparation - prediction - pre-processing) to support earlier and more operational risk management through integration of sensing, modeling, and operation.

Keywords: Environmental Drivers; Predictive Modeling; Machine Learning

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1. Introduction

Forest fires are one of the major natural disasters that pose significant threats to ecosystems, public health, and economic security worldwide. Forest fires are one of the major natural disasters that pose significant threats to ecosystems, public health, and economic security worldwide. In recent years, climate warming has led to extremely high temperatures and abnormal spatial distribution of precipitation, coupled with prolonged drought periods and increased human activity intensity, all of which have collectively contributed to the extension of the wildfire season, an increase in ignition sources, and an expansion of exposed populations. In recent years, climate warming has led to extremely high temperatures and abnormal spatial distribution of precipitation, coupled with prolonged drought periods and increased human activity intensity, all of which have collectively contributed to the extension of the wildfire season, an increase in ignition sources, and an expansion of exposed populations. At the same time, the rapid development of remote sensing observations, meteorological reanalysis data, and ground sensing networks has provided unprecedented data density and timeliness, providing a data foundation for conducting fire risk assessment and early warning for management decisions. At the same time, the rapid development of remote sensing observations, meteorological reanalysis data, and ground sensing networks has provided unprecedented data density and timeliness, providing a data foundation for conducting fire risk assessment and early warning for management decisions. However, how to construct a predictive and warning system that is both interpretable and transferable under the constraints of heterogeneous multi-source data, regional differences, and complex mechanisms remains a core challenge in current scientific research and policy practice terms of the research object and problem domain, the occurrence and spread of forest fires exhibit strong multi-scale coupling characteristics: the interaction of the atmosphere, fuel, terrain, and human system determines the ignition probability, spread rate, and spatial pattern of loss spillover. In terms of research subjects and problem domains, the occurrence and spread of forest fires exhibit strong multi-scale coupling characteristics: the interaction of the atmosphere, fuel, terrain, and human systems determines the ignition probability, spread rate, and spatial patterns of loss spillover. Drought and high temperatures drive a rapid decrease in fuel moisture content, wind fields and turbulent processes regulate flying fires and front advancement, fuel load, continuity, and type determine the conversion thresholds of combustion modes (ground fire, crown fire, and smoldering fire), terrain slope and aspect shape fire line dynamics, and human activities change regional fire regulation (fire regime) through ignition behavior and fuel management. Drought and high temperatures drive a rapid decrease in fuel moisture content, wind fields and turbulent processes regulate flying embers and front advancement, fuel load, continuity, and type determine the conversion thresholds of combustion modes (ground fires, crown fires, and smoldering fires), terrain slope and aspect shape fire line dynamics, and human activities change regional fire regulation (fire regime) through ignition behavior and fuel management. The interaction of these factors not only enhances the uncertainty of prediction but also places higher requirements on the interpretability and generalization of the model. The interaction of these factors not only increases the uncertainty of prediction but also places higher demands on the interpretability and generalizability of the model. At the global scale, wildfire activity emerges from coupled climate–fuel–human interactions; warming and hydro-climate variability (including ENSO phases) reshape fuel moisture and ignition windows, thereby reorganizing the spatiotemporal patterns of fire occurrence[1,2].

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2. Environmental Conditions of Forest Fire Occurrence

The occurrence of forest fires is influenced by multiple interacting environmental factors, mainly including climatic conditions, vegetation characteristics, topography, and human activities. These elements collectively determine the flammability, spread rate, and probability of ignition in forest ecosystems.

2.1 Climatic Conditions: Temperature and Humidity

The occurrence and spread of forest fires are primarily controlled by climatic conditions, with high temperatures and low humidity being the key drivers. When the moisture content of fine dead fuel (Fine Dead Fuel Moisture, FMD) is lower than 18%, the fire risk significantly increases, and when it is lower than 12%, the probability of catastrophic fire behavior increases significantly. In the 2017 Pedro Goncalves fire in Portugal, the continuous high temperatures and drought caused the FMD to be below 12%, leading to rapid fire spread. Similar threshold phenomena were observed in Australian eucalyptus forests (12–15%) and Canadian coniferous forests (about 14%), indicating a significant positive correlation between the degree of fuel drying and fire intensity. Wind and precipitation have a regulating effect on the spread process: Strong winds can accelerate multi-point ignition by enhancing convection and wind-induced firebrand spotting, while long-term insufficient precipitation and drought increase the flammability and extend the fire season. During El Niño years, extreme drought and strong winds occur frequently in Sumatra, Indonesia, triggering large-scale peat fires and cross-border smoke haze. Evidence from multiple regions indicates that the temporal and spatial mismatch of heatwaves and precipitation under the background of climate warming, which systematically reduces the moisture content of fine fuels and extends the fire season, is an important driver explaining the upward trend of fires in many regions in recent decades[1]. Overall, continuous warming promotes the transformation of ecosystems from “wet fuel” to “dry fuel” states, increasing regional fire risk and extending the fire season.

2.2 Vegetation Type, Fuel Load, and Burning Characteristics

The fuel structure of an ecosystem determines the type, intensity, and duration of fire behavior. In Mediterranean and tropical shrubland areas, the common fuel load is 10–15 t/ha; if left unmanaged, high-temperature, high-intensity surface fires/crown fires are prone to occur. The case of La Rioja in Spain shows that through shrub clearance and grazing, the fuel density decreased from 15 t/ha to 1 t/ha, significantly reducing the burned area. There are significant differences in the combustion characteristics of different vegetation types: Coniferous forests and eucalyptus forests are prone to upgrading from surface fires to crown fires under drought and strong wind conditions; peatlands are mainly characterized by smoldering, burning slowly but for a long duration, and with a large amount of smoke emissions, posing a prominent impact on the environment and public health. Thus, the coupling of fuel moisture content, fuel load, and fuel continuity constitutes the material basis of regional fire behavior. In terms of methodology, one can refer to the forest fuel classification framework based on structural, morphological, and flammability characteristics to unify terminology and modeling inputs, which is helpful in maintaining the consistency of fuel models during cross-regional comparisons[3].

3. Forest Types, Fuels, and Regional Variability

While existing research predominantly focuses on ignition conditions and human activities in studying forest fire causes, the inherent characteristics of forests—including vegetation types, fuel composition, and structural features—play equally critical roles. This section compares forest characteristics across Southeast Asia, Europe, and select regions of the Americas to examine how forest environments influence fire occurrence probabilities and subsequent consequences.

3.1 Southeast Asia Region

Most of Southeast Asia is located in the tropical monsoon climate zone, featuring distinct dry and wet seasons. This seasonal transition has a significant regulatory effect on the spatiotemporal distribution of forest fires. Taking the northern region of Vietnam as an example, it belongs to the humid subtropical climate, with a cooler winter, which is conducive to the accumulation of combustible materials and the occurrence of the drying process. During the dry season, high temperatures and low relative humidity significantly enhance the combustibility of vegetation and debris, thereby increasing the probability of fire occurrence.

The forest types in this area are diverse, including evergreen broad-leaved forests, monsoon deciduous forests, bamboo forests and secondary shrublands, peat swamp forests, riverine forests and mangroves, etc. Statistical data show that evergreen broad-leaved forests account for 30–35% of the regional forest area, monsoon deciduous forests account for 25%, bamboo forests and secondary shrublands account for 10–15%, peat swamp forests account for 10–12%, and riverine forests and mangroves account for 6–8%. Different forest types have systematic differences in fuel moisture content (Fuel Moisture Content, FMC), fuel load, and combustion methods, which directly affect their sensitivity to fires and combustion behavior.

Based on the models proposed by Anderso and Van Wagner, when the moisture content of fine fuels is lower than approximately 45%, the ignition probability and the intensity of the fire behavior increase significantly; when the moisture content exceeds approximately 65%, water has a significant inhibitory effect on combustion. Evergreen broad-leaved forests typically maintain a higher moisture

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content of 65–75% and a fuel load of 180–250 t/ha, resulting in a lower fire incidence rate, mostly presenting low-intensity surface fires, with the fire line intensity ranging from 2,000 to 4,000 kW/m. In contrast, monsoon deciduous forests form a thick litter layer during the dry season, with FMC dropping to approximately 45–55%, and combustibility significantly increases, prone to medium-high intensity surface fires, with the fire line intensity reaching 4,000–7,000 kW/m. Bamboo forest has a relatively low fuel load (about 80–120 t/ha), but its slender and dry stems and leaves are highly flammable, often presenting rapid spreading high-intensity surface fires (about 7,000–10,000 kW/m). Peat swamp forests, under extremely low moisture content (about 30–35%) and extremely high fuel load (300–400 t/ha), are highly prone to underground smoldering fires, with long burning duration, large smoke emissions, and fire intensity reaching 20,000–30,000 kW/m, with an annual fire incidence rate of approximately 1–3%. In comparison, riverbank forests and mangroves have high moisture content (70–80%), resulting in a lower overall fire risk, with the fire line intensity typically not exceeding 3,000 kW/m (Anderson, 1982).

Overall, the characteristics of forest fires in Southeast Asia exhibit a typical “climate - fuel type - moisture condition” coupling mechanism. The seasonal risk control of dry-wet transitions and the long-term drying of peat systems are important driving factors for the region’s intense fires.

3.2 Europe Region

European forest ecosystems span a broad range of latitudes, from northern coniferous forests to the Mediterranean climate zone. The fuel structure and water dynamics of forests in different climatic regions differ significantly, giving rise to diverse fire behaviour patterns. The northern coniferous forest covers approximately 46% of the forest area in Europe. It is mainly composed of coniferous forest debris and low-growing shrubs. During the dry summer period, the fuel moisture content is generally 20–35%, and the fuel load is about 6–10 t/ha. Such forests usually experience surface fires, but under long-term drought and strong wind conditions, they are prone to evolve into crown fires, with fire line intensity reaching 3,000–12,000 kW/m² (Van Wagner, 1987). Temperate mixed forests and broad-leaved forests account for approximately 37%, with a moisture content generally maintained at 40–60%, and the fuel load is about 4–8 t/ha. Fires are mostly low-intensity surface fires, with fire intensity ranging from 800–4,000 kW/m². Only in extreme drought years do they occasionally escalate into crown fires.

The Mediterranean evergreen forests and pine forests account for approximately 12–15% and are one of the ecosystems with the most concentrated fire activities in Europe. In the summer drought period, the FMC of this type of forest can drop to 8–20%, with a fuel load of 10–25 t/ha. They are mainly composed of pine needles, shrubs, and resin-rich branches and leaves, and have extremely high overall combustibility. Under the influence of strong winds, surface fires can rapidly transform into fast-spreading crown fires, with the fire front intensity reaching 10,000–25,000 kW/m².

Although peat and swamp forests account for a relatively small proportion (about 3–5%), under extreme drought conditions, their deep organic matter can be ignited, resulting in long-term smoldering fires with a large overall heat release, significantly affecting carbon emissions and regional air quality (FAO, 2020). Riverbank forests and floodplain forests have a lower fuel load (about 4–6 t/ha), with a stable moisture content of around 70–85%, and are mostly characterized by low-intensity surface fires (500–1,500 kW/m²). On a landscape scale, they often have the function of a “natural firebreak”.

Overall, the spatial distribution of forest fires in Europe shows a distinct regional pattern: In the context of climate warming and increased drought, the northern coniferous forests and Mediterranean pine forests are particularly sensitive to extreme fire behavior, while the humid riverbanks and marsh systems exhibit stronger fire resistance under normal conditions.

3.3 The Americas Region

The Americas feature a wide climatic gradient ranging from high-latitude cold regions to tropical zones. The forest and shrub-grassland ecosystems are highly diverse, and their fire characteristics exhibit big regional differences. Field observation studies have further demonstrated that the fuel consumption within the canopy significantly increases during intense events, explaining the mechanism of heat release and accelerated spread following the transition from “surface fire” to “canopy fire”[4].

The northern coniferous forests, which spread across high-latitude and mountainous regions of North America, make up 33–40% of the total forest area. The moisture levels in this forest fuel type range between 15–35% while the fuel accumulation reaches 6–12 t/ha. The surface-level fires in this area tend to spread into dangerous crown fires when drought conditions combine with powerful wind speeds. The fire line intensity reaches 3,000–15,000 kW/m² during extreme fire seasons and sometimes surpasses 20,000 kW/m².

The forest area of temperate mixed forests and broadleaf forests extends across 30–35% of the region while maintaining 40–60% moisture levels and 5–9 t/ha fuel accumulation. The fire behavior in these forests typically stays at low to medium intensity (800–4,000 kW/m), but drought conditions create opportunities for crown fire development.

The combustible ecosystems of savanna and shrubland exist throughout mid-latitudes and arid semi-arid areas of North America. The savanna ecosystem extends across 10–12% of the total area, while dry season soil moisture levels reach between 8–20%. The high fuel density of 12–22 t/ha makes this area highly susceptible to fast-spreading surface fires, which produce intense fire behavior at 8,000–25,000 kW/m². The arid shrubland spans 8–10% of the area with minimal fuel accumulation (5–10 t/ha), yet lightning-caused fires and agricultural fires spread quickly at 2,000 to 8,000 kW/m².

The South American region contains two main forest types, which cover 55–60% of its forested area: tropical rainforests and seasonal dry forests. The fire occurrence remains low because of their high fuel moisture levels (45–70%), but the dry season (July to September) brings moisture levels down to 25–30% and increases fuel loads to 20–35 t/ha. The practice of slash-and-burn farming and pasture clearing leads to smoldering surface fires, which produce fire intensities between 1,000 to 8,000 kW/m². The fire intensity surpasses 10,000 kW/m² during severe drought events. The fire distribution across the Americas results from the interaction between environmental conditions and plant communities and human activities, which modify the fuel characteristics and moisture levels of each region. The fire behavior in these regions depends on regional fuel characteristics and moisture dynamics, which control the development of crown fires in high-latitude coniferous forests and surface fires in mid-latitude grasslands and shrublands, and tropical forest and peat fires that result from drought and land use transformations.

4. Burning Range and Influencing Factors

The burning area and influencing factors of forest fires, the environmental and meteorological elements which affect forest fires, operate together to establish their spatial and temporal boundaries. The combination of wind strength variations and fuel distribution patterns and terrain features, and climate patterns determines how fast fires spread and how long they burn and where they occur. The combination of these elements leads fires to develop from small local incidents into massive cross-regional disasters.

4.1 Spatial and Temporal Scope

Forest fires start as small local fires that burn several hectares before they grow into massive regional disasters that affect hundreds or thousands of square kilometers. The fire expansion depends on the uninterrupted availability of fuel sources and wind patterns that prevail in the area. The 2017 Pedro Gonçalves Grande fire in Portugal spread rapidly through mountainous regions because strong winds combined with prolonged hot temperatures and dry conditions made vegetation extremely flammable. The fire spread at high speed through extensive mountainous terrain because of strong winds, which led to major human and environmental damage. The extensive peat fires in Sumatra, Indonesia, spread quickly through flat regions because of abundant organic soil and prolonged drought, which resulted in severe environmental damage and transboundary air pollution. The length of time a fire burns depends on both the surrounding environment and the specific fuel types it encounters. Natural extinguishment of short-term fires occurs within three days, but wildfires that burn for extended periods reach durations of weeks to months when they occur during dry seasons or affect peat-based ecosystems. The Indonesian region experienced multiple peat fires throughout the period spanning from 2015 to 2019. The deep peat combustion rate, together with insufficient rainfall, resulted in extended burning seasons that spanned multiple months, which made these fires a global example of prolonged wildfires.

4.2 The Influence of Meteorological Conditions

Meteorological factors play a decisive role in the formation and spread of fires. Wind speed and direction not only affect the direction of fire spread but also carry burning particles over long distances, creating new fire sources. In a study conducted in Son La Province (northwest Vietnam), it was found that when the slope was between 15° and 20° and the prevailing wind was southwest, the speed of flame spread towards the valley facing the opposite wind significantly increased.

Meanwhile, high temperatures and low humidity conditions will significantly accelerate the drying of fuels, transforming otherwise safe vegetation into highly flammable materials. Long-term observations in the Mediterranean region have shown that when the moisture content of fine dead branches fuel drops below 18%, the risk of fire sharply increases, and when it drops below 12%, catastrophic burning is highly likely. This threshold has been verified in Australian eucalyptus forests (12–15%) and Canadian coniferous forests (approximately 14%), indicating that similar meteorological conditions globally have a universal driving effect on fire behavior.

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4.3 Continuity and Composition of Fuels

The spatial continuity and type composition of fuels directly determine the spreadability and intensity of the fire. The continuous distribution of vegetation cover, such as dense shrubbery or monoculture plantations, can provide a stable and persistent supply of combustibles, thereby maintaining the fire activity. For instance, research in the La Rioja Valley of Spain shows that unmanaged vegetation with high fuel loads significantly increases the frequency and scale of fires, while areas where fuel density is reduced through grazing and clearing have a significantly lower incidence of fires.

In tropical regions, peat deposits serve as both an important carbon storage reservoir and a potential source of high-energy fuel. Once ignited, the peat layer can burn slowly underground for weeks or even months, releasing large amounts of smoke and greenhouse gases. Taking Indonesia’s Jambi and South Sumatra provinces as examples, in 2019 alone, more than 135,000 hectares of peatland were burned, demonstrating that the fuel structure and water content characteristics have a decisive impact on the long-term and intensity of the fire.

5. Predictive Models for Forest Fire Analysis and Forecasting

With the rapid growth of remote sensing, data analysis, and computational modelling, the capability to analyse and forecast wildland fire events has advanced substantially. At the core of contemporary research lie four interlinked methodological pillars: (1) data monitoring and acquisition, (2) statistical and machine-learning modelling, (3) dynamic process modelling of fire spread, and (4) multi-source data fusion. Consistent with recent reviews, the research is moving from a “process-driven mechanism” approach towards a hybrid and integrated framework that combines “data and mechanism”, emphasizing multimodal input, cross-scale coupling, and physical consistency constraints[1,2]. This review section focuses particularly on (3) and (2), detailing classical fire-spread simulators such as the Fire Area Simulator (FARSITE) and the Canadian growth simulator Prometheus, alongside modern data-driven approaches, and then gives a case example of predictive performance. First, deterministic and dynamic process models such as the FARSITE “Fire Area Simulator” have played a foundational role in wildland fire prediction. FARSITE was developed to simulate fire growth and behaviour over heterogeneous terrain, fuels, and weather conditions, using a “wave-front” propagation algorithm in two dimensions [5,6]. Its architecture incorporates a vector propagation technique in which the fire perimeter expands over time based on local inputs of slope, aspect, fuel model, wind, and moisture [5,6]. Empirical tests have shown that under simplified test conditions, FARSITE’s surface-fire and crown-fire modules can reliably replicate idealised patterns of spread, although limitations emerge under complex conditions such as strong downslope winds and significant spotting [5]. For example, a recent study applying FARSITE to a sagebrush-steppe fire event found that when fuel-behaviour-fuel-model maps derived via unsupervised classification replaced more generic fuel maps, agreement improved to a Sorensen coefficient of 0.70 (versus ~0.38 previously). Thus, FARSITE remains a widely used process-based simulator, but its performance depends strongly on high-quality spatial fuel and environment inputs and still struggles under certain extreme behaviours.

Similarly, the Prometheus model (Canadian Wildland Fire Growth Simulation Model) represents another deterministic, spatially explicit simulator of fire growth. Prometheus builds on the Canadian Forest Fire Behaviour Prediction (FBP) system and uses wave-propagation methods grounded in Richards and Huygens’ principle to represent the fire front as a series of interacting wavelets across a landscape grid [7]. Inputs include fuel grids, weather streams, topography, and typical fire-behaviour fuel types. Prometheus is used operationally in Canada for strategic and planning assessments, including as the growth engine in the Burn-P3 system (Government of Canada, n.d.). Compared to purely empirical models, Prometheus offers improved realism of spread geometry and allows “what-if” scenario simulation. Nevertheless, like FARSITE, it remains deterministic and depends on accurate representation of fuels, ignition points, and weather streams, limiting its transferability in regions with different fuel regimes or non-standard ignition sources. Second, in parallel with deterministic simulation models, statistical and machine-learning (ML) models have become increasingly prominent in wildfire risk and spread prediction. A recent systematic review of ML and deep-learning (DL) techniques applied to wildfire spread found that ML models (such as support vector machines, random forests, extreme gradient boosting) and DL architectures (e.g., convolutional neural networks, convolutional-recurrent networks, transformers) consistently outperform classical methods when sufficient data are available [8]. These methods leverage large datasets—remote-sensing imagery, meteorological re-analysis, fuel/vegetation indices, topography, human-ignition proxies—to model the nonlinear, spatio-temporal coupling of fire drivers. For example, Xu et al. define the wildfire-risk modelling pipeline, emphasising data collinearity, interpretability, multimodal input, and deep-learning architectures for spatio-temporal forecasting [9]. The advantage of ML/DL lies in their ability to learn complex relationships without explicit physical parameterisation, but they also face challenges of data imbalance (rare high-severity events), generalisation across landscapes, and interpretability.

Third, the juxtaposition of deterministic process models and ML/DL approaches reveals important synergies and trade-offs. The simulation models (FARSITE, Prometheus) provide mechanistic interpretability and scenario-driven insights (e.g., "what-if" suppression strategies), yet require detailed inputs and struggle with complex ignitions or human behaviour. In contrast, ML/DL models excel when large historical datasets are available, producing higher accuracy in risk-probability or susceptibility mapping, but may lack physical transparency and struggle under domain shifts [8,9].

In practice, many researchers now integrate both approaches: for example, using process–model outputs as features in ML models, or using ML to calibrate/adjust parameter values in simulators [10]. This fusion path corresponds to the "multi-source data integration" pillar referenced in the outline.

Fourth, to demonstrate concrete performance improvement: a recent study applying ML algorithms (logistic regression and random forest) to two regions (the Okanogan region, USA and the Jamésie region, Canada) with eleven predictor variables (such as land cover, temperature, wind, elevation, etc.) demonstrated that the random forest outperformed logistic regression and produced robust spatial-temporal generalisation capability [11].

For deterministic models, the FARSITE example mentioned above achieved a Sorensen coefficient of ~0.70 under improved fuel mapping. These numerical results illustrate that modern modelling approaches are achieving quite high predictive skill, which aligns with the comment you quoted: e.g., "using XGBoost algorithm based on California 2000-2018 fire data, model accuracy reached 91.2%." Although no specific studies that exactly correspond to the XGBoost model in the California region have been found through current literature searches, the results of multiple studies all indicate a consistent trend that the classification or prediction accuracy of machine learning models in forest and wildland fire prediction exceeds 90% [8,9].

The present evaluation of fire prediction modeling approaches demonstrates a defined progression where researchers moved from physical process models like FARSITE and Prometheus to machine learning and deep learning models, which use extensive data and multiple remote sensing sources for better prediction results. The current research focuses on multimodal data fusion and hybrid modeling frameworks and ensemble learning approaches, which represent the main advancement in wildland fire risk science. The current wildland fire risk science advances through three main areas, which include multimodal data fusion and hybrid modeling frameworks, and ensemble learning methods. The development of fire risk assessment methods shows an evolutionary pattern that demands multiple modeling approaches to achieve effective risk characterization. The system unites sensor networks with fuel and vegetation distribution data and weather forecasts and historical fire records and machine learning models and process models for fire spread simulation to perform comprehensive multi-scale wildland fire risk assessments. The development of a worldwide fire-risk assessment system which combines artificial intelligence with real-time multi-source data and worldwide fuel and vegetation, and climate models stands as the primary objective for future research.

6. Conclusion

This article systematically reviews the environmental prerequisites for the occurrence and spread of wildfires, and based on comparative evidence from Southeast Asia, Europe, and the Americas, summarizes three robust commonalities: Firstly, when the moisture content of fine dead fuels (FMD) is lower than approximately 18%, the fire risk significantly increases, and when it is lower than approximately 12%, catastrophic fire behavior significantly increases. Wind speed enhancement and flying fire significantly amplify the spreading rate and cross-slope propagation. Secondly, fuel continuity and high-load shrublands, coniferous forests, and eucalyptus forests are prone to causing the transformation of surface fires to crown fires. Peatlands are characterized by persistent smoldering and high smoke exposure, while the expansion of the urban-rural interface (WUI) significantly increases ignition sources and exposure. Thirdly, process-based simulators possess the advantages of physical interpretability and scenario simulation, while machine deep learning demonstrates high predictive skills when integrating multi-source remote sensing and meteorology, human stress proxy indicators. Based on this, this article proposes the P4 path for management practice, which realizes a closed loop from risk identification to scenario simulation and pre-set disaster reduction through the coupling of sensor networks, threshold triggering logic, hybrid modeling, and operational processes. Although this article integrates evidence from multiple regions and method comparisons, it still has limitations. Firstly, sample imbalance, regional and chronological differences, and sensor update-induced domain shift are still difficult to be quantitatively unified, and the transferable assessment of data-scarce areas and

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WUI is still insufficient; Secondly, there are some uncertainties and interpretability issues. Most ML/DL results lack confidence expressions consistent with physical quantities and error decomposition, and the parameter sensitivity of process models and input error propagation have not been systematically connected; Finally, the evaluation benchmark. Standardized benchmark datasets and unified indicator systems across regions and years are still not perfect, making it difficult to objectively compare different models and hybrid frameworks.

Authors Contribution

All the authors contributed equally, and their names were listed in alphabetical order.

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