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Systematic Review

A Systematic Review of Models for Fire Spread in Wildfires by Spotting

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Abstract

Fire spotting (FS), the process by which firebrands are lofted, transported, and ignite new fires ahead of the main flame front, plays a critical role in escalating extreme wildfire events. This systematic literature review (SLR) analyzes peer-reviewed articles and book chapters published in English from 2000 to 2023 to assess the evolution of FS models, identify prevailing methodologies, and highlight existing gaps. Following a PRISMA-guided approach, 102 studies were selected from Scopus, Web of Science, and Google Scholar, with searches conducted up to December 2023. The results indicate a marked increase in scientific interest after 2010. Thematic and bibliometric analyses reveal a dominant research focus on integrating the FS model within existing and new fire spread models, as well as empirical research and individual FS phases, particularly firebrand transport and ignition. However, generation and ignition FS phases, physics-based FS models (encompassing all FS phases), and integrated operational models remain underexplored. Modeling strategies have advanced from empirical and semi-empirical approaches to machine learning and physical-mechanistic simulations. Despite advancements, most models still struggle to replicate the stochastic and nonlinear nature of spotting. Geographically, research is concentrated in the United States, Australia, and parts of Europe, with notable gaps in representation across the Global South. This review underscores the need for interdisciplinary, data-driven, and regionally inclusive approaches to improve the predictive accuracy and operational applicability of FS models under future climate scenarios.

Keywords: fire management; fire spotting; fire spotting model; firebrand; model classification; wildfire propagation

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1. Introduction

Climate change is already altering the structure and function of temperate forest ecosystems, with significant implications for disturbance regimes such as wildfires. Extensive research has demonstrated that rising temperatures and shifting precipitation patterns are increasing the frequency, intensity, and severity of wildfires [1–6], underscoring the importance of understanding and modeling these dynamics. In this context, a key concern is the predicted shift in the frequency and intensity of extreme disturbance events, notably global wildfire occurrences [7–9]. These events have a profound influence on vegetation structure, species composition, and landscape dynamics. Empirical studies confirm increasing wildfire activity in the United States [10,11], Canada [12], Australia [13–15], Portugal [2,16,17], and Spain [18]. This rise is evident in both fire frequency and total area affected by these fires [19,20].

The dynamics of wildfire activity are influenced by a complex interplay of factors, including fuel availability, vegetation topography, ignition sources, and prevailing weather conditions such as temperature, wind speed, and atmospheric pressure [20]. These variables stand out as the principal determinants of short-term and long-term variations in fire activity [21], influencing fuel moisture and flammability. At the same time, broader climatic conditions influence biomass and fuel accumulation present in an area, as well as fire potential, alongside human influences [21].

Historically, projections of future fire regimes have often relied on the analysis of monthly and seasonal averages of weather variables, such as temperature, relative humidity, wind speed, and precipitation, along with indices like the Fire Weather Index System, to model wildfire behavior under climate change. This approach has been widely applied in fire-prone areas globally, including in the Mediterranean [22–24], where it has helped assess changing fire potential under future climate scenarios. However, such averages can obscure crucial variations in fire weather extremes, especially those conditions conducive to large fire outbreaks [25]. Besides extreme weather dynamics that enhance low humidity and dryness [26], wildfire behavior is further intensified by factors such as topography, fuel variability, and fire spotting [27]. Wildfires cause extensive environmental and socioeconomic damage, generating large quantities of firebrands that burn vegetation materials, including twigs, bark, foliage, and grass. These firebrands can be transported by wind and, upon landing, may ignite a new location ahead of the main fire. If the ignition occurs, the resulting fire is referred to as a spot fire, and the process is known as fire spotting. The fire spotting process consists of four key phases: firebrand generation, lofting in the convective plume, wind-driven transport, and spot fire ignition [28,29]. Each phase contributes to the complex dynamics of wildfire spread, especially under extreme weather conditions.

Depending on the spotting distance, spot fires ignited by smoldering or flaming firebrands influence wildfire spread by increasing its intensity and severity. Furthermore, extreme weather conditions, vegetation type, and terrain characteristics contribute to extreme fire behavior [27]. The fire spot can occur in short, medium, or long spotting distance ranges [30]. Short-distance spotting influences firefighting tactics and safety, while medium-distance spotting affects combat positions and strategies. Long-distance can divert fire suppression resources, complicating wildfire containment efforts [31].

Crown fires and certain forest tree species, such as eucalyptus, significantly contribute to the fire spotting phenomena [13,14]. Eucalyptus forest bases are commonly associated with extreme fire behavior due to high firebrand generation rate [32,33] and increased likelihood of new ignitions [34,35], particularly in older eucalyptus trees [36]. Eucalyptus trees are highly flammable and produce firebrands with aerodynamic properties that accelerate the movement of the fire front. These firebrands can travel for kilometers [33,37], crossing non-fuel locations such as rivers, roads, bridges, firebreaks, and the wildland–urban interface (WUI), posing a high risk to human lives and structures. Firebrand spotting is often a primary cause of structure ignitions [33]. Numerous studies have demonstrated that firebrand accumulation around structures is a critical factor in ignition and wildfire-related damage. Notable contributions include experimental evaluations by Manzello and Suzuki [38], structural vulnerability research conducted at the Institute for Business and Home Safety (IBHS) facility [39], and Nguyen and Kaye [40,41]. These studies have significantly advanced our understanding of urban ignition pathways and the economic impacts of ember exposure. While this body of research is substantial, the present review focuses specifically on modeling the phases of fire spotting, firebrand generation, transport, and ignition, and excludes studies centered on ember accumulation near buildings or structural vulnerability.

The fire spotting process is inherently nonlinear [42], influenced by spatial and temporal variations, meaning that small changes in wind, vegetation type, or terrain can result in unpredictable spotting behavior. Additionally, fire spotting exhibits a probabilistic nature due to the complex interplay of firebrand generation, wind transport, and ignition conditions [28,29]. While advanced wildfire models can incorporate variable environmental inputs, many traditional deterministic models rely on fixed conditions. However, fire spotting dynamics are inherently stochastic, influenced by turbulent wind patterns, heterogeneous fuels, firebrand characteristics, and fuel distribution [29,43]. These factors introduce uncertainty, necessitating the use of probabilistic modeling approaches for more accurate predictions [44].

Few fire studies have traditionally or systematically reviewed spotting or related phenomena of fire spread. An early review by Pastor et al. [45] on wildland fire mathematical modeling from 1967 to 2000 provided historical insights into fire spotting, crown fire, and surface fire spread model approaches, including the classification of models and highlighting their relevance in assessing wildfire behavior. Wadhwani et al. [33] provided a valuable review of firebrand generation and transport studies, focusing on parametric analysis and the development of Computational Fluid Dynamics (CFD) models. However, they excluded firebrand ignition studies while also emphasizing the need for better quantification of firebrand generation and transport influences. However, they excluded firebrand ignition studies while also emphasizing the need for better quantification of firebrand generation and transport influences.

In contrast, Manzello et al. [46] reviewed firebrand behavior in large outdoor fires, including WUI and urban scenarios. Their study covered key mechanisms, generation, lofting, combustion, transport, and ignition, and emphasized the role of firebrand showers in the rapid spread of fire. They also highlighted Japan's vulnerability to firebrand-induced ignitions and the lack of related research in English. This work provides essential insights into the ignition phase of spotting. Meanwhile, Or et al. [47] examine the advantages and limitations of current wildfire models, focusing on the effects of fire on soil, hydrology, and ecology, highlighting their relevance to wildfire spread and behavior, but not significantly on the spotting phenomenon.

There remains a need for continuous advancement in fire spotting models to improve wildfire prevention and mitigation strategies. A comprehensive approach will enhance predictive capabilities by minimizing uncertainties [48]. Selecting suitable fire spotting models is critical for realistic comparisons with experimental fire observations and operational fire management applications. This systematic literature review (SLR) builds on previous related reviews by expanding their scope to evaluate models and approaches that aim to characterize or describe the fire spotting process in wildfires, focusing on studies published over the past 24 years (2000–2023). Study gaps were identified to provide recommendations for future research. Following the PRISMA approach, research was conducted across three databases: Scopus (SC), Google Scholar (GS), and Web of Science (WOS), ensuring a structured assessment of advancements in fire spotting. The following sections include Material and Methods, Results, Discussion, Prevailing Gaps, Conclusions, and Future Directions, each presenting a detailed analysis that highlights progress in fire spotting modeling approaches and identifies opportunities for future development in the field.

2. Materials and Methods

The systematic literature review (SLR) was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [49] to ensure methodological rigor, transparency, and reproducibility throughout the identification, screening, eligibility assessment, and inclusion of relevant studies. The review protocol was registered with the Open Science Framework (OSF): https://doi.org/10.17605/OSF.IO/GWS95. The methodology includes a structured search protocol and strategy, clearly defined inclusion and exclusion criteria, classification of fire spotting model frameworks, and bibliometric analysis using VOSviewer (version 1.6.10) to explore research trends and thematic networks.

2.1. Search Protocol and Strategy

A preliminary search was conducted in November 2023 using the keywords "spotting," "spot fires," "firebrands," and "wildfires'' for a search across the databases Scopus (SC), Web of Science (WOS), and Google Scholar (GS). This initial step aimed to provide an overview of the accessible and catalogued scientific literature in the subject area from 2000 to 2023. It also helped refine the search terms for the full review and revealed the absence of prior SLRs focused specifically on fire spread models driven by spotting. To conduct a comprehensive search and identify potential knowledge gaps, a structured strategy was employed using the three selected databases. Searches in SC and GS were conducted via Harzing's Publish or Perish software (Windows GUI Edition 8.12.4612.8838) [50], on 11 December 2023, while the WOS search was performed directly on the website on 13 December 2023.

As a secondary study, this SLR defined specific inclusion and exclusion criteria to identify, evaluate, and synthesize primary studies related to the main research question, models for fire spread in wildfires caused by spotting. The objective was to assess the prevalence and evolution of methods and modeling approaches used to fully characterize, describe, and simulate the fire spotting process in wildfires from 2000 to 2023. The overall SLR process followed a defined sequence of phases and steps, as shown in Figure 1. In addition, the research questions (RQs) guiding the review are detailed in Table 1.

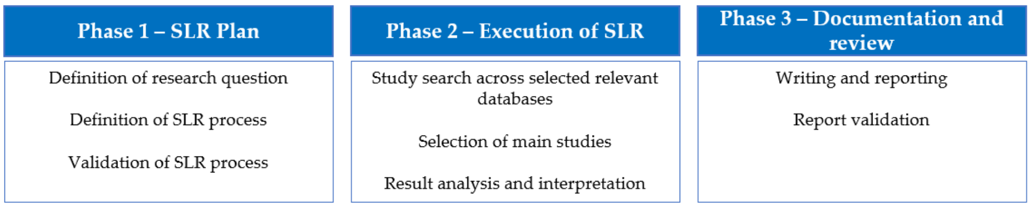

Figure 1. The sequence of phases and steps followed in the SLR process.

Table 1. Research questions guiding the SLR.

No.	Research Question (RQ)	Rationale
RQ1	What fire spotting concepts, models, and approaches evolved between 2000 and 2023, and what insights do they provide from both quantitative and qualitative perspectives?	To systematically identify, analyze, and compare research developments while applying predefined inclusion and exclusion criteria.
RQ2	What are the most commonly used methods and approaches employed in fire spotting studies, and how do they compare across different research frameworks?	To classify and evaluate dominant research techniques, offering a structured overview of fire spotting models.
RQ3	Which countries have contributed most to fire spotting research, and what trends	To highlight influential contributors and track evolving patterns in fire spotting studies.

	have emerged regarding research frequency and variability?	
RQ4	What significant findings have been reported in fire spotting research, and where do knowledge gaps or underexplored concepts remain?	To identify understudied topics and evaluate recommendations for future research directions.
RQ5	Based on the findings from RQ1-RQ4, what significant research gaps remain, and how should future investigations aim to address them?	To synthesize knowledge, highlight critical research gaps, and propose directions for future advancements.

Figure 1 outlines the three main phases of the SLR: planning, execution, and documentation and review. In Phase 1, the research questions were defined, along with the overall SLR process and its validation. Phase 2 involved the database search, selection of main studies, and analysis of the results. Finally, Phase 3 focused on writing, reporting, and validating the findings to ensure the accuracy and transparency of the review. Table 1 provides a structured overview of the five RQs that guided the SLR. Each question is accompanied by a clear rationale that outlines its purpose in examining the development of fire spotting models, methodological trends, geographic research distribution, key findings, knowledge gaps, and future research directions. Together, Figure 1 and Table 1 establish the analytical framework that guided the selection, classification, and evaluation of the included studies.

Table 2 presents the research string strategy applied across the databases, developed by the authors based on their conceptual understanding of fire spotting. The strategy focuses on key aspects such as firebrand generation, transport, spot fires (ignition), impacts, and consequences, including fire suppression.

Table 2. Search string strategy for the SLR.

Databases	Main Keyword	Control Vocabulary	Spotting Concept
Scopus	spotting fire	wildfire, urban fires, forest fire, wildland, WUI	Source: where and how spotting originates
		embers, firebrands, hot spot	Generation: what elements are produced
Web of Science		fire propagation	Transport: how firebrands are carried
		fuel bed, spot fire, secondary fires	Deposition: where firebrands land and accumulate
Google Scholar		fire behavior, fire suppression	Impact: what consequences result from spotting
		fire risk, fire hazard, fire safety fire simulation	Hazard: specific risks associated with spotting Mitigation: strategies for prevention and suppression

The research for primary articles was conducted independently in each of the three databases using a two-step approach. Step 1 involved the use of the main keyword alone (e.g., "spotting fire"), while Step 2 combined the main keyword with a selected control vocabulary (e.g., "spotting fire" AND "wildfire"). Search results were compiled in an Excel spreadsheet and underwent a two-phase duplicate removal process: Phase 1 eliminated duplicates within each database, and Phase 2 removed duplicates across the combined dataset. A notable challenge arose in Google Scholar, where document types were not always clearly identified. Only peer-reviewed journal articles and book chapters were included for analysis. The following subsection outlines the inclusion and exclusion criteria used to finalize the selection of studies for this SLR.

2.2. Inclusion and Exclusion Criteria

Following the PRISMA methodology, specific inclusion and exclusion criteria were established to ensure the selection of studies directly relevant to the research scope. These criteria were based on publication year, document type, language, and thematic alignment with fire spotting modeling. Table 3 summarizes the criteria applied.

Table 3. Inclusion and exclusion criteria for SLR.

No.	Exclusion Criteria	Inclusion Criteria
1	Studies published before the year 2000	Studies published between the years 2000 and 2023
2	Studies written in languages other than English	Studies written and published in English
3	Theses, dissertations, conference articles, posters, reviews, demo documents, grey literature (e.g., reports, software guidelines, laws, or regulations)	Peer-reviewed journal articles and book chapters Studies within the defined scope of study (related to spotting or its modeling)
4	Extended versions of previously published articles	
5	Studies outside the defined scope of review (not related to spotting)	
6	Duplicated records	
7	Studies focused on ember accumulation near buildings, structural vulnerability, and broad fire dynamics without a focus on spotting, or vegetation effects unrelated to fire spotting behavior.	Studies modeling fire spotting phases (generation, transport, ignition) within wildland or WUI contexts, including urban settings where the focus remains on spotting dynamics rather than accumulation or structural impact.

After removing duplicates, titles and abstracts were screened based on defined criteria. Additional filters were applied to limit the dataset to English-language studies published between 2000 and 2023 and to include only book chapters and peer-reviewed journal articles. Studies meeting these conditions were then assessed for their relevance and alignment with the SLR objectives. Full-text evaluations followed, with additional exclusions applied to studies outside the scope of analysis. The final set of included studies was determined based on whether they fell into one of two main categories: (i) studies integrating fire spotting models into fire propagation frameworks to evaluate their influence on wildfire behavior; or (ii) studies addressing fire spotting as standalone investigations, focusing on specific phases or impacts of the spotting process. A third category, (iii) studies focused on ember accumulation near buildings, broad fire dynamics, vegetation effects unrelated to spotting, or structural vulnerability, was excluded, as outlined in Table 3 (criterion 7). This categorization ensured alignment with the core research questions and maintained methodological consistency in evaluating fire spotting models.

The detailed flow of the study selection process is presented in the Results section using the PRISMA 2000 flow diagram. In addition to the systematic screening and synthesis, two complementary analyses were conducted to enhance understanding of the field.

First, to better interpret the modeling approaches used in the selected studies, a classification of fire spotting models was developed based on their integration into existing fire spread modeling frameworks. Second, a bibliometric network analysis was conducted to examine collaboration patterns, keyword co-occurrences, and thematic trends in fire spotting modeling research. These components are described in the following subsections.

2.3. Fire Spotting Models Classification

To facilitate a structured analysis of the modeling strategies identified in the selected studies, fire spotting models were categorized using adapted frameworks from established classifications of fire spread models. This approach provides a clear basis for understanding the underlying assumptions, computational methods, and practical applications of each modeling approach. A well-defined classification system facilitates comparison across models, aids in identifying approaches suitable for specific wildfire contexts, and informs future model development by highlighting dominant methodological trends and regional research contributions. Given the inherent complexity of wildfire behavior, influenced by fuel characteristics, terrain variability, wind dynamics, and fire spotting processes, this review refines and applies three widely recognized classification schemes originally developed for fire spread models. The adapted framework provides a systematic characterization of fire spotting models, highlights critical gaps and underexplored areas in the existing literature. The adapted classification is presented across three tables: Table 4 outlines a traditional classification based on the nature of equations (Pastor et al. [45]). In contrast, Table 5 focuses on applicability and computational approaches (Or et al. [47]), while Table 6 categorizes cellular automata models with an emphasis on grid-based simulations (Krougly et al. [51]).

Table 4. Traditional model classification based on the nature of equations, adapted from Pastor et al. [45].

Model type	Methodological Basis	Nature of Equations	Application and Validation
Empirical	Based on statistical correlations	Derived from observed relationships	Limited applicability
Semi-empirical	Combines theoretical principles with empirical adjustments	Balance physics laws with experimental data	Practical application
Theoretical	Rooted in fundamental physical laws	Detailed mathematical formulations	Broad applicability but requires complex validation

Table 5. Model classification by applicability and computational methods, adapted from Or et al. [47].

New Model Type	Methodological Basis	Fire Representation	Approach and Application
Statistical-empirical	Statistical correlations; machine learning	Does not model physical mechanisms; focus on observed relationships	Limited applicability; machine learning for predictions
semi-physical	Combes physical principles with empirical adjustments	Simplifies physics using approximations; dimensional analysis	Balance of theory and practice; small-scale validation
Physical-mechanistic	Fundamental laws;	High-resolution simulations; solve conservation equations	Broad applicability; complex validation

	detailed simulations		
Other models *	Analogies with similar phenomena	Captures patterns without detailing the physics of the process	Useful for understanding patterns; may lack complexity

* Analogies with similar phenomena (cellular automata, percolation, diffusion).

Table 6. Categories of Cellular Automata models synthesized from Krougly et al. [51].

CA Model Categories	Methodological Basis	Model Specifications	Approach and Application
CA1—Deterministic Models/Simulators [1]	Fire spreads from cell to cell based on predefined rules without incorporating randomness.	CA is combining with deterministic models (e.g., physics-based models, such as Rothermel's model).	Fire propagation is based on fixed delays influenced by fuel type, slope, and wind orientation.
CA2—Stochastic Models (Random Chance of Fire Spread) [2]	Fire spread involves randomness, with probabilities governing the state changes in cells.	Percolation models: Fire spreads if a generated random number exceeds a specified threshold.	Competing probabilities determine fire spread and burnout behavior.
CA3—Stochastic Models (Continuous-Time Markov Chain Model) [3]	Incorporates randomness (e.g., fire spotting) into fire spread to simulate uncertainty and variability.	Markov chain models: Fire spread is influenced by random delay probabilities and local/neighborhood conditions.	Produces irregular fire patterns due to stochastic delays; transition rates follow Markov chains.

[1]—Deterministic Cellular Automata Model; [2]—Stochastic Cellular or "lattice" model; [3]—Continuous-Time Markov chain (CTMC) Representation of the Entire Grid.

Table 4 presents three primary categories: empirical models, which use statistical correlations and offer simplicity but limited generalizability; semi-empirical models, which integrate physical principles with empirical adjustment to balance theory and application; and theoretical models, which are grounded in first principles and describe fire dynamics through mathematical, chemical processes, and physical formulations.

Table 5 presents a modern classification of fire behavior models based on methodological foundation, fire representation, and practical application. This classification reflects recent advancements in computational methods and a growing shift toward data-driven approaches. Statistical-empirical models rely on observed data patterns, often using machine learning algorithms, but they lack representation of underlying physical mechanisms. Semi-physical models combine simplified physical principles with empirical adjustments and are typically validated at small scales. In contrast, physical-mechanistic models are grounded in fundamental physical laws and involve high-resolution simulations to solve conservation equations, requiring complex validation and high computational resources. The final category, "other models," encompasses analogy-based approaches that utilize comparisons derived from similar phenomena to capture general behavioral patterns [47].

Table 6 categorizes cellular automata (CA) models for fire spread based on methodological foundation, model specifications, and simulation approaches. The first category (CA1), CA simulators, employs deterministic rules where fire spread is governed by environmental parameters such as fuel type, terrain slope, and wind direction, resulting in consistent and predictable behavior. The second category (CA2) comprises stochastic models based on percolation theory, where fire spread is determined by probability, offering a more realistic representation of uncertainty. The third category (CA3) encompasses stochastic models that utilize Continuous-Time Markov Chains (CTMC), representing fire spread as probabilistic transitions that occur over continuous time. These models capture complex interactions and random delays influenced by neighboring cell states and local conditions [51].

This classification supports comparison across modeling approaches and clarifies how different methods address fire spotting dynamics. A summary of the identified models and their key characteristics is provided in Table 7.

Table 7. Summary of fire spotting model classification of the final 102 relevant studies.

Research Focus Area	Model Type/ Approach	New Model/ Approach	Year Range	Country/References
Review	Literature review	Physics-based refinement Empirical, CFD * updates Land surface modeling improvements Mathematical integration with GIS *	2003–2023	United States ([28,47,52]) Australia [33], Spain [45], Portugal [53]
Firebrand Generation	Semi-empirical, Empirical, Hybrid	Semi-physical, Statistical-empirical, ML *	2015–2022	United States ([54–56]) Canada [57] Australia [58]
Firebrand Transport	Theoretical, semi-empirical, Empirical, Stochastic	Semi-physical, Statistical-Empirical, Physical-mechanistic	2006–2022	United States (43,60–65]) Australia ([37,59–61]) Portugal ([62,63]), China [64], Japan [65], France [66], Canada [67]
Ignition	Theoretical, semi-empirical, Empirical	Semi-physical, Statistical-empirical, Physical-mechanistic	2009–2023	United States ([68–72]), China ([73–76]) Chile ([77,78]), Portugal [79], France [80], Russia [81], United Kingdom [82]
Physics-based fire spotting models	Theoretical, semi-empirical	Physical-mechanistic, Semi-Physical, Statistical-mechanistic	2008–2021	Canada ([29,83]) United States [84] France [85]
Integration of spotting in existing models	Theoretical, Semi-empirical, Hybrid, CA *	Semi-physical, Physical-mechanistic, Other Models, ML *	2000–2023	United States ([20,86–90]), Spain ([21,42,44,91–98]) Greece ([99,100]), Canada ([51,101]), France [102], Italy [103], Japan [104], China [105]
Empirical research	Semi-empirical, Empirical, Computational modeling, Empirical analysis, Literature review	Semi-physical, Physical-mechanistic, Statistical-empirical, Multi-scale data collection and Modeling for firebrand-driven wildfire dynamics	2004–2023	United States ([11,106–110]) Australia ([13,14,36,111–118]) Canada ([119–121]), Spain [18], Portugal [32], Chile [122], France [123], Japan [124]
Integration of spotting in the operational fire spread model	Semi-empirical, Hybrid	Semi-physical, Other Models	2014–2023	Spain ([125,126]), United States [127], Australia [128]

* CFD—Computational Fluid Dynamics; GIS—Geographic Information Systems; ML—Machine Learning; CA—Cellular Automata model.

2.4. Bibliometric Network Analysis of Fire Spotting Research Using VOSviewer

To complement the systematic review, a bibliometric network analysis was conducted to explore the structural and thematic development of fire spotting modeling research. This analysis aimed to uncover collaborative patterns, thematic clusters, and conceptual linkages within selected literature. A total of 102 studies were analyzed using bibliographic data extracted in RIS format and processed with VOSviewer (version 1.6.10) following the official VOSviewer manual [129]. The analysis included three key types of networks:

1. Co-authorship network, highlighting collaboration patterns, key contributors, influential research groups, and geographic distribution of fire spotting modeling research.
2. Keyword co-occurrence network, based on author-defined keywords, identifies thematic trends and reveals how research topics have evolved over time, indicating dominant themes and interdisciplinary linkages.
3. Term co-occurrence network, derived from text mining of titles and abstracts, reveals deeper conceptual patterns, highlighting underlying connections between topics, identifying knowledge gaps, and indicating emerging methodologies.

Each network is composed of nodes (representing authors, keywords, or terms) and links (representing co-occurrence or collaboration relationships). The size of each node reflects the frequency of occurrence, while the thickness of links indicates the strength of association between items. Nodes with higher connectivity and frequency appear larger and are typically positioned more centrally in the network, often acting as bridges across thematic clusters. Custers are generated using VOSviewer's modularity-based algorithms [129], which group closely related nodes based on co-occurrence patterns. Clusters identification follows a two-part system: (i) each cluster is assigned a unique numerical identifier, and (ii) for visual clarity, distinct colors are applied only to the most prominent and central clusters. Smaller or peripheral clusters are displayed in gray but retain their numerical identifiers for reference and analysis. To optimize visualization, network layout was refined using association strength normalization, with adjustments to clustering resolution and layout parameters to enhance interpretability while maintaining data integrity.

To maintain the thematic resolution of the dataset, no terms or keywords were merged during processing. Author-supplied keywords such as "firebrand" and "firebrands" or "ember" and "embers" were retained as separate items. Despite their lexical similarity, co-occurrence and clustering analyses revealed that these terms are used in distinct thematic contexts. For example, in the keyword co-occurrence network, "firebrand" and "ember" appear together in one cluster, typically associated with physics-based modeling of ignition mechanisms and plume dynamics. In contrast, "firebrands" and "embers" appear in a separate cluster, where they are more closely linked to post-fire investigation, ember trajectories, and fire spread modeling using Lagrangian and LES techniques (as further discussed in the Section 3). These distinctions reflect genuine variation in how authors frame research within specific methodological contexts. Merging such terms would risk obscuring meaningful conceptual distinctions and reducing the interpretive value of the analysis.

The Results section provides a detailed synthesis of the selected studies, structured around the predefined research questions (RQs). The overall methodological workflow is illustrated in Figure 2, which outlines the key phases of the systematic review process: (1) final study selection, (2) classification of fire spotting models and research focus area, (3) bibliometric network analysis, and (4) synthesis of findings mapped to research questions.

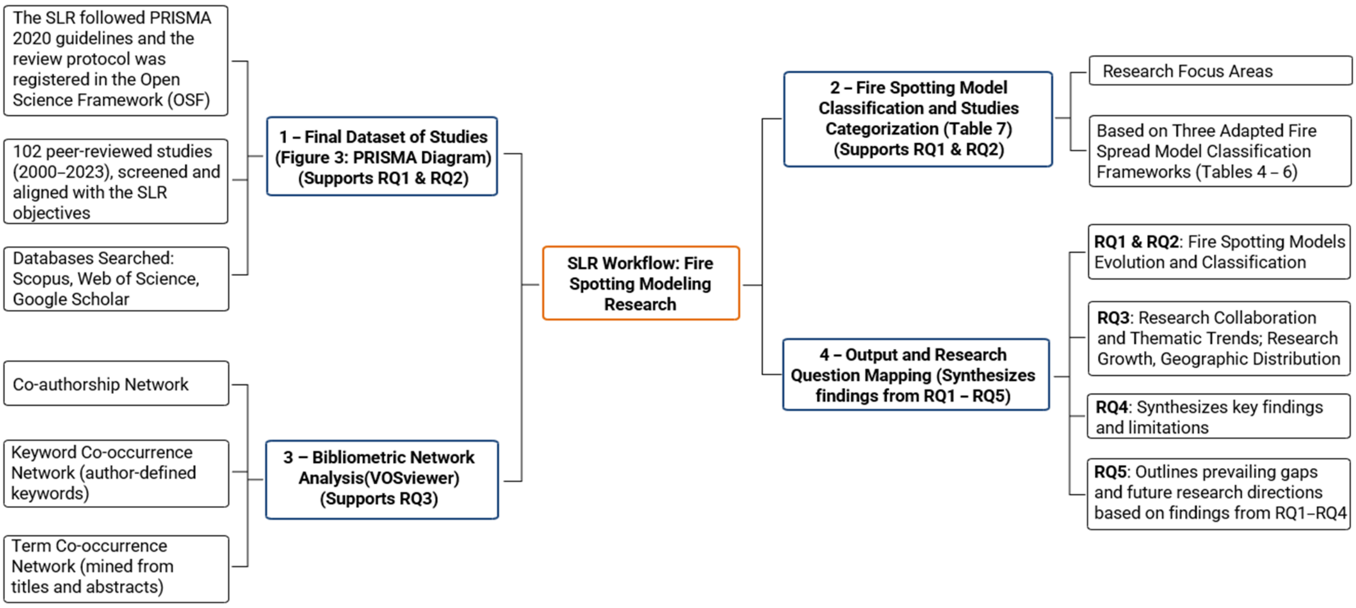

Figure 2. SLR Design and Workflow for Fire Spotting Modeling Research.

3. Results

3.1. Fire Spotting Models: Trends, Classification, and Approaches

This section addresses RQ1 and RQ2 by systematically analyzing and classifying fire spotting models and approaches. RQ1 examines the evolution of fire spotting models from 2000 to 2023, while RQ2 provides a structured classification of the dominant methods and computational frameworks used in this field. The study selection process is detailed in Figure 3, following the PRISMA 2020 flow diagram used to document the identification, screening, and inclusion of studies in this review.

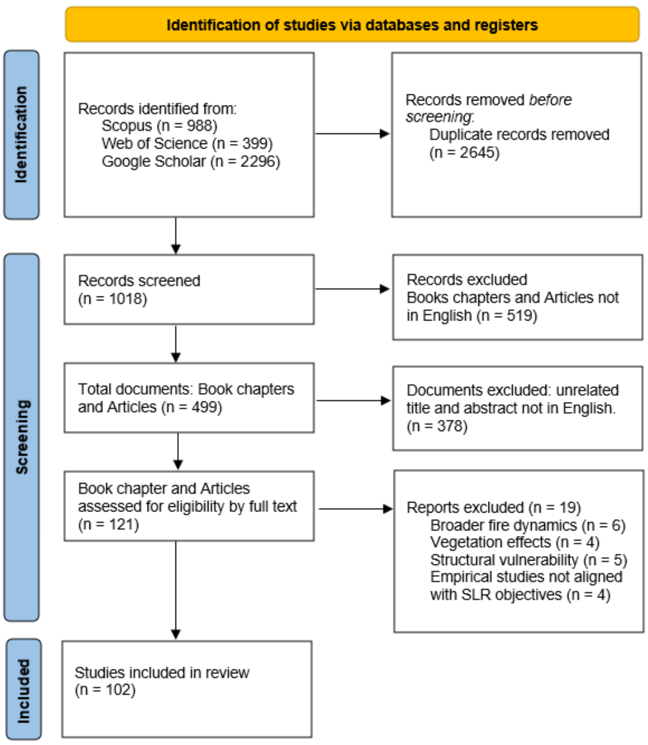

Figure 3. PRISMA 2020 flow diagram of the database search and final study selection process.

Figure 3 presents a clear visual summary of the systematic review process, detailing each step from the initial database search to the final inclusion of studies. The search yielded 3663 records: 968 from Scopus, 2296 from Google Scholar, and 399 from Web of Science. After removing duplicates, 2645 unique records remained for screening. Titles and abstracts were rigorously scrutinized, resulting in the exclusion of 519 studies due to a lack of relevance. A full-text review was conducted on 499 reports, all of which met the predefined criteria and were retained for further evaluation. Despite this, 378 records were excluded at various stages, reflecting the application of stringent selection criteria. The final selection was guided by targeted keyword searches and the overarching research questions (RQ1–RQ5). After duplicate removal and preliminary exclusions, the dataset was refined to 121 studies. Full-text review led to the exclusion of 19 studies that did not meet the specific objectives of this SLR. These excluded studies addressed broader fire dynamics (n = 6), vegetation effects (n = 4), structural vulnerability (n = 5), or consisted of empirical work unrelated to fire spotting models (n = 4). The final set of 102 studies is summarized in Table 7, with detailed findings provided in Appendix A (Tables A1–A8). A model-specific classification of fire spotting models and approaches is presented in Appendix B (Tables A9–A16). Additional visualizations of bibliometric analysis (Figure S1–S15) and the complete list of selected studies in RIS format (Lista S1) are available in the Supplementary Materials. Table 7 provides a thematic classification of the 102 selected studies, organized by research focus, modeling approaches, year ranges, and country of origin (based on the corresponding author). This structured overview highlights the diversity of modeling techniques, ranging from empirical and semi-empirical to physics-based and hybrid approaches, as well as emerging trends such as the integration of machine learning and operational fire spread modeling. The geographic distribution underscores strong contributions from the United States, Australia, and several European countries. These thematic patterns and methodological developments are further analyzed in the following subsections and synthesized in the Discussion section, with reference to predefined research questions (QRs).

3.2. Research Collaboration and Thematic Trends in Fire Spotting Studies

This section addresses RQ3 by examining collaborative patterns and thematic development in fire spotting research through bibliometric network visualizations. Three types of networks are analyzed: co-authorship (Figure 4), keyword co-occurrence (Figure 5), and term co-occurrence (Figure 6). Each visualization is accompanied by a cluster summary table outlining the main thematic areas identified through the analysis. In all figures, node colors represent distinct thematic clusters, each assigned a unique numerical identifier, while gray nodes indicate smaller or peripheral clusters. The first network analyzed is the co-authorship structure, visualized in Figure 4.

Figure 4 illustrates collaborative patterns within fire spotting research, revealing distinct research groups formed through frequent co-authorship. The network was constructed using full counting, with all co-authorships equally weighted and no parameter modifications, ensuring a neutral and reproducible cluster structure. Each node represents an author, with node size indicating the author's publication output, and links representing co-authorship relationships. A total of 46 clusters were identified, representing distinct research teams. Larger nodes indicate prolific authors, while central nodes represent those who bridge groups, facilitating knowledge exchange and advancing fire spotting modeling.

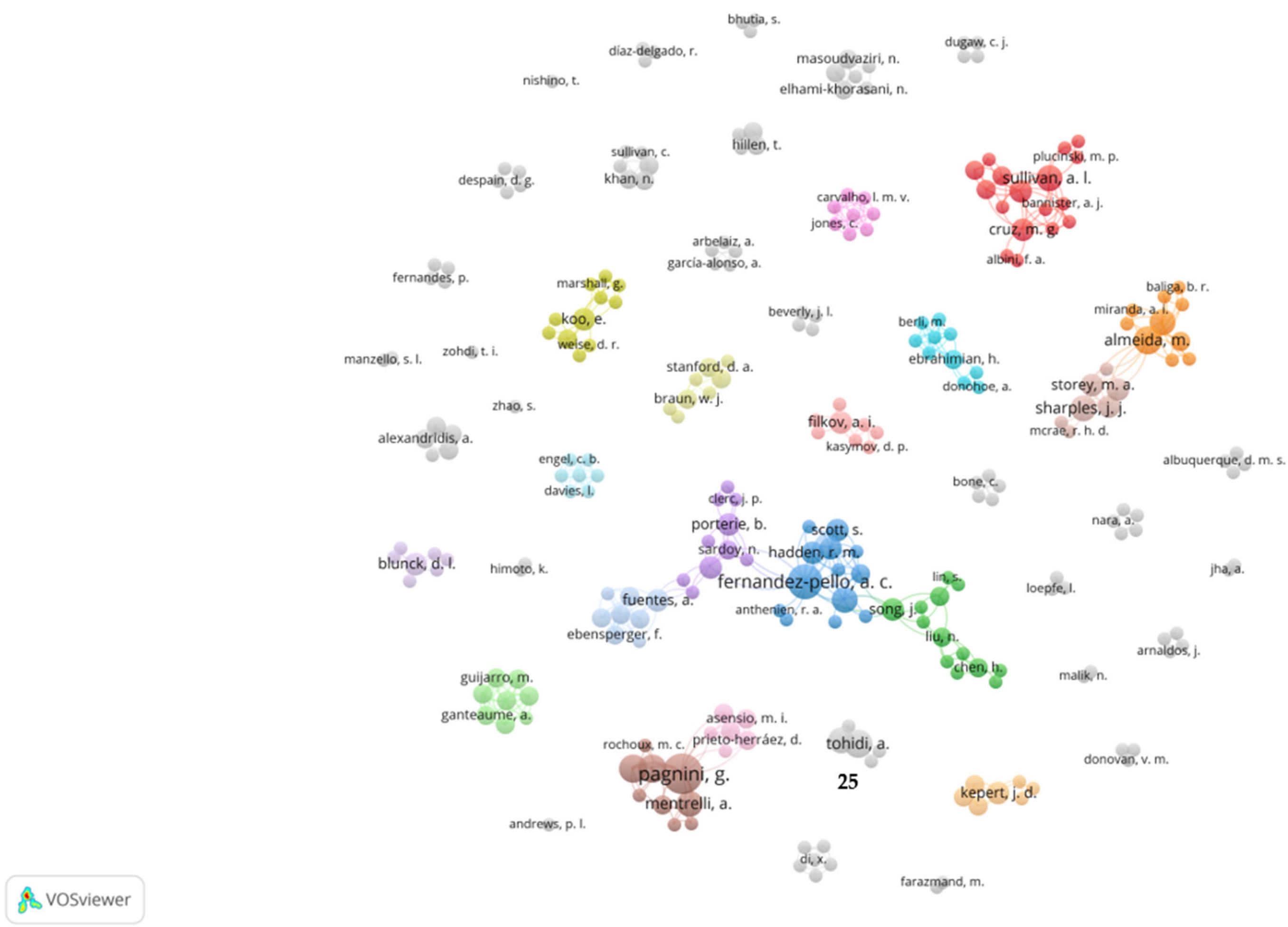

Figure 4. Co-authorship network visualization based on bibliographic data.

Among the 46 clusters, several isolated groups represent niche or emerging topics with limited direct collaboration. These clusters address diverse aspects of fire spotting and fire spread, ranging from empirical studies to advanced computational modeling and technological innovations. For instance, empirical contributions include the use of infrared imagery and photogrammetric monoplotting to analyze firebrand dynamics and past wildfires. Modeling approaches involve stochastic methods and cellular automata to simulate fire spread and spotting, incorporating firebrand transport, ignition probability, and landscape variability. Additional work explores machine learning frameworks for predicting firebrand production and fire spread patterns, integrated with digital twin technology to enable real-time, adaptive simulation in complex environments. Other notable developments include operational virtual reality tools for fire spread training, custom particle tracking software, and the detection of firebrands in turbulent flows. Studies also apply physics-based coupled fire–atmosphere models and computational fluid dynamics (CFD) to simulate firebrand lofting and plume dynamics, as well as long-distance transport.

For in-depth analysis, only clusters with at least five publications and strong inter-author connectivity were selected, representing the field's most influential contributors. These include leading groups associated with Fernandez-Pello, Pagnini, Almeida, Sullivan, and Tohidi. Table 8 summarizes the key research clusters by geographic origin (based on the corresponding authors' countries), core research areas, and provides a brief description of each thematic cluster. The clusters span a range of approaches, from empirical and field-based studies in Australia and Portugal to physics-based modeling and simulation innovations in Spain, France, the USA, and China. Clusters 8 and 18 highlight cuttingedge work that integrates spotting and turbulence into operational fire spread models, utilizing probabilistic and computationally efficient methods. Clusters 2, 3, 5, and 12 focus on ignition thresholds and firebrand behavior through laboratory experiments and theoretical modeling. This diversity reflects a maturing yet fragmented field, where interdisciplinary collaboration between empirical research and advanced modeling remains a key opportunity for future progress. The table also underscores regional strengths, with Spain and the USA standing out in model development and integration, while Australia and Chile focus on field-based and ignition-driven investigations. This integration of knowledge fosters methodological collaboration and stimulates innovation across both thematic and regional boundaries.

Table 8. Key fire spotting research clusters from the co-authorship network.

Cluster/Corresponding Author's Country	Research Area	Brief Description
Cluster 1 ■ Australia (7), USA (1)	Generation, Transport, and Empirical Research	Investigates the fundamental processes of wildfire behavior with a focus on heat transfer, fire spread, and spotting dynamics. Integrates empirical research, reviews, and modeling efforts to understand the role of environmental conditions, fire characteristics, fuel characteristics, and firebrand aerodynamics and combustion. Supports operational decision-making, especially in the Australian context.
Cluster 2 ■, China (4) Cluster 3 ■, USA (7), UK (1) Cluster 5 ■, France (3) Cluster 12 ■, Chile (3)	Transport, Ignition, and Fire Spotting Integration	Covers firebrand transport, ignition thresholds, and smoldering behavior through experimental, numerical, and modeling studies. Research includes ignition delay, firebrand combustion, and aerodynamic transport under varying environmental conditions (e.g., wind, fuel moisture). Innovations include cooperative spot ignition, the combined effects of metal hot particles and thermal radiation, and small-world network modeling to assess the influence of spotting on fire spread. Studies also address 2D and 3D firebrand trajectories, emphasizing the effects of plume and wind. Physics-based fire spotting models contribute to improved predictions of firebrand landing, residual mass, and ignition potential.
Cluster 7 ■, Portugal (4) Cluster 17 ■, Australia (4)	Transport, Ignition, Empirical Research	Focuses on firebrand dynamics, combustion, and spot fire behavior. Studies include firebrand orientation, airflow effects, and empirical trajectory prediction. Also investigates the impact of spot fires and terrain on the rate of fire spread, emphasizing long-distance spotting and fire channeling in complex landscapes.
Cluster 8 ■, Spain (9), Italy (1) Cluster 18 ■, Spain (2)	Fire spread behavior, Fire Spotting Integration, Operational Tools	Addresses the integration of random effects, such as fire spotting, turbulence, and ignition delay, into wildfire spread models. Uses advanced techniques like Level Set Method (LSM), Discrete Event System Specification (DEVS), reaction-diffusion equations, Ensemble Kalman Filters analogies, and surrogate modeling. Probability density

		functions (PDFs) are applied in post-processing to represent uncertainty and variability in firebrand landing and ignition potential. Operational tools such as LSFire+ and WRF-SFIRE incorporate models like RandomFront and PhyFire, enabling GIS integration, real-time wildfire simulation, and the use of computationally efficient spotting indices. The research also examines the impact of atmospheric stability, slope, and flame geometry, thereby enhancing the realism and predictive accuracy of fire spread modeling.
Cluster 25, USA (5)	Generation and Transport	Focuses on the empirical and modeling studies of firebrand generation and transport from coniferous trees. Involve wind tunnel experiments, aerodynamic analysis, and stochastic modeling (e.g., Monte Carlo simulation). Supports fire spread models by improving understanding of firebrand lofting, flight behavior, and the potential integration of spotting dynamics.

The second network analyzed is the keyword co-occurring structure, visualized in Figure 5. This network is based on author-assigned keywords extracted from bibliographic data. A total of 326 keywords were analyzed using full counting in VOSviewer, with clustering and visualization settings optimized through association strength normalization, layout adjustments, and a cluster clustering resolution (0.6). This refinement reduced the number of clusters from 35 to 28, with the largest connected network comprising 262 items. Keyword weights were based on their frequency across 102 studies. The visualization reveals central themes, such as spotting, firebrand, wildfire, fire spread, simulation, and ignition, highlighting their prominence in the field. In contrast, peripheral clusters, such as digital twin (cluster 23), birth-jump processes (cluster 16), and Spetses Island (cluster 15), represent emerging methods, niche modeling techniques, or localized case studies with limited integration. Strongly connected clusters indicate close thematic relationships across subfields, while isolated nodes reflect more specialized or developing areas. Tables 9 and 10 provide detailed summaries of the central and peripheral clusters identified in this analysis.

Table 9 summarizes the central clusters that define the core of fire spotting modeling research. These clusters encompass dominant themes such as firebrand dynamics, ignition mechanisms, fire spread simulation, atmospheric interactions, and model validation. Topics include urban-WUI fire behavior, stochastic and physics-based modeling, experimental and simulation-based approaches, and fire–atmosphere coupling. Techniques range from cellular automata and Lagrangian particle models to Monte Carlo simulations and machine learning. Clusters 1–13, 18, 22, and 25 reflect a strong emphasis on empirical and theoretical studies, advanced computational tools, and interdisciplinary integration. Collectively, these clusters represent the mature and evolving foundation of fire spotting research.

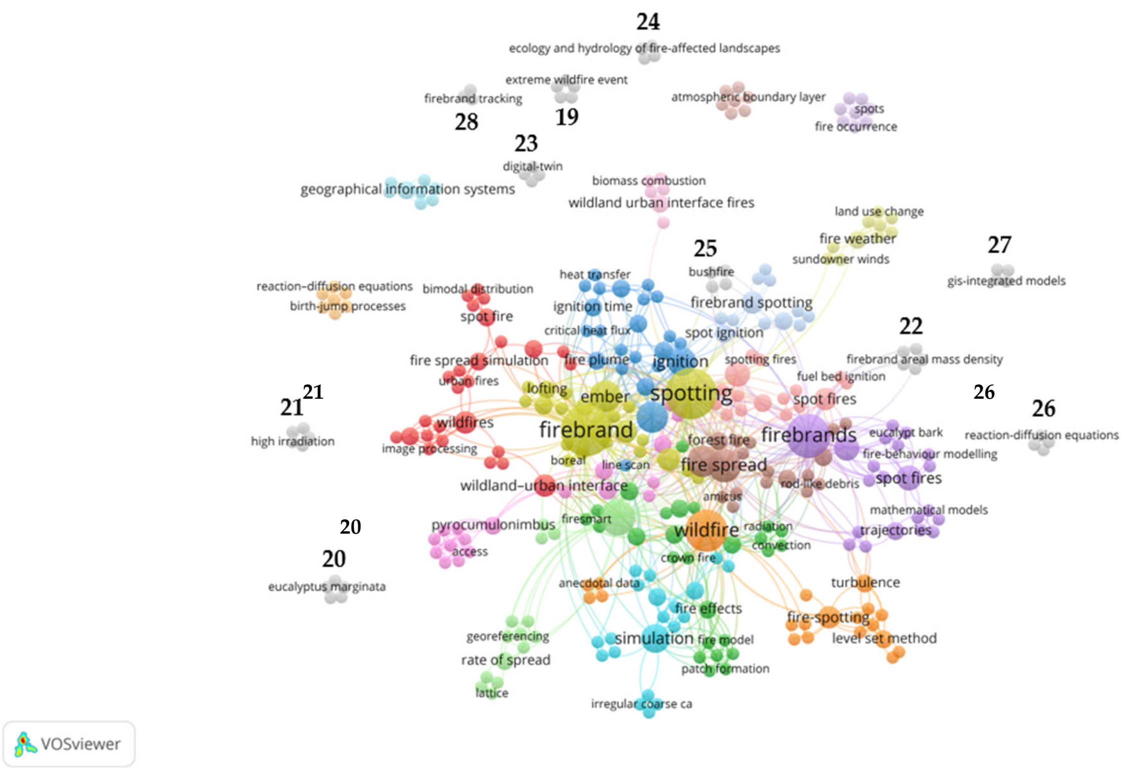

Figure 5. Keyword co-occurrence network visualization based on author keywords.

Table 9. Thematic central clusters derived from Author keyword co-occurrence analysis.

Cluster	Theme	Brief Description
Cluster 1	Urban Fire Spread and Firebrand Dynamics	Investigates firebrand dynamics and their influence on wildfire behavior, urban fire spread, and WUI * ignition using advanced simulation and stochastic modeling. Emphasizes computational techniques, including image processing and virtual reality, for risk assessment and suppression planning. Grounded in experimental studies, with a focus on firebrand aerodynamics, spotting behavior, and urban ignition pathways.
Cluster 2	Fire Spotting Dynamics and WUI Protection Strategies	Explores fire spotting behavior and its integration with fuel distribution and landscape patterns. It includes simulation of wildfires using coupled landscape models and probabilistic cellular automata (CA) (e.g., EMBR) to assess patch formation and spread patterns. Highlights case studies that employ the EMBR model to simulate fire behavior in Yellowstone National Park (USA), estimating fire perimeter development, burn area, and the influence of spotting on fire propagation. Emphasizes WUI protection strategies, including defensible space and community planning, supported by tools such as FireSmart and FireWise. Investigates how surface and crown fires influence potting distance to inform fire management strategies. Examines the interactions between atmospheric conditions and fuel moisture, including heat transfer processes such as radiation and convection, in the dynamics of firebrands and spotting behavior.
Cluster 3	Extreme Fire Behavior and Ignition Dynamics	Examines the extreme fire behavior and ignition in wildland fuels, emphasizing crown fire development, canopy structure, and heat transfer. Incorporates wild speed, moisture content, and packing ratio, thermal radiation to model ignition timing and intensity by hot particles, with a focus on spotting and WUI fire risk under high-heat flux conditions.
Cluster 4	Fire Spotting and Physics-Based Fire Modeling	Investigates ember transport and fire spotting in wildfires and WUI using physics-based models (fire dynamics simulator (FDS) and dimensional analysis), focusing on plume dynamics, ember trajectories, flammability, ground-level ember distribution, and thermal degradation. Analyzes boreal forest fire spread

		using spectrogram and acoustic methods to assess spotting and fire front progression.
Cluster 5	Ember Dynamics and Fire Spread Modeling	Investigates ember trajectories using Lagrangian particle models and Large-Eddy Simulation (LES). Employs mathematical modeling and post-fire analysis in urban and forest environments to examine firebrand behavior and assess fire-break performance and fire spot fires behavior in diverse forest fuel types.
Cluster 6	Stochastic Fire Spread and Simulation Models	Focuses on wildfire spread modeling using stochastic processes, numerical simulations, and turbulence-resolving tools such as OpenFOAM and LES, supported by wind tunnel data for model calibration and validation. Applies Poisson processes and right-censoring methods within terrain-informed systems, such as the Terrain Analysis System (TAS) and GIS. Utilizes irregular coarse cellular automata to simulate urban mass fire-spread, predicting fire spotting short- and long-range propagation. Incorporates small-world network and percolation theory to capture complex fire forest dynamics and spotting behavior.
Cluster 7	Empirical and Simulation-Based Wildfire Modeling	Quantifies dynamic fire behaviors using empirical data, including direct, indirect, and anecdotal sources. Investigates fire spread using the Rothermel model, which incorporates fireline intensity, flame characteristics, and terrain slope to evaluate the influence of atmospheric stability and topographic factors on fire behavior. Explores stochastic wildland fire propagation by enhancing fire front rate of spread estimation through the incorporation of random phenomena such as fire spotting and turbulence, using modelling approaches including the level set method, reaction-diffusion, discrete event system specification (DVES), and ForeFire.
Cluster 8	Stochastic Fire Risk Modeling	Addresses the spread and spotting dynamics across various landscapes, including post-earthquake and urban conflagration scenarios, with applications in management. Highlights advanced probabilistic methods, including Monte Carlo simulation, large deviation theory, generalized polynomial chaos, and Gaussian process, for sensitivity analysis and experimental validation. Emphasize decision support systems and software tools for risk assessment in wildland and WUI fire contexts.
Cluster 9	Fire Behavior in Forest and Atmospheric Conditions	Examines wildfire and fire spotting behavior under critical conditions using coupled fire–atmosphere modeling, with emphasis on crown fire, surface, and ground fire dynamics. Focuses on dry eucalypt forest fires and megafire scenarios, integrating experimental data and fire meteorology to assess ignition thresholds and spread mechanisms. Utilizes ACCESS * and the Vesta model to simulate fire–atmosphere interactions, including pyrocumulonimbus development. Highlights case studies, such as the Waroona fire in Australia, to validate simulations and support risk assessment in eucalypt-dominated landscapes.
Cluster 10	Fuel Influence on Fire Spread and Spotting	Investigates wildfire dynamics and fuel bed ignition across diverse forest fuel types (eucalypt, ponderosa pine, sagebrush, and douglas-fir) using thermal model, Monte Carlo simulation, and nonlinear regression to evaluate their capability to generate spot fires and assess fire spotting behavior in wildfire and WUI environments. Examines bushfire risks and forward spread rate in eucalyptus forest near the WUI zones, analyzing spotting and wildfire spread patterns.
Cluster 11	Spatial Fire Behavior Modeling	Explores wildfire behavior using remote sensing, monophotogrammetry, aerial wildfire photography, and the WSL monoplotting tool to estimate the rate of fire spread and map fire perimeters and ignition patterns. Investigates torching behavior to predict the maximum spot fire distance, improving understanding of firebrand transport and fire behavior. Develops a spatial model, using lattice-based Markov methods to simulate stochastic fire spread. This framework

		captures uncertainty and variability in fire propagation, enabling more accurate predictions of emergent fire behavior across landscapes.
Cluster 12	Firebrand Generation and Transport	Examines firebrand behavior and ignition mechanisms in wildland and WUI fires. Utilizes probabilistic approaches, including the Monte Carlo method and Large Deviation Theory, to simulate rare events such as long-range spotting. Investigate firebrand transport and accumulation using firebrand generators to assess spotting behavior and cooperative ignition, supporting analysis of spot ignition dynamics in WUI environments.
Cluster 13	Fire Regime and Landscape Dynamics	Explores landscape-scale fire modeling and environmental interactions, emphasizing integration of fire behavior simulators such as FARSITE with dynamic variables including fire weather and sundowner winds. Investigates the influence of fire weather on spotting behavior, as well as the effects of suppression strategies, including fire regime, vegetation growth, and land use change, on landscape-scale dynamics.
Cluster 18	Fire Physics and Ignition Processes	Analyzes biomass combustion and ignition mechanisms, including smoldering and spot fire ignition, using a coupled-physics fire model to simulate spotting behavior in wildland and WUI fires.
Cluster 22	Machine Learning for Firebrand Characteristics and WUI Fire Risk	Studies the behavior of firebrands in the WUI environment, focusing on firebrand generation rate and spatial distribution. Applies machine learning, particularly k-nearest neighbors, to estimate firebrand aerial number density and aerial mass density.
Cluster 25	Firebrand Aerodynamics in Bushfire	Analyzes bushfire-specific firebrand behavior through aerodynamic coefficients, surface density, and terminal velocity. Supports modeling of firebrand transport and deposition under bushfire conditions.

* WUI—Wildland–Urban Interface; GIS—Geographic Information System; ACCESS—Australian Community Climate and Earth System Simulator; FARSITE—Fire Area Simulator.

Table 10 presents peripheral clusters that reflect both emerging research directions and specialized modeling approaches in fire spotting studies. Clusters 14–17 represent foundational yet less central themes, including spatial burn analysis, complex systems modeling, mathematical formulations of fire spread, and atmospheric dynamics. These areas contribute valuable insights into fire occurrence, nonlinear propagation, and weather-driven fire behavior, often using advanced techniques such as cellular automata, reaction-diffusion equations, and high-resolution numerical weather prediction (NWP). Additional clusters (19, 21, 23, 24, 27, and 28) highlight recent developments and niche applications, including extreme wildfire events, fuel hazards assessments, ignition thresholds, and real-time simulation using digital twin and machine learning approaches. Topics such as ecological impacts, stochastic propagation models, GIS-integrated simulations, and firebrand tracking methods further illustrate the thematic diversity and technical innovation found at the periphery of fire spotting research. Collectively, these clusters represent evolving and interdisciplinary extensions of the core modeling landscape.

The third network analyzed is the term co-occurrence structure, visualized in Figure 6. This network was derived from text-mining titles and abstracts, rather than author-supplied keywords. The term co-occurrence analysis, based on 342 terms, employed binary counting with a minimum of two occurrences, covering 60% of the most relevant terms. Visualization was optimized using association strength normalization, with adjusted layout settings (Attraction = 2, Repulsion = 0), and a clustering resolution of 1.2, resulting in 13 thematic clusters.

Table 10. Thematic peripheric clusters derived from Author keyword co-occurrence analysis.

Cluster	Theme	Brief Description
Cluster 14	Fire Occurrence and Spatial Patterns	Analyzes fire occurrence, recurrence, and size distribution using fractal dimension and Lorenz curves. Integrates land cover data and post-fire features, such as residual vegetation islands, to assess spatial burn patterns.
Cluster 15	Complex Systems and Wildfire Dynamics	Investigates spotting and forest wildfires using cellular automata within the framework of complex systems, capturing emergent fire spread dynamics across heterogeneous and mountainous landscapes. Integrates GIS to simulate real-world conditions, including case studies like Spetses Island in Greece, to enhance understanding of wildfire propagation in diverse terrains.
Cluster 16	Mathematical Models of Wildfire Spread and Spotting	Focuses on birth-jump models and nonlinear integro-differential equations that couple growth and spatial spread. Derived via random walk and reaction-diffusion frameworks, these models approximate reaction-diffusion equations under concentrated kernels. Key results include thresholds for fire propagation (local spread) and spotting (nonlocal spread), such as the critical domain size for sustained spread and the minimal wave speed for advancing fire fronts.
Cluster 17	Atmospheric and Weather Modeling for Wildfires	Focuses on the atmospheric boundary layer and its roles in fire dynamics, particularly during the Black Saturday bushfires in Australia. Investigates how shallow convection and stable layers affect wind-direction variability, influencing fire propagation and spotting behavior. These processes are modeled using mesoscale and high-resolution numerical weather prediction (NWP).
Cluster 19	Extreme Wildfire Events and Fire Spread	Analyzes the rapid spread of fires during extreme events using geovisualization and thermal imagery to monitor wildland fire dynamics.
Cluster 20	Fuel Hazard and High-Intensity Fire	Evaluates fuel hazard ratings, high-intensity fire experiments, ember propagation, and spot fire behavior in specific fuel types like eucalyptus marginata.
Cluster 21	Fire Ignition Limits and Simulation	Studies ignition thresholds under high irradiation and models smoldering and spotting using numerical simulations.
Cluster 23	Digital Twin and Fire Propagation	Covers innovative modeling approaches, combining digital twin technology and machine learning (ML) algorithms to simulate ember flow and fire propagation in real-time systems.
Cluster 24	Ecology and Physics of Wildfire	Explores ecological and soil impacts of wildfire with a focus on hydrology and physical fire behavior.
Cluster 26	Stochastic Wildfire Propagation Models	Uses randomized level set and reaction-diffusion methods to simulate wildfire spread across complex terrains.
Cluster 27	Wildfire Spread Modeling and GIS Integration	Focuses on spatially explicit wildfire spread modeling using simplified physical principles and numerical methods integrated with GIS environments to support a complex simulation model.
Cluster 28	Firebrand Detection and Tracking	Focuses on detection and tracking methods for firebrands in wildland and structural fire environments to understand the mechanisms of fire spotting.

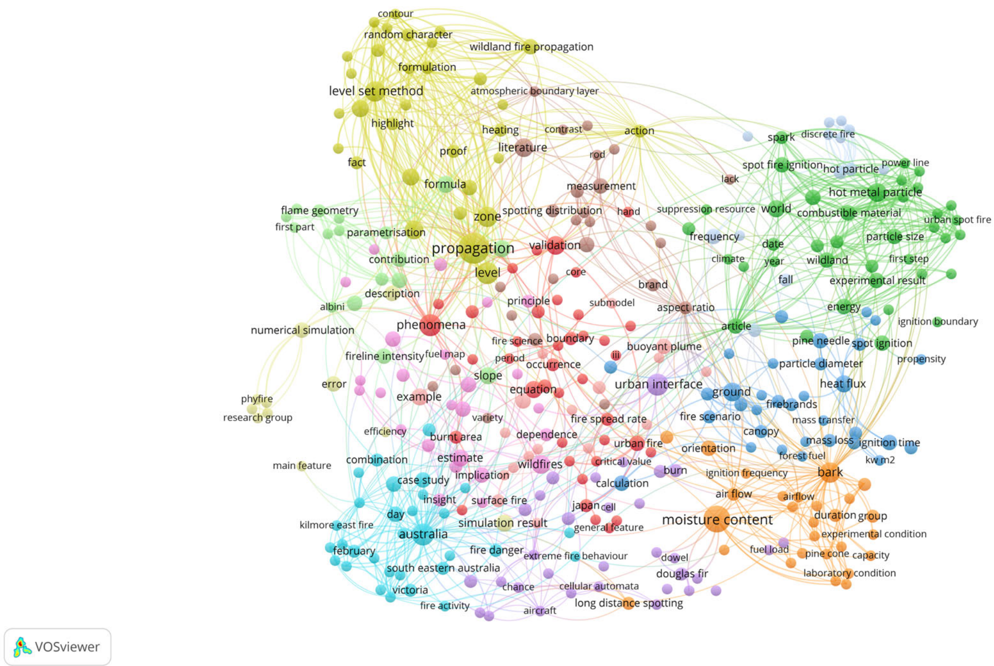

Figure 6. Term co-occurrence network visualization based on the Text Data.

Through modularity-based clustering, terms in Figure 6 were grouped into thematic categories, revealing interconnections between research concepts. The network showcases a diverse vocabulary, featuring representative terms such as propagation, urban interface, moisture content, hot metal particle, wildfire, level set method, phenomena, validation, and Australia, which reflect the broad scope of fire spotting research. These clusters highlight the multifaceted nature of the field, encompassing physical phenomena, modeling techniques, environmental factors, and application contexts. This text-based co-occurrence analysis complements the author's keyword map by revealing deeper thematic relationships that extend beyond explicitly provided keywords.

Table 11 presents the clusters, each associated with a thematic label and brief description, covering topics that range from ignition processes and transport modeling to urban interface risk and simulation performance.

Table 11. Thematic classification of clusters from term co-occurrence analysis.

Cluster	Theme	Brief Description
Cluster 1	Urban Fire Spread, WUI, and Model Validation	Emphasizes modeling and validation of fire spread in urban and WUI contexts. Focuses on real-world case studies in Japan, North America, and Spain, addressing secondary fire development, spatial fire patterning, and firefighting effectiveness.
Cluster 2	Ignition Process and Anthropogenic Firebrand Source	Focuses on ignition mechanisms, especially from anthropogenic sources (e.g., welding, power lines), within WUI contexts. Emphasizes metallic particles, smoldering/flaming studies, and experimental findings to understand ignition thresholds and fire spread potential.
Cluster 3	Theoretical and Experimental Modeling of Ignition Thresholds	Investigates thermal ignition thresholds by analyzing interactions between single and idealized firebrands with forest fuels under controlled heat flux and delay-time conditions. Combines theoretical and empirical models to characterize ignition propensity.

Cluster 4	Mathematical Modeling of Fire Spread with Random Effects	Covers theoretical wildfire spread models that incorporate random effects such as turbulence and fire spotting using a probability density function to capture stochastic dynamics. Highlights probabilistic modeling approaches, including the level set method, and reaction-diffusion equations for simulating wildfire behavior.
Cluster 5	Firebrand Generation Process and Landscape-scale Wildfire Risk	Integrates firebrand production dynamics with landscape-scale wildfire modeling, supported by a cellular automata model and empirical quantification. Emphasizes fuel type, environmental conditions, and vegetation influence firebrand generation and treats assessment in WUI and heterogeneous landscapes.
Cluster 6	Regional case studies and Fire-Atmospheric Modeling	Focuses on real-world wildfire case studies (e.g., Kilmore East, Black Saturday) and atmosphere-fire coupled models in Australia. Investigates extreme fire behavior, including pyrocumulonimbus clouds formation, long-range spotting, and the influence of climatic and topographic conditions. Emphasize simulation accuracy by integrating high-resolution atmospheric data from the UK Met Office Unified Model.
Cluster 7	Aerodynamics and Experimental Ignition	Investigates the influence of fuel moisture and aerodynamics on ignition probability and combustion dynamics. Focuses on laboratory experiments examining airflow, flaming phases, and spotting distances in European forest fuels.
Cluster 8	Stochastic Firebrand Transport Modeling and Dynamics	Studies the mechanisms of firebrand transport, including the influence of the atmospheric boundary layer, firebrand flight trajectories, landing distributions, and stochastic modeling used to predict firebrand dispersal patterns. Emphasizes the role of aerodynamic characteristics and variation in initial conditions in determining the range and impact of spot fires.
Cluster 9	Wildfire Modeling Gaps and Challenges	Evaluates the limitations and uncertainties in wildfire spread modeling, especially regarding rate of spread (ROS), environmental sensitivity, and database-driven predictions. Highlights the need to address gaps in model performance and reliability in the context of destructive wildfires.
Cluster 10	Firebrand Trajectory and Spotting Submodels	Focus on modeling firebrand trajectories, landing patterns, and recipient fuel interactions. Incorporates stochastic simulation and submodels to improve the accuracy of spot fire prediction within broader wildfire spread models
Cluster 11	Physics-Based Fire Spread Modeling, Model Development, and Parameterization	Develops physics-based wildfire models emphasizing terrain influence, flame behavior, and energy conservation. Combines energy conservation principles with model parameterization for accurate wildfire propagation.
Cluster 12	Experimental and Theoretical Ignition Studies	Combines experimental and theoretical investigations of ignition in natural fuels by hot particles. Includes laboratory studies of cellulose beds, particle

		size/temperature effects, and theoretical modeling of ignition processes.
Cluster 13	Numerical Simulation and Efficiency	Centers on computational wildfire modeling and simulation. Focus on performance accuracy and efficiency of tools such as PhyFires within academic research and simulation results analysis.

Recent literature demonstrates a growing integration of fire ignition processes, firebrand dynamics, and spread modeling across multiple spatial and physical scales. These clusters reveal a progression from micro-level ignition studies to landscape-scale simulations, emphasizing the evolution of fire spotting research into a structured, multi-thematic domain. Clusters 2 and 3 explore ignition processes: Cluster 2 focuses on anthropogenic ignition sources and smoldering/flaming behavior in WUI contexts, while Cluster 3 addresses theoretical and experimental modeling of ignition thresholds for forest fuels.

Clusters 1 and 5 emphasize the generation of firebrands and the spread of fire in complex environments. Cluster 5 examines firebrand production and wildfire risk at the landscape scale, supported by empirical studies and cellular automata modeling. Cluster 1 highlights urban and WUI fire spread, including model validation and secondary fire development. Clusters 7 and 12 investigate experimental ignition dynamics, focusing on airflow, moisture content, and fuel characteristics under laboratory conditions. Clusters 4, 8, and 10 advance stochastic modeling of wildfire spread, incorporating turbulence, atmospheric boundary layer effects, firebrand transport, and probabilistic submodels to improve spotting predictions. Cluster 6 integrates fire–atmosphere coupled modeling with real-world case studies (e.g., Black Saturday), utilizing high-resolution simulations from the UK Met Office Unified Model (with a horizontal grid spacing of less than 0.6 km to resolve boundary-layer circulations that influence wind variability and firebrand lofting [114]). Finally, clusters 9 and 13 address modeling gaps and computational challenges, highlighting the need to improve the rate of spread estimation, environmental sensitivity, and overall model efficiency in operational wildfire situations.

Despite these advances in research, several gaps persist. A notable limitation is the lack of validation using real-time field data, which is essential for assessing the operational robustness of many models. Integrated frameworks that combine ignition, transport, and propagation remain underdeveloped, particularly in urban contexts where dynamic spotting and suppression strategies are critical. Furthermore, modeling of mixed urban–natural fuel environments is still limited, and the development of scalable stochastic transport models for real-time prediction is urgently needed to support decision-making in rapidly evolving fire scenarios.

3.3. Evolution of Fire Spotting Research: Publication Trends and Key Studies Areas

This section addresses RQ3 by analyzing growth, geographic distribution, and research focus on fire spotting studies. Statistical analyses and visualizations offer an overview of key modeling trends, illustrating how research output has evolved over time. The geographic distribution of contributions highlights the global research landscape, while the number of publications per country offers insight into regional research output. Thematic analysis identifies the dominant topics within the field, and the evolution of publications illustrates the growth and development of spotting modeling studies.

Figure 7 presents a comprehensive visualization of scientific contributions, organized by the corresponding author's country, which combines geographic distribution and ranking of published papers from 2000 to 2023. Countries are color-coded according to the number of publications or co-authored papers, with darker shades indicating higher output levels. The United States leads with 32 publications, underscoring its central role in research on empirical analysis, fire spotting dynamics, and wildfire propagation modeling. Australia follows with 18 publications, reflecting its significant investment in research on wildfire science and environmental resilience, likely driven by recurring catastrophic bushfires. Spain (15) highlights Europe's growing engagement, while Canada (9), China (6), Portugal (6), and France (5) demonstrate active participation from Western Europe and parts of East Asia. Japan, Chile, and Greece each contribute three or two publications, making them emerging regional centers of specialized research.

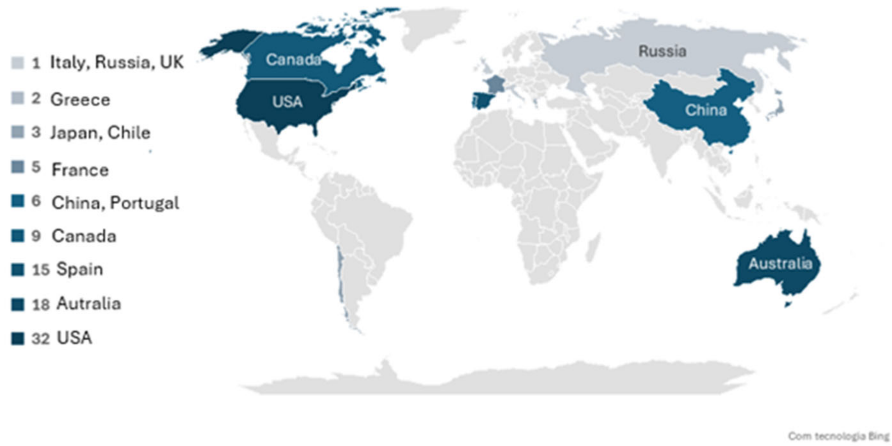

Figure 7. Geographic distribution and number of contributions by country (2000–2023).

However, Figure 7 also reveals geographic disparities. Much of Africa, South and Southeast Asia, and parts of Eastern Europe are either absent or minimally represented in the dataset. This lack of representation may result from limited research funding, infrastructural constraints, or lower visibility in indexed databases, presenting opportunities for international collaboration and capacity building.

The quantitative distribution of publications further supports these observations. The United States is the dominant global research hub, followed by Australia and Spain, which demonstrate strong academic engagement. Mid-tier contributors, including Canada, China, Portugal, and France, actively address related themes, often supported by climate adaptation or forestry programs. Countries with fewer than five publications, including Japan, Chile, Greece, the United Kingdom, Russia, and Italy, may be in the early stages of research development in this field or contribute more indirectly through international co-authorships not fully reflected in author affiliation data.

Figure 8 categorizes scientific publications in fire spotting research, highlighting diverse thematic focuses. The most significant areas are the integration of fire spotting in fire spread models and empirical research, each accounting for 24.51%, emphasizing advancements in predictive fire behavior. Firebrand transport accounts for 17.65%, reflecting its significant role in fire spread dynamics, while ignition process studies, which examine how firebrands initiate new fires, constitute 14.71%, highlighting a crucial aspect of fire spread. Firebrand generation and fire spotting incorporation in operational fire spread tools represent 4.90% and 3.92%, respectively, indicating specialized or emerging areas. Physics-based fire spotting models (including multiple spotting phases) are less frequently studied, accounting for 3.92%, suggesting their complexity or early-stage development. This distribution highlights prevailing research priorities in fire spotting, emphasizing the consolidation of conceptual frameworks, the integration of fire spotting into existing or new fire spread models, and the empirical validation of these approaches. It also reveals gaps and opportunities for further development, particularly in firebrand generation, incorporating fire spotting into operational models, and developing physics-based spotting models.

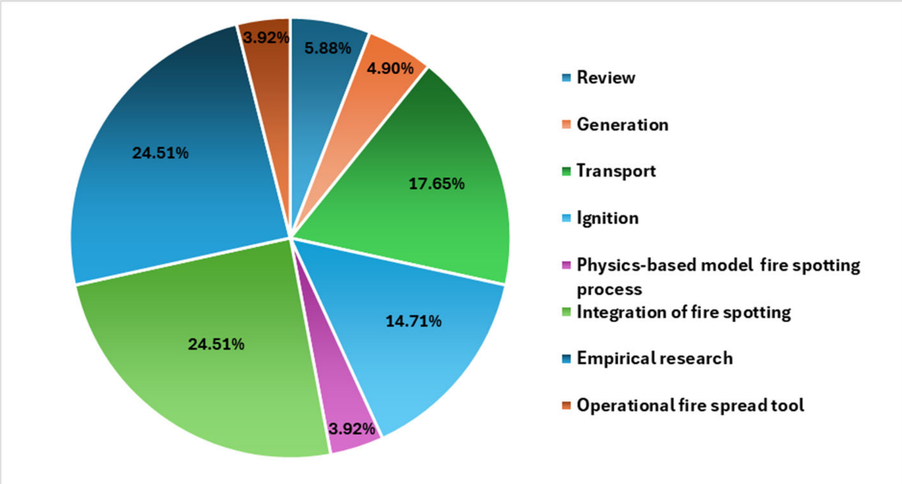

Figure 8. Distribution of research focus areas in fire spotting modeling (102 studies).

Figure 9 shows the annual number of publications from 2000 to 2023. Between 2000 and 2006, publication activity remained minimal, with no more than one paper published per year. A gradual increase is observed beginning in 2007, followed by a notable upward trend from 2010 onwards. Peaks in output occurred in 2011, 2014, 2017, 2019, and 2022, with the latter reaching the highest volume, comprising 12 publications. Although fluctuations are evident, the overall trend suggests a growing academic interest in the topic, particularly over the last decade. The decline in publication output observed in 2013 (1 publication) and again in 2018 (3 publications) contrasts with higher productivity in the surrounding years, possibly linked to shifts in research funding priorities or thematic focus within the field. Despite the variability, the sustained increase after 2010 reflects a maturing and expanding research domain.

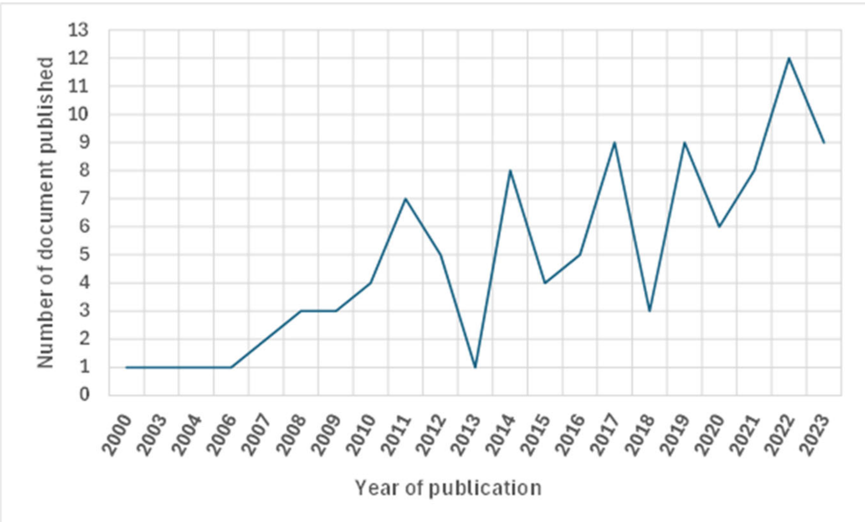

Figure 9. Annual publication trends in fire spotting research (2000–2023).

4. Discussion

This section addresses RQ4 by synthesizing key findings from the reviewed studies and identifying recurring knowledge gaps or underexplored areas in fire spotting modeling. Building on the thematic focus areas outlined in Table 7, the discussion integrates insights from the literature to highlight prevailing research trends, methodological limitations, and opportunities for future investigation.

4.1. Key Findings and Research Gaps in Fire Spotting Modeling

Several review studies identified in this Systematic Literature Review (SLR) provide a comprehensive assessment of the fire spotting process, focusing on firebrand generation, transport, ignition mechanisms, and wildfire propagation. These studies emphasize the critical role of firebrands in wildfire spread and predictive modeling. Pastor et al. [45] established a fundamental classification of wildfire models, tracing their mathematical evolution since the 1940s and demonstrating how predictive accuracy has improved the integration of GIS and multi-model approaches. Meanwhile, Or et al. [47] provide a comprehensive review of wildfire dynamics, categorizing major modeling approaches while focusing on physical processes, fire spotting influences, and environmental impacts, particularly those related to soil and hydrology. Fernandez-Pello [52] emphasized the need for enhanced modeling tools to assist land managers in wildfire suppression, fuel treatment, and evacuation planning. Similarly, Koo et al. [28] analyzed firebrand transport and combustion models, emphasizing the need for empirical approaches and refining predictive models for fire spotting distances. Their findings support the development of advanced firebrand transport simulations to enhance wildfire spread modeling. Rego et al. [53] reviewed firebrand studies on generation and transport, identifying spotting as a multiple-stage process involving firebrand generation, lofting, transport, and ignition of unburned fuel. Key factors such as wind and fuel moisture play critical roles in spotting. Small firebrands from pine and eucalyptus are more prone to ignite fuel beds, with size and weight influencing their ignition potential. According to Rego et al. [53], firebrands' density decreases exponentially with distance from the main fire, affecting the likelihood of ignition in unburned areas. Despite significant progress in understanding the fire spotting process, key gaps remain in accurately modeling the behavior of firebrands. Computational Fluid Dynamics (CFD) models used in wildfire applications are constrained by limited physical input data, such as firebrand generation rates, lofting behavior, and combustion characteristics, as well as the high computational cost required to simulate fire dynamics at adequate spatial resolution across large domains. Wadhwani et al. [33] emphasized the need for target studies to enhance CFD modeling and parametric assessments for firebrand transport. Integrating these findings into GIS-based wildfire prediction tools could improve model prediction. However, CFD models remain underdeveloped, requiring further parametric studies to enhance the predictability of fire spread and inform mitigation strategies. Additionally, more research is needed on specific aspects of firebrand dynamics, including their generation rate, size distribution, and transport mechanisms, to refine fire spotting models and improve wildfire risk assessment.

4.2. Firebrand Generation

Understanding firebrand generation is essential for predicting wildfire spread and spotting behavior. Several studies have investigated different aspects of this process using semi-empirical ([54,56,58]), hybrid [57] and empirical [55] modeling approaches. According to Wickramasinghe et al. [58] study, the firebrand generation rate was 3.22 pcs/MW/s (pcs-number of firebrand pieces) for single tree burning and 4.18 pcs/MW/s for forest fire models, emphasizing the role of wind, vegetation type, and fuel moisture content. Tohidi et al. [56] demonstrated that laboratory-scale firebrand generation experiments are reasonable analogs for wildfire conditions. They characterized the firebrand size and shape distributions of firebrands from coniferous trees. The surface area scales with mass to the 2/3 power, with combustion mechanism and limb failure influencing firebrand size more than tree height. Caton-Kerr et al. [54] investigated the mechanical behavior of thermally degraded wooden dowels, confirming that breakage mechanisms are governed by recoverable elastic strain during loading. Their findings contribute to the formation of a comprehensive failure theory for wood subjected to thermal degradation under simultaneous wind loading conditions. Using a hybrid model approach that combined stochastic, probabilistic, and semi-empirical methods, Thomson et al. [57] estimated fire spot rates. Their findings highlight the effectiveness of this methodology, which works with and without barriers, assessing wildfire risk under various conditions, and proves practical for real-world applications. Expanding the scope of empirical modeling, Jha & Zhou [55] introduced machine learning (ML) techniques to predict firebrand production. Their results validate the K-Nearest Neighbors (KNN) model, which achieved over 90% accuracy in predicting firebrand real mass density (FAMD) and firebrand number density (FAND), providing the value of ML-driven approaches for modeling and numerical simulation of firebrand generation.

4.3. Firebrand Transport

The firebrand transport phase has been evaluated using empirical, semi-empirical, and theoretical approaches. Among the 18 studies, five applied an empirical approach ([37,59,61,62,130]), eight employed semi-empirical approach ([60,64,65,131–135]), and four used a theoretical approach ([63,66,67,136]]). Additionally, only study [43] utilized a stochastic model. Various models, ranging from statistical-empirical to physical-mechanistic, have been implemented using these approaches. The most frequently applied models are physical-mechanistic models, statistical-empirical models, and semi-physical models, as observed in the 18 studies investigating the firebrand transport phase.

Ellis [37] investigated the aerodynamic behavior of jarrah and karri bark flakes, identifying their low terminal velocities (2.5 to 8 m/s) and rapid spin as key factors in their lofting within a convection plume generated by low to moderate-intensity fires (0.5 to 2.5 MW/m). Terminal velocity was influenced by bark flake shape, spin, and surface density, with rapid spinning reducing descent speed by up to 18% compared to non-spinning flakes. Spotting behavior was further driven by bark traits, ignition ease, number of detachable flakes, combustion during flight, and free-fall dynamics. Almeida et al. [62] emphasized the influence of particle orientation, flow velocity, and combustion regime on firebrand combustibility, demonstrating their effects on flaming and smoldering durations, as well as maximum spotting distance. Page et al. [130] analyzed spotting distance during the 2017 fire season in the USA, showing that maximum spotting distances increased with the combined effects of wind speed and fire growth, but decreased with fire perimeter shape, canopy height, and terrain steepness. Most spotting distances were ≤ 500 m; the medium-range spotting (1–3 km) was rare, with high wind and rapid fire growth increasing the likelihood of exceeding 1 km. High wind estimates also improved Albini's model by reducing the underprediction of spotting distance. Storey et al. [59] identified source fire areas as the primary driver of long-distance spotting (greater than 500 m), with weather, vegetation, and topography as secondary influences. Spotting distance and the number of long-distance spot fires increase significantly with larger source fire areas combined with strong winds, dense forests, and steep slopes, highlighting the need for improved bark spotting maps in wildfire modeling. Cruz et al. [61] developed an empirical-based wildfire spread model, reporting 35–46% errors during development, with improved accuracy for spread rates above 2 km/h. However, long-range spotting remains uncertain due to complex fire–atmosphere interactions, potentially leading to underprediction.

Tohidi & Keye [131] emphasize the importance of full six degrees of freedom (6-DOF) aerodynamics, encompassing three translational and three rotational motions, in accurately simulating firebrand trajectories. Their experimental dataset enhances the prediction of rod-like debris flight and addresses limitations in previous estimations of spotting distance. Song et al. [64] observed a bimodal distribution of burning and extinction modals in small firebrands, demonstrating that critical wind speed affects transport distance and mass loss, which aligns with experimental data. Oliveira et al. [135] found that the initial aspect ratio and orientation of cylindrical firebrands significantly influence their trajectories and travel distances, emphasizing the importance of incorporating oscillations and rotational motions for accurately predicting fire spread by spotting. Thurston et al. [60] demonstrated that turbulent plume dynamics (TPD) significantly influence long-range spotting, doubling maximum spotting distances compared to nonturbulent plumes. TPD also controls both lateral and longitudinal firebrand dispersal, reinforcing the need to incorporate TPD parametrizations into fire spread models for greater accuracy and physical fidelity. Koo et al. [132] demonstrated that firebrands travel farther when terminal velocity assumptions are not applied. Burning dynamics shape their lifetimes, thin disks burn on their faces, while cylinders burn around their circumference. Canopy firebrands exhibit longer travel distances than those from surface fires, with coupled fire–atmosphere interactions significantly affecting their trajectories and landing patterns. Mendez & Farazmand [133] applied Large Deviation Theory to efficiently quantify rare landing events (l-probability events at the tail of the landing distribution) with low computational cost, highlighting that a hybrid approach, incorporating Monte Carlo and Importance Sampling methods, improves wildfire spotting predictions. Their work supports enhanced modeling of landing distributions, especially in frameworks such as cellular automata and non-local transport (birth-jump) models. Albini et al. [134] developed a mathematical model to estimate maximum spotting distances from crown fires, integrating empirical data with simplified physical principles. Himoto & Tanaka [65] validated a physics-based urban fire spread model, showing alignment with the Hamada model for fire spread rates and confirming firebrand scattering patterns. These studies demonstrate the versatility of semi-empirical models in capturing the complex behavior of firebrands, thereby improving fire spread predictions and refining distance estimations.

Pereira et al. [63] found that maximum spotting distances align with the Albini model but underpredict high-intensity fires by 40%. Smaller particles travel farther due to buoyancy and lower char content, with deposition following an inverted exponential pattern. Sardoy et al. [66] demonstrated that firebrand landing behavior depends on density and thickness, while those lingering in the thermal plume travel distances independent of diameter, correlating with wind speed and fire intensity. Anthenien et al. [136] analyzed the effects of firebrand shape, showing that disks travel the farthest while burning, whereas spheres travel the shortest. Charring lowers density, increasing travel distances for spheres and cylinders, while ember distance scales linearly with wind speed. Bhutia et al. [67] compared plume models and coupled fire–atmosphere Large Eddy Simulation (LES) approaches, demonstrating that fire spotting within the Atmospheric Boundary Layer (ABL) exhibits probabilistic behavior, with higher release heights increasing the downwind distances. LES results remain preliminary and require further validation. Tohidi & Keye [43] developed a stochastic model that accurately predicts firebrand flight statistics, highlighting the nonlinear and highly variable nature of spotting distributions due to initial and boundary wind conditions. They also concluded that lofting is inherently linked to downwind distance and cannot be decoupled.

4.4. Ignition Phase

Across 15 studies focus on the firebrand ignition phase, two followed theoretical approach ([76,81]), ten employed semi-empirical approach ([68–73,75,77,78,82]) and three ([74,79,80]) applied empirical approach. The most frequently applied models are semi-physical and statistical-empirical. Ganteaume et al. [80] conducted an empirical study to evaluate the flammability of fuel beds composed of grasses, litter, and bark samples, as well as the ignition capability of firebrands. Their findings indicate that grasses are more flammable than litter, with Pinus species being the most flammable among the litters. Increased bulk density and fuel moisture content delay ignition and reduce other flammability parameters. They observed that flaming firebrands exhibited higher ignition frequencies in still air, whereas glowing firebrands require airflow to achieve ignition, highlighting how both the combustion phase and wind conditions influence ignition. Additionally, ignition probability of the fuel bed depends on the type or weight of the firebrand, with cone scales of *Pinus pinaster*, *P. halepensis*, and *Eucalyptus globulus* leaf and bark exhibiting at least twice the ignition probability of Pine bark when falling in the flaming phase. These results highlight the impact of firebrand composition, size, and combustion state on ignition dynamics. Yang et al. [74] investigated spot fire ignition probability (IP) of larch fuel beds exposed to different firebrands under varying wind speeds and moisture content (MC) conditions. The study found that IP was zero without wind, and that both MC and wind speed strongly influenced IP, whereas packing ratio had little to no effect within the experimental ranges tested. Firebrand ignition occurred even at a high MC of 50%, with IP increasing with wind speed and decreasing with MC. Among the tested fuel bed properties, firebrands such as cones showed the highest IP, followed by large and small twigs, which were affected by their shape and size. Two empirical models linked IP to fuel bed properties and wind speed. These findings contribute to clarifying the spot ignition mechanism, reducing associated losses. Urban et al. [71] evaluated the ability of firebrands to produce smoldering ignition in a moist natural porous fuel bed (coastal redwood sawdust). The authors determine the minimum conditions of ignition (ignition boundaries) under which different fuel moisture contents (FMCs) can undergo smoldering ignition when exposed to single glowing wood firebrands of varying sizes. Their results show that the larger firebrands can ignite sawdust with higher FMC, with 40% being the maximum FMC at which ignition occurred. Firebrands smaller than 3.17 mm in diameter failed to initiate ignition even in dry sawdust. The ignition boundary predictions from the energy model align qualitatively with the results of multivariate logistic regression. Meanwhile, Álvarez et al. [77] employed an electric heater as an idealized firebrand to determine the ignition delay time of Eucalyptus globulus leaves. Their model effectively predicted ignition delay times across different volume fractions but exhibited limited accuracy in temperature evolution due to large variability in eucalyptus leaves. Viegas et al. [79] analyzed the ignition behavior of Mediterranean fuel beds exposed to different firebrands, including pine and bark. Ignition occurred exclusively with flaming firebrands under no-wind conditions, with the fuel bed's moisture content determining both ignition probability and time delay. Fuel bed properties had more influence on ignition behavior than firebrand characteristics. Time delay ranged from 1 to 12 s for flat eucalyptus bark, less than 20 s for *Pinus pinaster* cones, and under 5 s for *Pinus halepensis* cones, highlighting the critical role of fuel morphology and water retention. Another study by Yin et al. [75] examined the relationship between ignition time and moisture content (MC) for pine needles attacked by glowing firebrands. They found a linear relationship between the square root of ignition time ($\sqrt{t_{ig}}$) and MC, validated through six groups of firebrand ignition experiments. The tests were conducted on pine needles with MCs ranging from 12.9% to 65% were tested at a wind speed of 3 m/s (±0.2 m/s). This supports earlier findings that fuel moisture suppresses ignition and can serve as a predictive variable for delay modeling. Valenzuela et al. [78] developed and validated an analytical model to assess the ignition of wildland fuels exposed to a time-decreasing incident heat flux. Their results demonstrated that ignition delay times increase with steeper negative slopes of the heat flux. Each initial incident heat flux value corresponds to a critical slope (β_{cri}) below which ignition is possible. If the slope exceeds this critical value, ignition does not occur.

Fang et al. [73] evaluated how the combined effect of thermal radiation and hot metal particles influences the ignition of a pine needle fuel bed. Their study found that ignition probability significantly increases when both heat sources are present. Larger particle sizes and higher temperatures reduce the critical radiation flux required for ignition. Additionally, ignition delay time decreases as the radiation heat flux increases. The researchers identified a clear linear relationship between the critical radiation heat flux and the parameters of the hot particle, offering a foundational step toward understanding fuel ignition mechanisms driven by the coupled effects of firebrands and flame radiation. Fernandez-Pello et al. [68] investigated the ignition of natural fuel beds using hot particles, embers, and sparks. Their results revealed a hyperbolic relationship between particle size and temperature, with larger particles requiring lower temperatures to ignite the fuel bed than smaller ones. Both energy and temperature determine ignition capabilities, with smoldering ignition being more easily achieved than flaming ignition. Flaming ignition can occur if the ember is flaming and air velocities are moderate, whereas sparks require an accumulation interaction for ignition. Hadden et al. [82] employed a semi-empirical approach to investigate the ignition mechanisms in homogeneous cellulose fuel beds ignited by hot spherical steel particles in wildland fires. Their results show that smaller particles require higher temperatures to achieve ignition, confirming that the ignition propensity depends on both particle size and temperature. There is no unique correlation between particle energy and ignition propensity. The Hot spot ignition theory agrees qualitatively, but not quantitatively, with experimental results. Scott et al. [69] also developed a semi-empirical model for the ignition of powdered cellulose and pine needles fuel beds by hot spherical steel particles. The model predicts a qualitative relationship between the particle size and the temperature required for flaming or smoldering ignition of the studied fuel beds. It shows that smaller particles require higher temperatures for ignition, aligning with the size-temperature relationship seen in earlier work in [82]. Urban et al. [70] investigated smoldering spot ignition of powdered natural fuels by a single hot metal particle (stainless steel and aluminum). Their results showed that the ignition boundary for flaming and smoldering ignition exhibits a hyperbolic relationship between particle size and temperature, with smaller particles requiring higher temperatures to ignite. Smoldering ignition occurs at lower temperatures than flaming ignition for both metal particles. The simplified numerical model qualitatively aligns with experimental results, providing insight into the smoldering ignition process and the impact of particle melting. Zhu & Urban [72] introduced a novel concept of cooperative ignition, evaluating how the thermal interaction of two nearby heaters (representing idealized firebrands) influences fuel bed ignition dynamics. Their findings suggest that smaller heaters require higher heat fluxes to ignite the fuel. Placing a second heater in close proximity accelerates ignition by reducing the threshold heat flux needed for ignition. Using numerical modeling, the study highlighted the importance of thermal interactions in the flaming ignition process. It investigated a range of firebrand sizes (5–50 mm) and separation distances, capturing qualitative ignition behaviors and showing quantitative agreement in most cases.

Two theoretical studies [76,81] employ physics-based modeling to investigate ignition processes in wildland fuels, offering detailed mechanistic insights into soldering and flaming ignition scenarios, respectively. Lin et al. [76] developed a physics-based 2D computational model to assess the smoldering ignition of typical solid fuels exposed to a localized irradiation spot. Their analysis revealed that the ignition time decreases as the radiant heat flux increases, while the minimum flux required for ignition increases as the irradiation spot diameter decreases. For spots under 20–50 mm, traditional assumptions of constant ignition temperature and fuel-burning flux were invalid. Thermally thin or thick fuel dimensions are not applicable for smoldering spot ignition due to significant radial conductive heat loss. The minimum irradiation for smoldering ignition increases with fuel thickness, whereas the moisture content has a minimal impact. Matvienko et al. [81] introduced a 3D computational model to simulate flaming ignition in a fuel bed impacted by glowing wildland firebrands. Their results revealed that pine bark samples failed to ignite the fuel bed (FB) under all tested conditions. In contrast, pine twigs ignited the FB at bulk densities ranging from 60 to 105 kg/m^3 and airflow velocities ≥2 m/s. The mathematical model shows that a single pine bark firebrand, ≤5 cm long and heated to ≤1073 K, does not produce flaming ignition. Only larger and hotter particles demonstrated the capacity to ignite the adjacent FB layers in flaming mode, with the firebrand length identified as a major factor in ignition initiation. The model accurately predicts ignition times, aligning with the observed results.

4.5. Physics-Based Fire Spotting Models

Understanding fire spotting mechanisms is critical for analyzing wildfire propagation and assessing ignition risk in both forested and urban interface environments. Among 102 selected studies, only four fully address three or more phases of the fire spotting process. Of these, two applied a theoretical approach ([83,85]), while the other two employed a semi-empirical approach ([29,84]). According to the newly adopted model classification, two studies employed physical-mechanistic modeling ([29,83]), one applied statistical-mechanistic modeling [85], and one utilized a semi-physical model [84].

Hillen et al. [83] used the birth-jump model, represented by nonlinear integro-differential equations, which is particularly valuable for analyzing complex and dynamic phenomena where growth and spatial spread are interdependent. They evaluated birth-jump processes in the context of forest fire spotting, demonstrating that increased firebrand spotting rates accelerate the spread of the wildfire front. The study found that higher spotting rates reduce the minimum domain size required for fire propagation and increase the minimum invasion speed (the lowest rate at which the fire can spread) under both constant and no-wind conditions. A larger initial spotting spread (variance ds (0)) increases these effects, indicating that fire spotting is a key driver in escalating fire spread velocity. In a study by Martin & Hillen [29], which evaluated the spotting distribution of wildfires, a physical-mechanistic model offers insights into fire spread, management, and breaching. The model is based on detailed physical processes of fire spotting, including fire plumes, firebrand launching, wind transport, falling and terminal velocity, combustion during transport, and ignition upon landing.

In the numerical study of ground-level distribution of firebrands generated by line fires, Sardoy et al. [85] applied a statistical-mechanistic model revealing that firebrands follow a bimodal landing distribution, characterized by short-distance flaming and long-distance charring firebrands. The normalized mass of flaming firebrands correlated with flight time, posing greater fire danger due to frequent ground impact and remaining mass. Short-distance distributions followed a lognormal distribution, allowing for incorporation into fire propagation models and providing key parameters to describe the separation between the short- and long-distance landing regions, as well as to determine the combustion state of firebrands, whether they burn in the air or land on the ground. Masoudvaziri et al. [84] shifted the focus toward community-level application with the SWUIFT model, which tracks fire spread across wildland–urban interface (WUI) areas via radiation and spotting mechanisms. The model is computationally efficient and accurately predicts the fire spread rate and the number of affected structures in WUI communities.

4.6. Fire Spotting Integration of New or Existing Fire Spread Models (FSM)

A total of twenty-five studies have addressed the integration of fire spotting in new or existing FSM frameworks. These studies span a range of modeling, categorized under the new model classification as follows: eight studies ([44,90,93–97,104]) employed a hybrid model approach/semi-physical model, that combines physical principle with stochastic or empirical components. Another seven studies took a semi-empirical approach/semi-physical model ([20,21,42,91,92,98,103]). Nine applied cellular automata (CA) frameworks/Other models ([51,86–89,99–101,105]), using CA-based models (CA2, CA3 and hybrid CA) or probabilistic transitions to simulate fire spread and spotting behavior. Only one study [102] adopted the theoretical approach/ physical-mechanistic model.

Trucchia et al. [42] and Pagnini & Mentrelli [91] contribute to the refinement of fire simulation models by incorporating stochastic elements and surrogate modeling techniques. Trucchia et al. [42] evaluated the merits of sparse surrogates for global sensitivity analysis of multi-scale and nonlinear problems, particularly in applications involving turbulence and fire-spotting models within wildland fire simulators. Their findings highlight wind as a dominant factor in the generation of secondary fires (spot fires), with wind magnitude and the long-distance parameter (which controls the tail of the density function related to firebrand landing distance) identified as key variables in fire propagation and spotting. These results confirm that fire spotting is a wind-driven, ballistic phenomenon. Moreover, the Least-Angle Regression (LAR)-based Generalized Polynomial Chaos (gPC) surrogate enables the filtering of parameters with large length scales, supporting the conclusion that sparse surrogates are a promising strategy for analyzing new models and their sensitivity to input parameters in wildfire applications. Pagnini & Mentrelli [91] propose a hybrid framework that combines a randomized level set method with reaction-diffusion equations to improve the simulation of fire dynamics, including the modeling of firebreak crossings. The incorporation of randomization effectively captures the stochastic nature of fire propagation, accounting for turbulent heat convection and fire spotting, although the results remain at the proof-of-concept stage. Their earlier work [92] simulates turbulent convection effects and accounts for accelerated fire spread due to hot-air preheating and the landing of an ember. It also improves the prediction of fire front dynamics, including flanking and backing fires, areas where traditional models often fall short. Additionally, the model corrects the rate of spread (ROS) formula based on firebrand jump lengths, offering a more realistic representation of downwind fire spread. Like their last study, this work is also a proof-of-concept and requires future validation. Mentrelli & Pagnini [103] further validate the effectiveness of randomized level set methods in enhancing fire front localization and spread prediction, particularly in the presence of fire breaks. Their numerical simulations highlight the crucial role of fire spotting and turbulence in improving front propagation predictions. Asensio et al. [98] focus on operational enhancement through the development of the PhyFire model, integrated into an online GIS-based wildfire simulation tool. By automating complex data input and incorporating a fire spotting module, the model improves both accessibility and simulation accuracy. This integration streamlines the simulation process and enhances the model's ability to accurately represent real-world wildfire propagation. Zigner et al. [20] evaluate the performance of the FARSITE model in simulating wildfires under extreme, downslope wind conditions in Santa Barbara, California. While FARSITE effectively reconstructs fire spread when spotting is minimal, its predictive accuracy declines during rapid downslope spread scenarios due to the presence of spotting. Limitations in modeling slope orientation and estimating firebrand trajectory affect its performance, highlighting the need for improved representation of ember launch and landing dynamics during extreme wind events. Loepfe et al. [21] present a comprehensive model that uniquely integrates explicit human influence, making it a valuable tool for assessing climate change impacts and guiding local fire regime management. Additionally, their integrative model of human-influenced fire regimes and landscape dynamics accurately reproduces fire regimes, land cover changes, and tree biomass in northeastern Spain.

Pagnini [93] laid foundational work by showing how fire spotting and turbulence variability introduce randomness in fire front advancement. The results demonstrate that fire spotting is a significant factor in downwind fire propagation, and that variability in ember jump-length and mean wind direction influences fire advancement. Nishino [104] extended this understanding to urban environments by applying a physics-based urban fire spread model, demonstrating that stochastic spot fire modeling can accurately simulate real-world events such as the Itoigawa fire in Japan. These findings offer valuable insights for firefighting strategies in dense wooded urban areas with strong winds. In Spain, two studies by Egorova et al. examined the role of atmospheric stability [90] and the impact of flame geometry and slope [92] on fire spotting behavior and wildfire propagation, employing a hybrid modeling approach. The findings in [94] reveal that unstable atmospheric conditions increase the number of fire spotting and enhance turbulence, leading to rapid merging and the formation of unburned islands. In contrast, stable conditions limit turbulence, resulting in more independent fires but a lower burned area. With stable conditions, fewer fire fronts need to be managed in the short term; however, more independent fires exist compared to unstable conditions, which pose a higher risk due to the potential for merging fires. The numerical results from [96] demonstrated that the flame length is a significant factor in the fire spotting model, with longer flames leading to increased landing distances for firebrands and a higher likelihood of igniting independent fires. The presence of a slope accelerates the fire rate of spread by promoting the rapid merging of these independent fires. Fire spotting cannot be neglected in simplified fire-spread models used in operational software. Meanwhile, Egorova et al. [95] proposed a physical parameterization of fire spotting, determining the rate of fire propagation spread by considering flame geometry, horizontal mean wind, and terrain slope. Their findings affirmed a 2/3 power-law relationship between flame height and fireline intensity, reinforcing the importance of geometric parameters in modeling spot fire generation. Similarly, in a physical parametrization study of fire spotting by Trucchia et al. [44], RandomFront2.3 was introduced as a computationally efficient model that integrates fire intensity, wind conditions, and firebrand characteristics in relation to fire spotting behavior and analyzes the interactions between secondary fires and primary fires. Its implementation in WRF-SFIRE and LSFire+ demonstrates promise for operational scalability and real-time predictions of fire spread. Simulation showed varying contributions of firebrands to fire perimeter growth under different conditions, aligning with the physical processes observed in wildfires. The model's simplicity, due to its physical parameterization, makes it computationally less expensive and versatile for integration into large-scale operational fire spread models.

Kaur et al. [97] assessed the effects of turbulence and fire spotting in wildland fire simulators using a hybrid model approach. They compare the performance of Lagrangian (Discrete Event System Specification, DEVS) and Eulerian (Level Set Method, LSM) moving interface methods for wildland fire propagation. Both models performed comparably, with differences primarily attributed to the geometry of propagation direction. To model the fire-front motion, the study distinguished between two components: the drifting part, which captures the deterministic, directional advance of the fire front (modeled by DEVS and LSM), and the fluctuating part, which accounts for random phenomena such as turbulence and fire spotting that introduce stochastic variability into fire behavior. The validated DEVS-based wildfire model demonstrated improved performance by accurately reproducing fire behaviors, including flank and backfires, increased fire spread due to pre-heating, fire propagation across non-fuel zones, and secondary fire generation. The proposed formulation is versatile and independent of the method used to determine the drifting component, supporting its integration into simulators like WRF-SFIRE and ForeFire. The firebrand landing patterns have a significant impact on wildfire propagation dynamics and potential secondary ignitions. Zohdi [90] proposed a machine-learning framework for rapid adaptive digital-twin-based fire-propagation simulation in complex environments. This innovative approach was designed for mobile and laptop platforms. The system enables real-time responsiveness, making it particularly suitable for first responder applications. The framework integrates multistage submodels for ember trajectory, topography, and machine learning algorithms to simulate both ground and airborne fire spread. It accounts for hot-ember-driven propagation, debris distribution, and air-quality impacts, offering a comprehensive tool for dynamic fire behavior modeling.

Cellular automata (CA) models simulate local fire spread and the fire spotting effect by representing the landscape as grids of cells in different states, including burning, unburned, or burned. These states update at each time step based on predefined transition rules that incorporate neighboring cell interactions, using deterministic, probabilistic, or stochastic approaches to replicate fire dynamics. One of the earliest applications of the probabilistic CA approach to explicitly integrating fire spotting in wildfire research was introduced by Hargrove et al. [89] in 2000. Their model, EMBYR, employed a probabilistic model that combined adjacent cell spread, fuel characteristics, wind dynamics, and firebrand distribution, effectively capturing spotting behavior in heterogeneous landscapes. The study examined fire spread patterns using a CA2 model with percolation-like thresholds. It revealed how fire behavior shifts drastically near critical values of fire spread probability (I). At low I values, fires exhibited slow, dendritic patterns, while higher values produced rapid, solid spread. A critical threshold (I_c) was identified between 0.250 and 0.251, indicating a 50% chance of fire spreading by the adjacent spread alone. When $I = 0.30$, the inclusion of firebrands significantly accelerates spread, underscoring the need for better empirical data on fire spotting. Additionally, they demonstrated how fuel heterogeneity at the landscape scale influences fire patterns and risk, using the cumulative distribution of burned areas to quantify these effects. These findings highlight the variability and uncertainties in natural fire systems, as well as the challenges of predicting fire behavior near critical thresholds. Alexandridis et al. [99] developed a CA2 model to simulate the 1990 Spetses Island wildfire in Greece, introducing a new spotting integration technique. The model successfully reproduced observed fire dynamics, demonstrating its potential for predictive accuracy in spatially complex environments. However, the study emphasizes the need for validation on large-scale incidents to confirm its generalizability. Alexandridis et al. [100] extended this approach to mountainous and heterogeneous terrains, incorporating fire suppression tactics alongside spotting behavior. The models effectively captured fire spread dynamics under varied topographic and tactical conditions, supporting their use in the design of fire risk management policies. The integration of suppression strategies marks a step toward operational relevance, bridging simulation with real-world decision-making.

Boychuk et al. [101] introduced a stochastic forest fire growth model that integrates fire spotting into existing deterministic spread models. The model introduces variability in fire growth predictions, enabling the generation of probability contour plots and empirical distributions of burned areas and time to specific events. Krougly et al. [51] developed a stochastic model for generating disturbance patterns across heterogeneous forested landscapes. Using a space-time Markov process, the model predicts fire behavior based on user-defined inputs, with numerical results showing the total impact of disturbances under different initial conditions and scenarios. Masoudvaziri et al. [88] applied a stochastic model with probabilistic rules for risk assessment of Wildland–Urban Interface (WUI) communities. The study compared two case studies, Trails and Fountain Grove, highlighting how fire spotting and radiation influenced ignition patterns. The Trails community experienced a median of 74 structures ignited after 180 min, while Fountain Grove saw 185 structures ignited after 120 min, resulting in near-total destruction. Fire spotting was the primary spread mechanism in Trails, whereas both radiation and spotting contributed significantly to the spread in Fountain Grove. These findings highlight the significant role of community layout and initial ignition patterns in shaping wildfire dynamics and their subsequent impacts. The novel stochastic community model captures uncertainties in fire spread within the Wildland–Urban Interface (WUI) and assesses wildfire hazards and community vulnerabilities for risk evaluation.

Perryman et al. [86] developed a hybrid CA3 model that integrates physics-based fire spread with stochastic firebrand lift-off and dispersal mechanisms. Their simulations revealed that canopy base height and surface fuel loading had more impact on spread than wind speed or fuel moisture. Spot fires increased the spread rate by 6 to 931%, highlighting their critical role in fire management technologies. Danold & Malik [87] introduced a spatially extended radiant heat fire model using a hybrid CA3 framework. The model accurately matched observational data from low-intensity wildfires, capturing prolonged burn times and the persistence of lingering embers. Zhao [105] developed a hybrid CA model adapted for densely built urban environments, using irregular cells to present buildings. The model incorporates scattering as a measure of ignition probability, allowing for a realistic simulation of long-range spotting and urban fire spread. It also includes economic and life loss assessment modules.

Porterie et al. [102] proposed a theoretical, physics-based model using small world network to effectively simulate both forest fire spread through local interactions and fire spotting via long-range interactions. The model incorporates impact parameters to delineate the influence zones of burning sites, capturing both short-range radiative and convective effects of flames, as well as long-range spotting effects from firebrands. By considering the interactions between active (flammable) and inactive (non-flammable) sites, the model identifies critical geometric and dynamic thresholds, which help in understanding the conditions under which fire spreads or remains contained. In homogeneous systems, the presence of firebrands increased the spread rate and spotting distance. In heterogeneous systems, however, disorder diminished the effectiveness of firebrands and reduced the overall spread rate. The model also demonstrated that critical propagation channels could halt fire spread if disrupted.

4.7. Examining Empirical Research (Data-Driven Modeling) for Fire Spotting

Empirical studies have played a crucial role in characterizing firebrand behavior, ignition potential, and spotting dynamics. Across twenty-five studies, several provide quantitative datasets, laboratory and field experimental observations, and retrospective analyses (historical fire data) that directly support the calibration, validation, or formulation of fire spotting and wildfire propagation models.

Adusumilli et al. [106] quantified hot firebrand production across species and heights of the trees, revealing that sagebrush produces more specific hot firebrands for trees with comparable moisture content than ponderosa pine and Douglas-fir. The total number of hot firebrands increases with the height of the tree or shrub burned. The specific hot firebrand production is exponentially dependent on the moisture content of the tree but shows an inconclusive correlation with tree height. Almeida et al. [32] analyzed the physical mechanisms behind firebrand production, particularly from eucalyptus barks under torching conditions, demonstrating their high spotting potential based on size and burning conditions. They emphasized that future tests should include more scenarios, fuels, and additional cameras for accurate 3D analysis. Hudson & Blunck [107] emphasized the role of morphology, showing that sample diameter had the greatest effect on the time to ember generation, followed by the type of fuel. Small-diameter samples were relatively insensitive to changes in other parameters. Natural samples produced embers more slowly than dowels, underscoring the complexity of real-world fuels.

Ganteaume et al. [123] described and characterized firebrand properties based on fire spotting efficiency, showing a 100% ignition frequency for all tested firebrands, but varied in ignition time and flaming duration. Weight loss was exponentially related to time, with a decrease in the ratio of weight at temperature T to the initial weight as temperatures increased. Fuel moisture content has a significant impact on ignition time, flaming duration, combustion, and thermal decomposition. Three firebrand groups based on spotting efficiency were identified: heavy firebrands capable of sustaining flames (pine cones) for long-distance spotting; light firebrands with high surface-to-volume ratio (leaves and thin barks) for short-distance spotting; and light firebrands with low surface-to-volume ratio (other types) for short and occasionally long-distance spotting. Suzuki & Manzello [124] analyzed the characteristics of firebrands and quantified their production from actual urban fires in Japan, finding that over 60% of firebrands weighed less than 0.1 g and had an area smaller than 2 cm^2, with size and mass independent of their location. These results matched previous studies and laboratory-generated firebrands.

Filkov & Prohanov [111] developed a thermal imaging-based software to detect and track firebrand density distribution near the fire front, focusing on short-distance landing patterns and the merging of distinct fires in turbulent environments. The software achieved a maximum relative error of 12% for firebrand counts under 30. Their analysis showed that fireline intensity below 12,590 kW m^{-1} has a minimal effect on 2D firebrand flux, although occasional crowning events increase it. Firebrand size ($\geq 20 \times 10^{-5}$ m), temperature, and velocity were identified as key parameters for understanding the ignition process and fire propagation in communities. Future work aims to enhance small firebrand detection and tracking by utilizing stereo infrared (IR) imaging for 3D distribution mapping. Thompson et al. [119] applied an innovative proof-of-concept technique using acoustic analysis of in-fire cameras to detect and quantify firebrand production and travel distance during an experimental boreal crown fire. This semi-empirical approach identified key areas of spotting alignment with peak fire intensity and demonstrated the effectiveness of low-cost instrumentation. The method quantified the number of firebrands landing per square meter, showing clear temporal trends as the fire approached.

Donovan et al. [108] conducted a comparative analysis of spot fire distances in grasslands transitioning to Juniperus woodlands, with maximum spot-fire distance reaching up to 450% in Juniperus woodlands than in grasslands, exposing an additional 14,000 ha to spot-fire occurrences within the Loess Canyons Experimental Landscape. Their findings showed that woody encroachment increases the risk of wildfires. Prescribed fires used to control woody encroachment have lower maximum spot-fire distances and less land at risk than wildfires. Spot-fire distances are significantly higher in extreme wildfire scenarios, especially in encroached grasslands and Juniperus woodlands. Storey et al. [112] used aerial line scan imagery to analyze patterns across 251 wildfires in southeast Australia. Spotting follows a multimodal distribution, with clusters of short-range and isolated long-range spot fires, suggesting that current models, which assume exponential distributions, may underestimate long-distance spotting. A relatively high correlation was found between spotting distance and numbers, showing that wildfires can produce long-distance spots even with a small number of spots. Regional variations were linked to rainfall, topographic ruggedness, and fuel descriptors, with East Victoria identified as the most prone to spot fires. The findings enhance empirical understanding of spotting behavior and wildfire dynamics, extending the value of operational modeling. Future research should incorporate plume and firebrand dynamics to improve insights into spotting processes. Tohidi & Kaye [109] provide controlled laboratory data on lofting and downwind transport of rod-like firebrands. Their experiments demonstrated a strong correlation between maximum rise height and landing location, confirming that lofting and transport are interconnected processes. The sensitivity of firebrand trajectories to velocity field variability, particularly for high-aspect-ratio firebrands, provides valuable validation for transport models used in extreme fire scenarios. Toivanen et al. [116] simulated the Black Saturday Kilmore East fire using the Unified Model with coupled atmosphere-fire dynamics. Their results showed that spotting was essential to match 80% of the observed burnt area, and that a grid spacing of 1.5 km was sufficient for capturing broad fire spread features. However, finer-scale details were lost, indicating the need for higher-resolution modeling to characterize spotting dynamics accurately. Thurston et al. [117] explored the role of boundary-layer rolls in enhancing ember lofting and wind variability. Their simulations revealed that a horizontal grid spacing of less than 0.6 km is necessary to accurately model these effects, which can increase fire intensity and pose risks to firefighting crews. This study emphasizes the importance of atmospheric turbulence in long-range spotting and fire spread.

Hernández et al. [122] investigated the spontaneous ignition of wildland fuel by idealized firebrands. Their findings showed that the inverse of ignition time is linearly dependent on incident radiative heat flux, a behavior typical of thermally thin solid fuels. Additionally, the mass loss rate follows a quasi-linear relationship with incident radiative heat flux. Future work aims to develop thermal models for homogeneous fuels.

Beverly et al. [120] focused on assessing the exposure of the built environment to potential ignition sources generated from vegetation fuel. Using Albini's spotting models, they standardized mapping across Canadian communities. Their analysis showed that the amount, size, and arrangement of ignition-producing vegetation, as well as community morphology and occluding interface zones, influence the spatial patterns of elevated ignition exposure. Ignition exposure levels varied among communities, indicating the need for community-specific mitigation strategies. Storey et al. [118] examined the influence of spot fire and topography interaction on fire rate of spread (ROS). Their experiments demonstrate that spot fires can significantly increase the ROS in hilly terrain, particularly when merging with the main fire. They can overcome low spread potential on downslopes, and models may underestimate ROS and fire arrival times if these effects are excluded.

Filkov et al. [14] present quantitative data on dynamic fire behavior (DFBs) in Australian forest environments. Their analysis reveals that eighty of the 113 fires had one to seven DFBs, with 73% of these fires having multiple DFBs. Spotting, crown fires, and pyroconvective events were most frequent. Future research should focus on common DFBs to enhance predictive models. Díaz-Delgado et al. [18] analyzed spatial patterns of fire occurrence in Catalonia, Spain, using a GIS-based method. Their study finds that active fire suppression reduces the total number of fires but increases the impact of large fires. Burned areas are correlated with vegetation types, particularly shrublands and pine forests. The integration of GIS and fire history improves forest management strategies. Meanwhile, McCaw et al. [36] examine how fire behavior changes in dry eucalypt forest as fuel ages. Their findings show that fire spread, flame height, firebrand density, and spotting distance increase as fuels accumulate with age since the last fire. Due to understory shrub characteristics, the near-surface fuel layer dominated the headfire spread rate and provided a common descriptor for visually different fuel types. Visual hazard scores, reflecting surface and near-surface fuel, correlated more strongly with fire behavior than fuel load variables. Visual ratings of fuel structure should be suitable for inclusion in algorithms to predict fire behavior and fire threat. Sharples et al. [113] investigate wind-terrain interactions and their role in fire channeling and its implications for bushfire risk management. Their analysis identifies lee-facing slopes (>25 °C) as key drivers of rapid bidirectional fire spread and lateral growth of spot fires, as well as extensive flaming. Findings aid bushfire risk management and planning.

Cruz et al. [13] conducted a retrospective study of the catastrophic Kilmore East fire during Black Saturday in Victoria, Australia. Burning 100,000 ha in under 12 h due to dry fuel and strong winds, with spot fires reaching up to 33 km ahead of the main front. Wind shifts caused mass fire behavior and the formation of pyrocumulonimbus clouds. The study provides benchmark data for evaluating wildfire models and highlights the role of atmospheric instability and fuel conditions in driving extreme fire behavior. Peace et al. [115] used the ACCESS-Fire coupled atmosphere–fire model to simulate the Waroona fire. Their simulations accurately reconstructed fire spread and predicted deep, moist convection, indicating the development of pyrocumonimbus. The study demonstrates that fire–atmosphere interactions created conditions conducive to the transport of short-distance embers and the occurrence of ember showers. The ACCESS-Fire model demonstrated the capability to explore complex interactions and predict extreme fire behavior. Sullivan [114] presents a literature review focusing on the fundamental heat transfer processes in wildland fire behavior. The analysis identifies advection (incorporating buoyancy and convection), radiation, direct flame contact, and firebrand transport as key mechanisms of heat transfer. These processes are critical for the sustained spread of the fire, as they transfer heat to adjacent fuel and ignite it. The interactions of these heat transfer processes with the surrounding atmosphere, topography, and fuel moisture have a significant impact on fire behavior and its spread. Thermal degradation impacts volatilization and charring around the fire perimeter.

Shennan et al. [11] integrated geovisualization applications with ATIR imagery, fire features, growth form maps, and enhanced topographic rasters to visualize local topography changes. The tools were moderately effective in analyzing fire spread over multidirectional slopes and variations in spread magnitudes over time; however, no conclusive relationships were identified between spotting, fuel, and topography. Further research should explore the utility of these tools for enhancing fire modeling accuracy and validation, as well as 3D visualization and operational fire management. Lareau et al. [110] demonstrate the use of weather radar to track wildfires, showing a good alignment with conventional fire-tracking methods. Their radar-based approach reveals that long-range spotting significantly increases the rate of spread (ROS), often exceeding the estimates of standard models. This method enhances situational awareness during high impact fires and provides a valuable real-time tool for monitoring fire progression, particularly in scenarios where satellite or infrared data are limited. Moreover, Hart et al.'s study [121] explores the potential of georeferencing oblique aerial wildfire photographs as a source of fire behavior data. Using monophotogrammetry, they accurately estimate fire position, spread distance, and ROS. The method also enables characterization of flame dimensions, smoke plumes, and spotting events. This approach supports model validation and the development of new empirical relationships using wildfire photo databases.

4.8. Examining the Integration of Spotting in Operational Fire Spread Models

The four focused studies illustrate the progressive development of fire behavior modeling systems, with an increasing emphasis on hybrid approaches that aim to strike a balance between operational reliability and scientific rigor. Andrews [127] presented the history and current status of the BhavePlus fire modeling system, a widely used tool for predicting and planning wildfires. The study highlights that continuous updates have enhanced features; however, a future redesign is necessary to consolidate and incorporate new research findings. Asensio et al. [125] provided a historical review of the simplified physical fire spread model PhyFire. The model's evolution includes a GIS-integrated system to simulate complex processes such as forest fires. This effort involves a multidisciplinary development approach that addresses significant mathematical, numerical, and computational challenges while maintaining the overriding goal of developing an efficient, effective, and useful simulation tool. Plucinski et al. [128] offered a comprehensive overview of Amicus, a decision support system designed to improve the reliability and utility of operational bushfire behavior predictions in Australian vegetation. Amicus allows multiple scenario analyses and refining uncertainties. It integrates deterministic and anecdotal/local knowledge with formal models to address limitations in fire science. Moreno et al. [126] developed interactive fire spread simulations for virtual reality training tools for firefighters. These tools realistically simulate fire spread and provide support for extinguishment. The hybrid model combines CA3, physics-based algorithms, agent-based modeling, and empirical data. The unified forest and urban models support efficient computation and realistic fire training scenarios, enhancing training effectiveness and reducing accident risks.

5. Prevailing Gaps

This section addresses RQ5 by building upon the findings from RQ1 through RQ4 to identify unresolved challenges and limitations in fire spotting modeling research. It highlights recurring gaps across thematic areas, methodological constraints, and underexplored dimensions that warrant further investigation.

Current limitations in fire spotting research reveal critical challenges that constrain model accuracy and generalizability. Detection and tracking technologies remain insufficient for capturing 3D firebrand dynamics, especially under complex canopy structures and variable wind conditions. Correlations between firebrand production and vegetation parameters, such as tree height, are often inconclusive, hindering the development of scalable models. Landscape heterogeneity and vegetation transitions significantly influence spotting behavior, yet existing frameworks have shown limitations in integrating multimodal distributions. Plume dynamics and boundary-layer effects, which are essential for understanding ember lofting, are often simplified or omitted in transport simulations. Although turbulence and buoyancy effects are increasingly being incorporated, current transport models still struggle to accurately predict extreme spotting distances and require further experimental validation. Additionally, operational models face resolution constraints that limit their effectiveness in predicting long-range spotting.

Regarding real-world applicability, current wildfire models often underrepresent environmental variability. Most studies rely on controlled laboratory conditions that fail to capture the dynamic interplay of wind, terrain, and vegetation inherent to actual wildfire events. Scaling challenges further complicate the translation of small-scale experimental findings into large-scale predictive models, introducing uncertainty and reducing operational accuracy. Material degradation models frequently lack the nuance to capture the interplay of thermal stress, mechanical strain, and wind forces across diverse fuel types. These nonlinear interactions, influenced by variables such as particle size, moisture content, and heat flux, remain underexplored, particularly in phenomena like cooperative ignition and clustered firebrand landings. Hybrid and AI-based models show promise, but limited integration with real-time environmental data constrains their predictive capabilities. Stochastic and cellular automata models offer flexibility, especially in urban and WUI contexts, but require broader validation and data stream integration. Physics-based and integrated fire spotting models provide mechanistic depth and statistical rigor. However, they are often constrained by validation complexities, limited observational data, and high computational demands, especially when applied to large-scale or real-time scenarios. These gaps emphasize the need for fire spotting and wildfire models that are both scientifically robust and operationally viable, supporting real-time decision-making amid increasingly complex fire behavior. Furthermore, there is a need for region-specific wildfire modeling, improved integration of moisture and fuel morphology, and broader validation of emerging technologies such as thermal imaging and acoustic analysis to enhance firebrand characterization and transport modeling.

Complementary bibliometric analysis using VOSviewer reinforces both methodological and conceptual limitations in fire spotting research. Co-authorship mapping reveals fragmented collaboration networks, comprising 46 distinct clusters and minimal cross-group interaction, which indicates limited interdisciplinary integration and knowledge exchange. Keyword and term co-occurrence mapping highlights dominant themes in empirical and computational modeling, but also reveals the underrepresentation of real-time environmental variability, firebrand transport under turbulent conditions, and hybrid model integration. Conceptual fragmentation persists, with weak linkages between empirical field studies and operational modeling, limiting the translation of field data into predictive systems. Modeling frameworks often lack modularity and scalability, constraining adaptability across varying conditions and fire regimes. Multiscale dynamics are frequently oversimplified, neglecting critical cross-scale interactions essential for accurate fire behavior prediction. This fragmentation also impedes the integration of remote sensing, machine learning, and social dimensions into fire modeling. These patterns validate the need for more cohesive research efforts and broader methodological convergence to address the outlined limitations.

Additionally, the VOSviewer analysis reveals the absence of standardized validation protocols and centralized repositories, hindering reproducibility and meaningful model comparison. Many academic models remain underutilized in operational settings due to poor interface design and a lack of alignment with user needs. Finally, terminological inconsistencies and fragmented conceptual frameworks reflect a critical need for shared ontologies and improved semantic coherence across the wildfire science domain.

Drawing from publication trends and thematic distributions, key gaps emerge in both geographic representation and the in-depth exploration across modeling domains. Despite a growing body of literature, fire spotting research remains unevenly distributed. Thematic analysis reveals a strong emphasis on empirical studies, particularly those addressing fire dynamics behavior and spread model integration. However, areas such as firebrand generation, operational model incorporation, and physics-based spotting remain underexplored. Limited contributions from regions, including Africa, South and Southeast Asia, and Eastern Europe, highlight geographic disparities that likely stem from infrastructural limitations and visibility constraints, as reflected in the affiliations of corresponding authors across the 102 studies examined.

6. Conclusions

This systematic literature review has synthesized two decades of research (2000–2023) on fire spotting and fire spread modeling, revealing a growing academic and operational focus driven by the increasing frequency and severity of wildfires under changing climate conditions. Despite this momentum, the research landscape remains uneven, both thematically and geographically, with significant underrepresentation across Africa, Asia, and South America. Thematic analysis of 102 studies reveals a strong focus on integrating fire spotting into fire spread models and empirical research, while foundational aspects, such as firebrand generation, ignition dynamics, and operational implementation, remain underexplored. This imbalance highlights the need for conceptual consolidation and reveals significant research gaps in foundational processes and the broader integration of models.

While modeling approaches have evolved from semi-empirical to hybrid computational frameworks, current models still struggle to replicate the nonlinear, multi-phase dynamics of fire spotting. Addressing this limitation will require integrated architectures that couple physical processes with probabilistic and hybrid approaches, supported by GIS platforms, CFD-based fire–atmosphere modeling, and AI-driven tools for adaptive simulation. Sensitivity and uncertainty analysis should also be applied to enhance model robustness while maintaining computational efficiency.

Advancing the field will require high-fidelity datasets from controlled burns and remote sensing to support model calibration and validation, alongside the development of standardized validation protocols and open-access repositories. Interdisciplinary collaboration is essential, and expanding research capacity in underrepresented regions will ensure globally relevant, context-sensitive wildfire modeling, particularly in wildland–urban interface zones. By bridging semi-empirical with computational modeling within modular, scalable frameworks, fire spotting research can significantly enhance early warning systems, suppression planning, and long-term fire management. Operational relevance, global collaboration, and model adaptability will be central to building robust tools capable of responding to the evolving challenges of wildfire dynamics.

7. Future Directions

Addressing RQ5, this section builds on the insights from RQ1 through RQ4 to identify key priorities for future research in fire spotting modeling. It highlights strategic areas where further investigation is essential to improve modeling accuracy, incorporate emerging technologies, and tackle persistent gaps in data, methodologies, and interdisciplinary collaboration. The findings of this systematic literature review (SLR) suggest that future studies in spotting and fire spread modeling should prioritize advancements in data collection, interdisciplinary modeling frameworks, and operational integration. This includes incorporating environmental variability, fuel heterogeneity, and dynamic wind conditions into simulations of firebrand generation, transport, and ignition.

Large-scale experimental validations are crucial for refining scaling laws and enhancing the reliability of laboratory-to-field extrapolations. Comparative studies across vegetation types and fire regimes, supported by multi-sensor platforms, will enhance empirical understanding through high-resolution data captured during active wildfire events. Model enhancement remains a critical priority. Material degradation models must evolve to incorporate elastic-plastic deformation, thermal degradation under fire loading, and aerodynamic forces to better represent firebrand generation across diverse fuel structures. Transport and ignition modeling should address plume dynamics and boundary-layer effects, which are central to firebrand lofting and spotting behavior. Coupling the lofting and horizontal transport phases is essential, as initial firebrand conditions, mass, shape, combustion state, and elevation within the plume strongly influence firebrand behavior during flight and spatial distribution upon landing. Accurate modeling also requires full aerodynamic characterization, including three translational forces and three rotational moments, to ensure realistic firebrand transport behavior. Adaptive models that reflect multimodal spotting distributions and environmental heterogeneity are needed. Stochastic transport models should incorporate probabilistic formulations that account for atmospheric variability and terrain complexity, especially under high-intensity fire conditions. Enhancing grid resolution in coupled fire–atmosphere simulations will be crucial for accurately capturing long-range spotting.

Innovative hybrid approaches that combine physics-based fire spotting modeling within frameworks such as agent-based models (ABM), stochastic cellular automata (CA), and the randomized level set method can improve predictions of random fire front spread, burned area, and perimeter evolution. Nonetheless, fire spotting remains a complex challenge due to its stochastic, non-local, and multi-phase nature. Traditional models often struggle to capture the probabilistic ignition and long-range transport mechanisms involved. To overcome these limitations, researchers are incorporating conceptual frameworks from other scientific domains, drawing on analogs from biological dispersal, fluid dynamics, and network theory. Cross-disciplinary analogs, such as birth-jump models, percolation theory, and small-world networks, further enrich fire modeling paradigms by offering a more robust framework for simulating spotting behavior across probabilistic scales and identifying critical thresholds in fire spread. Future models should integrate cooperative ignition dynamics, fuel-specific thermal thresholds, and ignition delay behavior under clustered firebrand conditions.

Additionally, research should prioritize the development of unified, modular, and multiscale frameworks that integrate local fire spread with sequential processes such as firebrand generation, transport, and ignition. Such architecture enables scalable integration of environmental, vegetation, terrain, and human factors, while accommodating diverse algorithms, such as the spotting process within comprehensive fire spread models. Multiscale techniques are essential for capturing interactions ranging from fuel-level moisture at the microscale to landscape structure at the mesoscale and climate variability at the macroscale. Current modeling approaches face operational and computational challenges that must be addressed to improve accuracy and operational relevance. Field-based studies, while invaluable for empirical validation, are constrained by safety risks, high cost, and limited repeatability. Physics-based models, although capable of simulating complex fire spotting behavior, often struggle with scalability and convergence. Recognizing these limitations underscores the potential of hybrid modeling approaches that combine complementary methods, such as empirical data, physical-mechanistic models, computational fluid dynamics (CFD), GIS-based systems, digital twin frameworks, machine learning, and AI models. When properly integrated, these approaches can enhance wildfire prediction capabilities, particularly when combined with real-time environmental data.

Future work should also explore model sensitivity and uncertainty analysis using methods such as surrogate-based approaches to enhance robustness while preserving computational efficiency. Operational integration should guide future efforts. Bridging theoretical models with GIS platforms, fire management tools will support real-time decision-making. Remote sensing technologies, such as infrared detection and acoustic analysis, should be further explored for firebrand monitoring and model calibration.

While spotting is recognized as a key contributor to structure ignition, this review did not include studies focused on firebrand accumulation near buildings. This may limit the generalizability of findings, particularly economic impacts in urban areas. The decision to exclude such studies was made to maintain methodological consistency and focus on fire spotting models. Future reviews may expand this scope to include urban ignition pathways and structural vulnerability modeling. We also acknowledge that the literature search was limited to three major databases, which may have excluded relevant studies indexed elsewhere. Expanding database coverage in future reviews could improve comprehensiveness and reduce the likelihood of omitting some relevant domain-specific publications.

Validation across diverse geographic regions and fire regimes, including post-earthquake urban fires and WUI zones, is essential for global applicability. Incorporating both human and landscape factors will enhance risk assessments and support the development of more effective mitigation strategies tailored to complex, real-world scenarios. Expanding geographic representation through international collaboration will enhance contextual relevance. Standardized terminology and classification frameworks will improve conceptual clarity and bibliometric traceability. Continued empirical validation and integration of spotting into predictive tools will increase operational utility. Standardization, including protocols and open access repositories, will support benchmarking and reproducibility. Future models should provide decision-support tools tailored to the needs of fire managers, with an emphasis on usability and real-time application. Finally, semantic and ontological harmonization is needed to reduce fragmentation and improve the interoperability of wildfire-related literature and modeling domains.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/fire8100392/s1, Figures S1–S4: Co-Authorship Network; Figure S5–S8: Keyword Co-Occurrence Analysis; Figure S9–S12: Term Co-Occurrence Analysis; Figure S13–S15: Global and Thematic Patterns in Fire Spotting Modeling; Table S1: Thematic classification of clusters based on keyword co-occurrence analysis; Table S2:Thematic classification of clusters from term co-occurrence analysis; List S1: Final list of 102 selected studies in RIS format, used in VOSviewer software 1.6.20.

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Appendix A. Summary of Key Findings in Fire Spotting Research

Tables A1–A8: Summary of Key Findings in Fire Spotting Research.

Table A1. Summary of studies published between 2000 and 2023 that **review** the fire spotting process.

Authors & References	Title	Year	Country	Model type/ Approach	New Model/ Approach	Main findings
Fernandez-Pello [1]	Wildland fire spot ignition by sparks and firebrands	2017	United States	Literature review	Supports physics-based wildfire spotting model.	Enhanced models help land managers prescribe preventive measures and fuel treatments, allocate suppression resources, and issue evacuation orders.
Koo et al. [2]	Firebrands and spotting ignition in large-scale fires	2010	United States	Literature review	Examine firebrand's role in fire propagation and spot fire development.	Experiments informed empirical firebrand models, using Tarifa's terminal velocity approach as a foundation. The maximum fire distance was identified at the burnout limit, with transport models predicting the corresponding distances. Future research recommendations are provided.
Or et al. [3]	Review of wildfire modeling considering effects on land surfaces	2023	United States	Literature review	Classifies and revises fire models, with a focus on physical processes and land surface effects.	A comprehensive review of wildfire dynamics covers mechanisms, historical context, modeling approaches for wildfire spread, fire spotting, and representation.
Pastor et al. [4]	Mathematical models and calculation systems for the study of wildland fire behaviour	2003	Spain	Literature review	Reviews key developments in wildland mathematical fire modeling (1940–2000).	Wildfire modeling has evolved since the 1940s, integrating GIS and combining models to enhance prediction accuracy. Commonly used forestry tools are highlighted.
Wadhwani et al. [5]	A review of firebrand studies on generation and transport	2022	Australia	Literature review	Reviews firebrand studies on generation and transport, analyzing their role in wildfire propagation.	Significant research gaps were identified, emphasizing the need for targeted studies to enhance CFD models and investigate firebrand transport through parametric analysis.
Rego et al. [6]	Spotting	2021	Portugal	Literature review	Reviews fire spotting dynamics to improve management strategies, covering all phases and assessing wind and fuel moisture effects on wildfire propagation.	Firebrand spotting involves the generation, transport, and ignition of firebrands, with wind, fuel moisture, and fuel type influencing the ignition potential. Firebrand density decreases with distance, impacting ignition likelihood in unburned areas.

Table A2. Summary of studies on firebrand generation published between 2000 and 2023.

Authors & References	Title	Year	Country	Model Type/ Approach	New Model/ Approach	Main findings
Wickramasinghe et al. [7]	Determining Firebrand Generation Rate Using Physics-Based Modelling from Experimental Studies through Inverse Analysis	2022	Australia	Semi-empirical	Semi-physical	Firebrand generation rates were 3.22 pcs/MW/s * for single tree burning and 4.18 pcs/MW/s for forest fire models, emphasizing the role of wind, vegetation type, and fuel moisture in firebrand generation rates.
Tohidi et al. [8]	Statistical description of firebrand size and shape distribution from coniferous trees for use in Metropolis Monte Carlo simulations of firebrand flight distance	2015	United States	Semi-empirical	Statistical-empirical	Laboratory-scale firebrand experiments mimic wildfire conditions. Firebrand surface area scales with mass to the 2/3 power. Firebrand size depends more on combustion and limb failure than on tree height. The study characterized the size and shape distributions for nonlinear regression models, enabling the generation of virtual firebrands and Monte Carlo simulations of firebrand transport through the velocity field induced by the fire plume and the interaction with the atmospheric boundary layer.

Caton-Kerr et al. [9]	Firebrand Generation from Thermally-Degraded Cylindrical Wooden Dowels	2019	United States	Semi-empirical	Semi-physical	Dowel strength is influenced by recoverable elastic strain under two loading regimes. Findings aid in understanding breakage mechanisms and developing failure theory for thermally degrading wood under wind loading.
Thomson et al. [10]	On the time to first spotting in wildland fires	2022	Canada	Hybrid model	Combines stochastic, probabilistic, and semi-empirical methods to estimate the fire spot rates.	The proposed methodology is computationally efficient and applicable with and without barriers, estimating spot fire rates and assessing risks under various conditions. It is designed to support the practical implementation of wildfire scenarios in real-world settings.
Jha & Zhou [11]	Applying Machine Learning for Firebrand Production Prediction	2022	United States	Empirical	Statistical-empirical	The K-Nearest Neighbors (KNN) model achieved over 90% accuracy in predicting firebrand areal mass density (FAMD) and firebrand number density (FAND), effectively identifying high-risk ignition spots. Findings support the development of a numerical firebrand production simulator.

* pcs-number of firebrand pieces.

Table A3. Summary of studies on firebrand transport published between 2000 and 2023.

Authors & References	Title	Year	Country	Model Type/ Approach	New Model/ Approach	Main findings
Ellis [12]	The effect of the aerodynamic behaviour of flakes of jarrah and karri bark on their potential as firebrands	2010	Australia	Empirical	Statistical-empirical	Jarrah and karri bark flakes have terminal velocities of 2.5–8 m/s, which decrease by up to 18% due to rapid spin compared to non-spinning flakes. Their low terminal velocity enables lofting within convection plumes from low to moderate-intensity fires (0.5–2.5 MW/m), making them effective firebrands primarily due to vertical lift rather than their ability to glide. Spotting behavior depends on bark traits, ignition ease, number of detachable flakes, combustion during flight, and free-fall characteristics.
Tohidi & Kaye [13]	Aerodynamic characterization of rod-like debris with application to firebrand transport	2017a	United States	Semi-empirical	Semi-physical	Accurate firebrand flight predictions require full 6-DOF * aerodynamics (three translational and three rotational movements). Model results align closely with free-fall experimental data, helping to overcome the limitations in previous estimations of spotting distance. The study presents the most comprehensive experimental dataset on the transport of rod-like debris.
Almeida et al. [14]	Effect of particle orientation and of flow velocity on the combustibility of Pinus pinaster and Eucalyptus globulus firebrand material	2011	Portugal	Empirical	Statistical-empirical	Combustibility of firebrands from Pinus pinaster and Eucalyptus globulus depends strongly on particle orientation, flow velocity and direction, combustion regime, and particle properties. Models assess flaming and smoldering durations, as well as mass loss decay, under both wind and no-wind conditions, illustrating key factors for predicting the maximum spotting distance.
Song et al. [15]	The Wind Effect on the Transport and Burning of Firebrands	2017	China	Semi-empirical	Semi-physical	A bimodal distribution (burning and extinction modals) was observed in small firebrands under specific wind conditions (12 mm diameter and 5 mm thickness at 7 m/s). The extinction modal showed shorter transport distance and mass loss than the burning modal. The critical wind speed required to quench firebrands and produce this bimodal distribution increased with particle size and heating duration, aligning with experimental data.
Oliveira et al. [16]	Numerical prediction of size, mass, temperature and trajectory of cylindrical wind-driven firebrands	2014	Portugal	Semi-empirical	Semi-physical	The initial aspect ratio and orientation have a strong influence on the trajectories and travel distances of cylindrical firebrands. Accounting for their oscillatory and rotational motions is essential for accurately predicting fire spread through spotting.

Page et al. [17]	An analysis of spotting distances during the 2017 fire season in the Northern Rockies, USA	2019	United States	Empirical	Statistical-empirical	The maximum spot fire distance increases with the interaction of fire growth and wind speed, but decreases with changes in fire perimeter shape, canopy height, and terrain steepness. High wind speed estimates help prevent underprediction in Albini's model. Most spotting distances were ≤500 m; medium-range spotting (1-3km) was rare, with high wind and rapid fire growth increasing the likelihood of exceeding 1 km.
Storey et al. [18]	Drivers of long-distance spotting during wildfires in south-eastern Australia	2020	Australia	Empirical	Statistical-empirical	The source fire area is the primary driver of the maximum spotting distance and long-distance (>500 m) spot fires, with weather, vegetation, and topography as secondary influences. Spotting distance and the number of long-distance spot fires increase significantly with larger source fire areas, particularly under strong winds, dense forests, and steep slopes. Improved mapping systems for bark spotting are needed to support predictive wildfire models.
Thurston et al. [19]	The contribution of turbulent plume dynamics to long-range spotting	2017	Australia	Semi-empirical	Physical-mechanistic	Turbulent plumes can double the maximum spotting distance compared to non-turbulent plumes. Turbulent plume dynamics (TPD) govern the lateral and longitudinal spread of firebrands. Fire spread models need TPD parametrizations for accuracy and physical realism.
Koo et al. [20]	Modelling firebrand transport in wildfires Using HIGRAD/FIRETEC	2012	United States	Semi-empirical	Physical-mechanistic	Firebrands modeled without terminal velocity assumptions travel farther. Discs outperform cylinders aerodynamically. Burning dynamics influence firebrand lifetimes, thin discs burning on their faces and tall cylinders burning around their circumference burn out faster. Canopy firebrands travel farther than those from surface fires. Coupled fire-atmosphere interactions significantly shape firebrand trajectories and landing patterns.
Mendez & Farazmand [21]	Quantifying rare events in spotting: How far do wildfires spread?	2022	United States	Semi-empirical	Statistical-mechanistic	Large Deviation Theory efficiently quantifies rare landing events with low computational cost, whereas Monte Carlo and Importance Sampling methods are well-suited for high-probability distances near the mode. The most probable landing distance increases linearly with the mean wind velocity. A hybrid approach, combining these methods, improves wildfire spotting predictions and enhances modeling frameworks such as cellular automata and non-local transport (birth-jump) models.
Tohidi & Kaye [22]	Stochastic modeling of firebrand shower scenarios	2017c	United States	Stochastic model	Semi-physical	The model accurately predicts firebrand flight statistics compared to experimental data. Lofting is inherently linked to downwind distance and cannot be decoupled. Firebrand flight is sensitive to initial and boundary wind conditions, making transport highly stochastic and nonlinear, which affects the spotting distribution.
Albini et al. [23]	A mathematical model for predicting the maximum potential spotting distance from a crown fire	2012	United States	Semi-empirical	Physical-mechanistic	Initial comparisons with existing crown fire spotting data are promising, though further evaluation is needed. The model combines empirical data with simplified physical principles to estimate the spotting range based on the final diameter of the burning particle.
Cruz et al. [24]	An empirical-based model for predicting the forward spread rate of wildfires in eucalypt forests	2022	Australia	Empirical	Statistical-empirical	The model showed errors of 35–46% during development and 81–84% against independent datasets but dropped below 30% for spreads exceeding 2 km/h. Its modular design enables improvements without compromising functionality. Long-range spotting remains uncertain due to variable conditions and complex fire-atmosphere interactions, which may lead to underprediction.
Himoto & Tanaka [25]	Development and validation of a physics-based urban fire spread model	2008	Japan	Semi-empirical	Physical-mechanistic	The model accurately predicts urban fire spread, aligning with the Hamada model for spread rates. Past data validation confirms reliability, despite some discrepancies in the burnt area. Firebrand scattering follows log-normal and normal distributions for wind direction and orthogonal movement.

Pereira et al. [26]	Calculation of spotting particles maximum distance in idealised forest fire scenarios	2015	Portugal	Theoretical	Physical-mechanistic	The maximum spotting distance aligns with the Albini model but underpredicts high-intensity fires by approximately 40%. Smaller particles travel farther due to buoyancy and lower char content. Particles deposited in an inverted exponential pattern, landing mostly near the fire, while those up to 10 mm traveled several hundred meters, showing greater char variability.
Sardoy et al. [27]	Modeling transport and combustion of firebrands from burning trees	2007	France	Theoretical	Physical-mechanistic	The landing state depends on the product of initial firebrand density and thickness. Those remaining longer in the thermal plume travel distances that are independent of diameter, correlating with wind speed and fire intensity. Their normalized mass fraction at landing consistently correlates with flight time and initial characteristics, even with random canopy release.
Anthenien et al. [28]	On the trajectories of embers initially elevated or lofted by small scale ground fire plumes in high winds	2006	United States	Theoretical	Physical-mechanistic	Discs travel farthest while burning, spheres the shortest. Cylinders have the smallest impact mass fraction, and discs have the highest. Charring lowers density, increasing the travel of spheres and cylinders. Higher surface burning temperatures shorten propagation. Disc travel is diameter-independent within the tested range. The Ember distance is nearly linear with wind speed.
Bhutia et al. [29]	Comparison of firebrand propagation prediction by a plume model and a coupled–fire/atmosphere large–eddy simulator	2010	Canada	Theoretical	Physical-mechanistic	Fire spotting in the Atmospheric Boundary Layer (ABL) is a probabilistic phenomenon, with higher release heights resulting in increased downwind distances, which differs significantly from the 2D plume model. Couple fire/atmosphere Large Eddy Simulation (LES) results remain exploratory and require direct validation through testing.

* DOF-Degrees-Of-Freedom.

Table A4. Summary of studies on firebrand ignition published between 2000 and 2023.

Authors & References	Title	Year	Country	Model type/ Approach	New Model/ Approach	Main findings
Fang et al. [30]	Ignition of pine needle fuel bed by the coupled effects of a hot metal particle and thermal radiation	2021	China	Semi-empirical	Semi-physical	The coupled effects of hot metal particles and thermal radiation increase the ignition probability compared to the individual factors. Larger particle sizes and higher temperatures lower the critical radiation heat flux. The ignition delay time decreases as the radiation heat flux increases. A linear relationship between radiation flux and hot particle parameters helps understand ignition mechanisms.
Fernandez-Pello et al. [31]	Spot fire ignition of natural fuel beds by hot metal particles, embers, and sparks	2015	United States	Semi-empirical	Semi-physical	A hyperbolic relationship exists between particle size and temperature, with larger particles needing lower temperatures to ignite the fuel bed than smaller ones. Both energy and temperature determine ignition capabilities, with smoldering ignition easier than flaming ignition. Flaming ignition can occur if the ember is flaming and air velocities are moderate, while sparks require accumulation for ignition.
Hadden et al. [32]	Ignition of Combustible Fuel Beds by Hot Particles: An Experimental and Theoretical Study	2011	United Kingdom	Semi-empirical	Semi-physical	Smaller particles require higher temperatures for ignition, with ignition propensity dependent on particle size and temperature. There is no unique correlation between particle energy and ignition propensity. Hot spot ignition theory agrees qualitatively but not quantitatively with experimental results.
Yang et al. [33]	Spotting ignition of larch (Larix gmelinii) fuel bed by different firebrands	2022	China	Empirical	Statistical-empirical	Ignition probability (IP) is zero without wind. It is significantly influenced by moisture content (MC) and wind speed, while the packing ratio has almost no effect. Firebrand ignition was observed at a maximum MC of 50%, with IP increasing with wind speed and decreasing with MC. Cones have the highest IP, followed by large and small twigs, which are

						affected by shape and size. Two empirical models link IP to fuel bed properties and wind speed. These findings contribute to clarifying the mechanism of spot ignition and reducing corresponding losses.
Scott et al. [34]	Ignition of cellulose fuel beds by hot metal particles	2011	United State	Semi-empirical	Semi-physical	The model predicts a qualitative relationship between particle size and the temperature required for the flaming or smouldering ignition of powdered cellulose and pine needle fuel beds. Smaller steel particles demand higher temperatures to ignite the fuel bed, with ignition propensity depending on both particle size and temperature.
Ganteaume et al. [35]	Spot fires: fuel bed flammability and capability of firebrands to ignite fuel beds	2009	France	Empirical	Statistical-empirical	Grasses are more flammable than litter, with Pinus species being the most flammable among litters. Increased bulk density and fuel moisture delay ignition and reduce other flammability parameters. Flaming firebrands ignite more often without wind than glowing ones with air flow. Ignition probability depends on the type or weight of the firebrand. Cone scales of Pinus pinaster and P. halepensis, along with Eucalyptus globulus leaf and bark, have at least twice the ignition probability of pine bark when falling in flaming combustion.
Urban et al. [36]	Smoldering spot ignition of natural fuels by a hot metal particle	2017	United States	Semi-empirical	Semi-physical	The ignition boundary shows a hyperbolic relationship between particle size and temperature, with smaller particles needing higher temperatures to ignite the fuel. Smouldering ignition occurs at lower temperatures than flaming ignition for both metal particles (stainless steel and aluminium). The simplified numerical model explains the influence of smouldering ignition and melting, aligning qualitatively with experimental results.
Urban et al. [37]	Ignition of a spot smolder in a moist fuel bed by a firebrand	2019	United States	Semi-empirical	Semi-physical	Larger firebrands can ignite sawdust with a fuel moisture content of up to 40%. Firebrands smaller than 3.17 mm in diameter cannot initiate smoldering in dry sawdust. The ignition boundary predictions from the energy model align qualitatively with the results of multivariate logistic regression.
Álvarez et al. [38]	Use of an electric heater as an idealized firebrand to determine ignition delay time of Eucalyptus globulus leaves	2023	Chile	Semi-empirical	Semi-physical	The model accurately predicts ignition delay times for different volume fraction values but shows less accuracy in temperature evolution due to significant variability in eucalyptus leaves.
Viegas et al. [39]	Ignition of Mediterranean Fuel Beds by Several Types of Firebrands	2014	Portugal	Empirical	Statistical-empirical	Ignition occurred only with flaming firebrands under no wind. Fuel bed moisture content determines ignition probability and time delay. Fuel bed properties influenced ignition more than firebrand characteristics, with 1-12 seconds for flat eucalyptus bark, under 20 seconds for Pinus pinaster cones, and under 5 seconds for Pinus halepensis cones.
Yin et al. [40]	New correlation between ignition time and moisture content for pine needles attacked by firebrands	2014	China	Semi-empirical	Semi-physical	A linear relationship was observed between the square root of ignition time $\left(\sqrt{t_{ig}}\right)$ and moisture content (MC), based on data from six groups of firebrand ignition experiments conducted on pine needles with moisture ranging from 12.9% to 65% under 3 m/s (±0.2 m/s) wind speeds.
Lin et al. [41]	Modeling smoldering ignition by an irradiation spot	2022	China	Theoretical	Physical-mechanistic	Ignition time decreases as radiant heat flux increases. The minimum heat flux increases as the irradiation spot diameter decreases, in agreement with experimental and theoretical analyses. Assumptions of constant ignition temperature and fuel-burning flux are invalid for spots smaller than 20-50 mm. Fuel thickness is crucial for smoldering ignition, while moisture content has a minimal impact.
Matvienko et al. [42]	Simulation of fuel bed ignition by wildland firebrands	2018	Russia	Theoretical	Physical-mechanistic	Pine bark firebrands failed to ignite fuel beds under all tested conditions, whereas pine twigs achieved ignition at densities ranging from 60 to 105 kg/m^3 and airflow velocities $\geq 2\ m/s$. The mathematical model indicates that a single pine bark firebrand, ≤5 cm long, at ≤1073 K, does not ignite the fuel bed in flaming mode. The model demonstrates that only

						sufficiently larger and hotter firebrands can induce flaming ignition, highlighting firebrand length as a critical factor in ignition initiation. Model predictions align with experimental ignition times.
Zhu & Urban [43]	Cooperative spot ignition by idealized firebrands: Impact of thermal interaction in the fuel	2023	United States	Semi-empirical	Semi-physical	Smaller heaters need higher heat flux for ignition. A second nearby heater, within a critical distance, speeds up ignition (reduces ignition time) or enables it at a lower flux. Numerical modeling highlights the role of thermal interactions in the fuel for flaming ignition, examining firebrand sizes (5-50 mm) and separation distances. The model captures qualitative ignition behaviours and shows quantitative agreement in most cases.
Valenzuela et al. [44]	Ignition of Wildland Fuels Exposed to a Time-Decreasing Incident Heat Flux	2023	Chile	Semi-empirical	Semi-physical	The analytical model was validated using experimental data, which showed that ignition delay times increase with steeper negative heat flux slopes. Each initial incident heat flux value corresponds to a critical slope (β_{cri}) below which ignition occurs. For slopes steeper than this critical value, ignition does not occur.

Table A5. Summary of studies on physics-based fire spotting models published between 2000 and 2023.

Authors & References	Title	Year	Country	Model Type/ Approach	New Model/ Approach	Main Findings
Hillen et al. [45]	Birth-jump processes and application to forest fire spotting	2015	Canada	Theoretical	Physical-mechanistic	Birth-jump models demonstrate that spotting significantly increases the invasion speed of a forest fire front. Under both no-wind and constant-wind conditions, higher spotting rates (σ) reduce the critical domain size (minimum area required for fire spread) and raise the minimum invasion speed (the lowest rate at which the fire can spread). A larger initial spotting spread (variance ds (0)) increases both metrics, thereby intensifying wildfire propagation.
Martin & Hillen [46]	The spotting distribution of wildfires	2016	Canada	Semi-empirical	Physical-mechanistic	Grounded in firebrand physics, the spotting distribution model improves predictions of spot fire likelihood by integrating fire key physical processes, such as plume behavior, firebrand launching, wind transport, falling and terminal velocity, combustion during transport, and ignition upon landing. This multi-phase integration supports fire spread analysis, breach evaluation, and informed management strategies.
Masoudvaziri et al. [47]	Streamlined wildland-urban interface fire tracing (SWUIFT): Modeling wildfire spread in communities	2021	United States	Semi-empirical	Semi-physical	SWUIFT (Streamlined Wildland-Urban Interface Fire Tracing) is computationally efficient, accurately predicting wildfire spread rates and the number of affected structures in WUI communities, considering radiation and fire spotting pathways.
Sardoy et al. [48]	Numerical study of ground-level distribution of firebrands generated by line fires	2008	France	Theoretical	Statistical-mechanistic	Firebrands exhibit bimodal landing distribution: short-distance flaming and long-distance charring. The normalized mass of flaming firebrands correlates with flight time, increasing fire danger due to frequent ground impact and retained mass. Short-distance landings follow a log-normal distribution, which can be incorporated into fire propagation models, providing relevant parameters that describe the separation between the short- and long-distance landing regions and predict the combustion state (determining whether firebrands will burn in the air or land on the ground).

WUI—Wildland–Urban Interface.

Table A6. Summary of studies published between 2000 and 2023 examining the integration of spotting in existing or new fire spread models.

Authors &	Title	Year	Country	Model Type/	New Model/	Main Findings

References				Approach	Approach	
Trucchia et al. [49]	On the merits of sparse surrogates for global sensitivity analysis of multi-scale nonlinear problems: Application to turbulence and fire-spotting model in wildland fire simulators	2019	Spain	Semi-empirical	Semi-physical	Wind is a leading factor governing the generation of secondary fires (fire spotting). Key variables include wind magnitude and log-normal parameter σ (which control the tail of the density function related to firebrand landing distance), confirming that fire spotting is a wind-driven, ballistic phenomenon. Sparse surrogates, including Least-Angle Regression (LAR)-based Generalized Polynomial Chaos (gPC) and Gaussian Process regression, enhance model parameter analysis by filtering out information from parameters with large length scales. Applying sparse surrogates is a promising strategy for analysing new models and their dependency on input parameters in wildfire applications.
Pagnini & Mentrelli [50]	The randomized level set method and an associated reaction-diffusion equation to model wildland fire propagation	2016	Spain	Semi-empirical	Semi-physical	Combining the level set method and reaction-diffusion equation enhances fire dynamics modeling, including the simulation of firebreak crossing. Randomization accounts for turbulence and spotting. The proof-of-concept results require future validation.
Pagnini & Mentrelli [51]	Modelling wildland fire propagation by tracking random fronts	2014	Spain	Semi-empirical	Semi-physical	The model simulates turbulent convection effects and accounts for faster fire spread due to hot-air pre-heating and ember landing. It enhances the prediction of fire front dynamics and addresses the fire's ability to overcome firebreak zones. The model successfully simulates flanking and backing fires, which are challenging for traditional models, including the correction for the ROS formula based on the mean jump length of firebrands in the downwind direction. This study is a proof of concept and requires future validation.
Mentrelli & Pagnini [129]	Modelling and simulation of wildland fire in the framework of the level set method	2016	Italy	Semi-empirical	Semi-physical	The randomized level-set methods (LSM) integrate random effects, improving wildfire prediction, especially with fire breaks, and providing accurate fire front localization and spread simulations. The study shows that this model approach and reaction-diffusion equations yield similar models when incorporating random effects. Numerical simulations highlight the critical role of fire spotting and turbulence in enhancing predictions of fire front propagation.
Pagnini [52]	Fire spotting effects in wildland fire propagation	2014	Spain	Hybrid model	Semi-physical	Turbulence and fire spotting introduce randomness in the fire front position. Fire spotting is a significant factor in the downwind propagation of fires. Variability in ember jump-length and mean wind direction influences fire advancement.
Nishino [53]	Physics-based urban fire spread simulation coupled with stochastic occurrence of spot fires	2019	Japan	Hybrid model	Semi-physical	The model accurately explained spot fires in the Itoigawa fire and conservatively simulated urban fire spread. Useful for firefighting in dense wooded urban areas with strong winds.
Alexandridis et al. [54]	A cellular automata model for forest fire spread prediction: The case of the wildfire that swept through Spetses Island	20008	Greece	CA2 - random chance of fire spread model	Other Models	New spotting integration technique improves wildfire prediction. Accurately models the 1990 Spetses wildfire, with potential applications in fire risk management for heterogeneous landscapes. Requires validation on large-scale incidents.
Alexandridis et al. [55]	Wildland fire spread modelling using cellular automata: Evolution in large-scale spatially heterogeneous environments under fire suppression tactics	2011	Greece	CA2 - random chance of fire spread model	Other Models	Models of fire spread in large-scale, mountainous, and heterogeneous landscapes incorporate fire spotting and suppression tactics. Predicts fire spread dynamics accurately and supports the design of fire risk management policies.

Perryman et al. [56]	A cellular automata model to link surface fires to firebrand lift-off and dispersal	2013	United States	Hybrid CA: physics-based + spotting parametrization + CA3 (with stochastic and probabilistic rules)	Other Models	Canopy base height and surface fuel loading have more impact on spread than wind speed and fuel moisture. Spot fires increased the spread rate by 6 to 931%, highlighting their importance in fire management technologies.
McDanold & Malik [57]	Spatially extended radiant heat fire model	2023	Unite States	Hybrid CA3: fire physics + random spread	Other Models	The model matches observational data, simulating low-intensity wildfire behavior with prolonged burn times and lingering embers. Future improvements focus on accuracy and advanced analysis.
Zhao [58]	Simulation of Mass Fire-Spread in Urban Densely Built Areas Based on Irregular Coarse Cellular Automata	2011	China	Hybrid CA: deterministic + stochastic + spotting rules	Other Models	The model utilizes irregular coarse cells to represent buildings, thereby overcoming the limitations of regular grids. It matches observed fire spread patterns, integrates firebrand scattering and ignition probability for long-range spread modeling, and formulates economic and life loss assessment models for urban fire spread.
Boychuk et al. [131]	A stochastic forest fire growth model	2009	Canada	CA3 - stochastic CA with Markov chains	Other Models	The stochastic model enhances deterministic spread models by incorporating fire spotting, generating variability in fire growth predictions, and creating probability contour plots for burned areas and time to specific events.
Krougly et al. [130]	A stochastic model for generating disturbance patterns within landscapes	2009	Canada	CA3 - stochastic CA with Markov chains	Other Models	The model predicts disturbance patterns in landscapes based on user input. It simulates fire behavior in heterogeneous forested landscapes, and the numerical results show the total impact of disturbances under different initial conditions and scenarios.
Masoudvaziri et al. [132]	Toward Probabilistic Risk Assessment of Wildland–Urban Interface Communities for Wildfires	2023	Unite States	CA3 - stochastic model and probabilistic rules	Other Models	Examines wildfire impact in WUI communities. The Trails community had fewer ignited structures, primarily due to fire spotting, while Fountain Grove experienced rapid ignition from radiation and spotting. A stochastic community model captures uncertainties in fire spread and assesses wildfire hazards.
Egorova et al. [133]	Fire-spotting generated fires. Part I: The role of atmospheric stability	2020	Spain	Hybrid model	Semi-physical	Atmospheric stability affects wildfire propagation. Unstable conditions increase fire spotting and turbulence, which can lead to the merging of fires. Stable conditions limit turbulence, creating more independent fires and reducing burned areas.
Egorova et al. [134]	Physical parametrisation of fire-spotting for operational wildfire simulators	2021	Spain	Hybrid model	Semi-physical	Proposes a formula for fire spread rate based on flame geometry, wind, and terrain slope. Confirms a 2/3 power-law relation between flame height and fireline intensity, emphasizing flame length as a key factor in secondary fire generation.
Egorova et al. [136]	Fire-spotting generated fires. Part II: The role of flame geometry and slope	2022	Spain	Hybrid model	Semi-physical	Flame length influences firebrand landing distances and the likelihood of igniting independent fires. Slope accelerates the rate of fire spread by promoting the rapid merging of these fires. Fire spotting cannot be neglected in simplified fire-spread models used in operational software.
Kaur et al. [59]	Turbulence and fire-spotting effects into wild-land fire simulators	2016	Spain	Hybrid model	Semi-physical	The DEVS-based wildfire model accurately reproduces key fire dynamics, including flank and backfires, increased fire spread due to pre-heating, fire propagation across no-fuel zones, and secondary fire generation. DEVS and LSM models perform similarly, differing mainly in propagation direction geometry. The versatile formulation supports integration into simulators like WRF-SFIRE and ForeFire. Firebrand landing patterns have a significant influence on wildfire spread and potential secondary ignitions.
Asensio et al. [60]	Phyfire: an online gis-integrated wildfire spread simulation tool based on a semiphysical model	2021	Spain	Semi-empirical	Semi-physical	Integrating the PhyFire model into an online GIS interface enhances accessibility and automates the complex data input procedure, facilitating the simulation process.

						Additionally, incorporating the new module to simulate fire spotting enhances the model's efficiency and effectiveness in replicating real-world wildfire propagation.
Trucchia et al. [61]	RandomFront 2.3: A physical parameterisation of fire spotting for operational fire spread models-implementation in WRF-SFIRE and response analysis with LSFire+	2019	Spain	Hybrid model	Semi-physical	Models interactions between primary and secondary fires, improving perimeter growth predictions while maintaining computational efficiency using physical parameterization. It incorporates fire intensity, wind, and firebrand characteristics to evaluate their contributions to fire spread. Its simple, versatile design suits large-scale operational fire spread models.
Loepfe et al. [62]	An integrative model of human-influenced fire regimes and landscape dynamics	2011	Spain	Semi-empirical	Semi-physical	Accurately reproduced fire regimes, land cover changes, and tree biomass in NE Spain. Explicit human influence modeling makes it a unique tool for assessing the impacts of climate change and guiding local fire regime management.
Hargrove et al. [135]	Simulating fire patterns in heterogeneous landscapes	2000	Unite States	CA2 - Random fire spread model with percolation-like thresholds	Other Models	Low fire spread probability (I) values produce slow, dendritic patterns, while high values lead to fast, solid fire patterns. The critical value for (Ic = 0.250–0.251) marks a 50% chance of adjacent fire spread. At I = 0.30, fire spread increases with the presence of firebrands, underscoring the need for more accurate data. The findings highlight the variability, uncertainties, and challenges associated with predicting fire behavior near critical thresholds.
Porterie et al. [63]	Modeling forest fire spread and spotting process with small world networks	2007	France	Theoretical	Physical-mechanistic	Firebrands increase the spread rate and burn area in homogeneous systems, thereby reducing the fire impact length and increasing the spotting distance. Head fires advance by jumps, while spot fires may slow down propagation. In heterogeneous systems, increased disorder reduces firebrand effects and spread rate. Critical propagation channels can halt fire spread if cut off.
Zigner et al. [64]	Evaluating the ability of FARSITE to simulate wildfires influenced by extreme, downslope winds in Santa Barbara, California	2020	United States	Semi-empirical	Semi-physical	FARSITE accurately reconstructed fire spread when spotting was minimal. However, FARSITE and FlamMap struggled with rapid downslope spread due to spotting. Model limitations related to slope orientation and ember launch/landing locations affected predictions during extreme wind events.
Zohdi [65]	A machine-learning framework for rapid adaptive digital-twin based fire-propagation simulation in complex environments	2020	United States	Hybrid model	Machine learning with digital twin modeling.	Machine learning improves fire spread simulations for rapid, real-time modeling. The approach runs efficiently on laptops and handheld devices, supporting digital twin technology for first responders. It accurately computes ground and airborne fire propagation while assessing the impacts on debris and air quality.

CA—Cellular Automata model; WUI—Wildland–Urban Interface; DVES—Discrete Event System Specification; LSM—Level Set Method.

Table A7. Summary of studies published between 2000 and 2023 examining the **empirical research** for fire spotting.

Authors & References	Title	Year	Country	Model Type/ Approach	New Model/ Approach	Main Findings
Filkov & Prohanov [66]	Particle Tracking and Detection Software for Firebrands Characterization in Wildland Fires	2019	Australia	Empirical analysis	Firebrand characterization for theoretical and empirical models.	Detection software, aligning with experiments, showed a 12% error for firebrand counts under 30. Fireline intensity below 12,590 kWm^{-1} minimally affects 2D firebrand flux, but occasional crowning increases it. Firebrand size ($\geq 20 \times 10^{-5}$ m), temperature, and velocity enhance understanding of the ignition process and aid in investigating fire propagation in communities. Future work aims to improve small firebrand detection and tracking with a stereo infrared (IR) for 3D distribution.

Adusumilli et al. [67]	Firebrand Generation Rates at the Source for Trees and a Shrub	2021	United States	Empirical analysis	Firebrand generation studies for physics-based wildfire propagation models.	The total number of hot firebrands increases with the height of the tree or shrub burned. The specific hot firebrand production (firebrands produced per kilogram of dry mass burned) is exponentially dependent on the moisture content, but there are inconclusive height correlations. Sagebrush produces more firebrands than ponderosa pine and Douglas-fir.
Almeida et al. [68]	Analysis of firebrand release on the spot fire mechanism	2014	Portugal	Empirical analysis	Controlled laboratory experiments on firebrands released from torching trees.	Eucalyptus bark enhances firebrand production. Firebrand size varies depending on burning conditions, which affects spot fire potential. Future studies will assess more scenarios and improve 3D analysis.
Hudson & Blunck [69]	Effects of fuel characteristics on ember generation characteristics at branch-scales	2019	United States	Empirical analysis	Empirical data to create models and parameters to estimate the rate of ember generation.	Sample diameter has a significant influence on ember generation time, followed by fuel species. The small diameter samples were relatively insensitive to changes in other parameters. Natural samples take longer to produce embers than dowels, highlighting the role of fuel morphology.
Ganteaume et al. [70]	Laboratory characterization of firebrands involved in spot fires	2011	France	Empirical analysis	Characterize firebrand properties for spot fire prediction.	Firebrands exhibited 100% ignition frequency but varied in ignition time, flaming duration, combustion, and thermal decomposition. Weight loss was exponentially related to time, with a decrease in the ratio of weight at temperature T to the initial weight as temperatures increased. Fuel moisture content has a significant impact on ignition time, flaming duration, combustion, and thermal decomposition. Three firebrand groups based on spotting efficiency were identified.
Suzuki & Manzello [71]	Characteristics of Firebrands Collected from Actual Urban Fires	2018	Japan	Empirical analysis	Firebrand collection and comparison with laboratory-generated firebrands.	Over 60% firebrands weighed < 0.10 g with areas < 2 cm^2. Size and mass were independent of their location. The findings matched those of previous studies and laboratory-generated firebrands.
Thompson et al. [72]	Quantifying Firebrand Production and Transport Using the Acoustic Analysis of In-Fire Cameras	2022	Canada	Semi-empirical	Semi-physical	The proof of concept demonstrated the technique's ability to measure the distance traveled by firebrands and quantify its production rate (the number of firebrands per second). Key areas of medium-distance firebrand spotting align with peak fire intensity and low-cost instrumentation, which quantifies the number of firebrands landing per square meter, showing clear trends as the fire approaches.
Filkov et al. [73]	Frequency of dynamic fire behaviours in Australian forest environments	2020	Australia	Empirical analysis	Quantitative data on fire dynamics for predictive modeling.	Eighty of the 113 fires had one to seven DFBs, with 73% of these fires having multiple dynamic fire behavior (DFBs). Spotting, crown fires, and pyro-convective events were most frequent. Future research should focus on common DFBs to enhance predictive models.
Donovan et al. [74]	Spot-fire distance increases disproportionately for wildfires compared to prescribed fires as grasslands transition to Juniperus woodlands	2023	United States	Empirical analysis	Vegetation impact studies on the spread of fire spots.	Woody encroachment increases wildfire risk. Prescribed fires reduce the distance of spot fires compared to wildfires. Prescribed fires used to control woody encroachment have lower maximum spot-fire distances and less land at risk than wildfires. Spot-fire distances are significantly higher in extreme wildfire scenarios, especially in encroached grasslands and Juniperus woodlands. The maximum spot fire distance in Juniperus woodlands was 450% greater than in grasslands, exposing an additional 14,000 ha to increased wildfire risk.
Storey et al. [75]	Analysis of variation in distance, number, and distribution of spotting in Southeast Australian wildfires	2020	Australia	Empirical analysis	Aerial imaging for spotting pattern analysis.	Spotting follows a multi-modal distribution; current models may underestimate long-distance spotting. Regional variations in spotting are linked to rainfall, topographic

						ruggedness, and fuel description. Expanding research to include plume and firebrand dynamics is crucial for further improving insights into spotting processes.
Tohidi & Kaye [76]	Comprehensive wind tunnel experiments of lofting and downwind transport of non-combusting rod-like model firebrands during firebrand shower scenarios	2017b	United States	Empirical analysis	Laboratory data collection for transport modeling.	There is a strong correlation between the maximum rise height of firebrands and their landing locations. Lofting and transport processes are interconnected. The large aspect ratio has more sensitive landing locations to variability in the velocity field. Data validates firebrand transport models for extreme events.
Hernández et al. [77]	Spontaneous ignition of wildland fuel by idealized firebrands	2018	Chile	Empirical analysis	Firebrand ignition studies for thermal modeling.	The inverse of ignition time is linearly dependent on incident radiative heat flux, which is typical for thermally thin solid fuels. The mass loss rate follows a quasi-linear relationship with the incident radiative heat flux. Future work aims to develop thermal models for homogeneous fuels.
Cruz et al. [78]	Anatomy of a catastrophic wildfire: The Black Saturday Kilmore East fire in Victoria, Australia	2012	Australia	Empirical analysis	Retrospective study using existing models.	Burned 100,000 ha in under 12 hours due to dry fuel and strong winds. Spot fires reached up to 33 km ahead. Wind shifts caused mass fire behavior and the formation of pyrocumulonimbus clouds. Benchmark data aids wildfire model evaluation.
Beverly et al. [79]	Assessing the exposure of the built environment to potential ignition sources generated from vegetative fuel	2010	Canada	Empirical analysis	Standardized ignition exposure mapping using Albini's existing models.	The assessment method prioritizes mitigation activities, compares conditions over time within and between communities, and identifies priority areas for detailed site assessments in the wildland-urban interface. Ignition exposure levels varied among communities, indicating the need for community-specific mitigation strategies. The amount, size, and arrangement of ignition-producing vegetation, community morphology, and occluding interface zones influenced the spatial patterns of elevated ignition exposure.
McCaw et al. [80]	Changes in behaviour of fire in dry eucalypt forest as fuel increases with age	2012	Australia	Empirical analysis	Fire behavior analysis related to vegetation changes.	Fire spread, flame height, firebrand density, and spotting distance increase with fuel age. Near-surface layers of dominant headfire spread. Visual fuel ratings improve fire behavior predictions.
Sharples et al. [81]	Wind-terrain effects on the propagation of wildfires in rugged terrain: Fire channelling	2012	Australia	Semi-empirical	Semi-physical	Fire channelling, caused by bushfires and lee-slope eddies, requires slopes with temperatures exceeding 25°C and specific topographic aspects. Causes rapid bidirectional spread, lateral growth of spot fires, and extensive flaming. Findings aid bushfire risk management and planning.
Sullivan [82]	Inside the inferno: Fundamental processes of wildland fire behaviour: Part 2: Heat transfer and interactions	2017	Australia	Literature review	Heat transfer analysis in wildfire spread.	Wildland fire heat transfer involves advection, radiation, direct flame contact, and ember transport. Fire behavior is significantly influenced by the interactions of these heat transfer processes with the surrounding atmosphere, topography, and fuel moisture.
Peace et al. [83]	Simulations of the Waroona fire using the coupled atmosphere–fire model ACCESS-Fire	2022	Australia	Computational modeling	Fire spread simulation using coupled models.	Simulations accurately reconstructed the fire spread and predicted deep, moist convection, indicating the formation of pyrocumulonimbus. Fire-atmosphere interactions influenced the transport of short-distance embers and the formation of ember showers. The ACCESS-Fire model explores complex interactions and predicts extreme fire behavior.
Toivanen et al. [84]	Coupled Atmosphere-Fire Simulations of the Black Saturday Kilmore East Wildfires With the Unified Model	2019	Australia	Semi-empirical	Physical-mechanistic	Coupled atmosphere-fire simulations matched 80% of the burnt area. Spotting influenced wildfire spread. Coupling and long-range spotting are essential for accurate fire predictions. The grid spacing of 1.5 km may be sufficient for main fire spread features, although finer details are lost.
Thurston et al. [85]	Simulating boundary-layer rolls with a numerical weather prediction model	2016	Australia	Semi-empirical	Physical-mechanistic	Boundary layer rolls affect wildfire spread by causing wind-direction variability and enhancing ember lofting. The horizontal grid spacing of <0.6 km is needed to accurately model these effects, which increase fire intensity and threaten firefighting crews.

Lareau et al. [86]	Tracking Wildfires With Weather Radars	2022	United States	Empirical	Statistical-empirical	Radar-based wildfire tracking aligns well with conventional methods, emphasizing the role of long-range spotting in increasing the rate of spread (ROS) beyond standard estimates. Enhances situational awareness during high-impact fires.
Díaz-Delgado et al. [87]	Spatial patterns of fire occurrence in Catalonia, NE, Spain	2004	Spain	Empirical analysis	GIS-based wildfire patterns analysis.	Active fire suppression reduces the total number of fires but increases the impact of large fires. Burned areas are correlated with vegetation types, particularly shrublands and pine forests. GIS and fire history improve forest management strategies.
Shennan et al. [88]	Geovisualization and Analysis of Landscape-Level Wildfire Behavior Using Repeat Pass Airborne Thermal Infrared Imagery	2023	United States	Empirical	Statistical-empirical	Thermal infrared imagery helps visualize local topography changes influencing fire spread. Moderate effectiveness in analyzing fire movement; further research is needed for model validation and improvements in 3D visualization.
Storey et al. [89]	Experiments on the influence of spot fire and topography interaction on fire rate of spread	2021	Australia *	Empirical analysis	Spot fire effects on wildfire spread.	Spot fires significantly increase the rate of spread (ROS) in hilly terrain, particularly when they merge with the main fire. They can overcome low spread potential on downslopes, and models may underestimate ROS and fire arrival times if these effects are excluded.
Hart et all. [90]	Georeferencing Oblique Aerial Wildfire Photographs: An Untapped Source of Fire Behaviour Data	2021	Canada	Empirical analysis	Wildfire photo databases for model validation.	The method accurately estimates fire position, spread distance, and rate of spread, supporting model validation or the development of a new empirical relationship. Monophotogrammetry characterizes the dimensions of flames, smoke plumes, and spotting events.

* Portugal (experiment location); GIS—Geographic Information System.

Table A8. Summary of studies published between 2000 and 2023 examining the integration of spotting in operational fire spread models.

Authors & References	Title	Year	Country	Model Type/ Approach	New Model/ Approach	Main Findings
Andrews [91]	Current status and future needs of the BehavePlus Fire Modeling System	2014	United States	Semi-empirical	Semi-physical	The historical development of the BehavePlus model is widely used for wildfire prediction and planning. Continuous updates have introduced enhanced features, but a future redesign is needed to consolidate and incorporate new research findings.
Asensio et al. [92]	An historical review of the simplified physical fire spread model PhyFire: Model and numerical methods	2023	Spain	Semi-empirical	Semi-physical	The PhyFire model evolution integrates GIS to improve wildfire simulation. The multidisciplinary approach addresses mathematical, numerical, and computational challenges while ensuring efficiency.
Moreno et al. [93]	Interactive fire spread simulations with extinguishment support for Virtual Reality training tools	2014	Spain	Hybrid Model (CA3+Physics-based algrithms+ABM+empirical data)	Other Models	The developed virtual reality (VR) training tools for firefighters realistically simulate fire spread and provide support for extinguishment. VR training enhances the realism of fire scenarios, improving training effectiveness and reducing accident risks. The unified forest/urban model supports efficient computation and realistic fire training scenarios.
Plucinski et al. [94]	Improving the reliability and utility of operational bushfire behaviour predictions in Australian vegetation	2017	Australia	Semi-empirical	Semi-physical	Comprehensive overview of Amicus, a decision support system, assessing its reliability and utility. Amicus enhances fire behavior predictions in Australian vegetation by allowing multiple scenario analyses and refining uncertainties. Integrates deterministic and anecdotal/local knowledge with formal models to address fire science limitations.

CA3—Cellular Automata; ABM—Agent-Based Model.

Appendix B. Classification of Spotting Models and Approaches

Tables A9–A16 Classification of spotting models and Approaches.

Table A9. Summary of key studies (2000–2023) reviewing the fire spotting process and modeling strategies.

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Fernandez-Pello [1]	2017	United States	Review theoretical modelling, experimental works, and data on wildfire spotting processes.	Reviewed current wildfire spotting processes to provide a comprehensive understanding of the wildfire spotting problem by characterizing the distinct individual processes involved. Emphasized the integration of these models with existing flame spread models and incorporating topographical and wind data to enhance predictive capabilities.	Literature review	Summarize the state of the art of the wildfire spotting problem (describing it in distinct individual processes), providing the required information to develop predictive, physics-based wildfire spotting models.
Koo et al. [2]	2010	United States	Observational research (historical analysis of large-scale fires) Empirical and experimental studies and analysis of existing firebrand models.	The review covers three sequential mechanisms for fire spotting: generation, transport, and ignition of recipient fuel. Examines empirical data from experiments, including measuring drag on firebrands, analyzing flame and plume flow fields, collecting firebrands from various sources, and observing firebrand burning characteristics in wind tunnels under terminal velocity conditions, as well as the ignition characteristics of fuel beds.	Literature review	Review and analysis of historical data.
Or et al. [3]	2023	United States	Theoretical review and analysis of existing wildfire and fire spotting modelling approaches.	Improve understanding of the capabilities and limitations of modern wildfire models. Emphasize the persistent omissions of wildfire effects on soil processes and propose strategies through which the soil and hydrology communities can harness wildfire models to quantify thermal alterations of soils.	Literature review	Classifies and revises forest fire models, with a focus on physical processes and their effects on land surfaces.
Pastor et al. [4]	2003	Spain	Historical review and analysis of mathematical fire spread models.	Proposes a generic classification for wildland fire models, including surface fire spread models, crown fire initiation and spread models, spotting models, and ground fire models.	Literature review	Provides a comprehensive review of the most important work in wildland fire mathematical modelling (1940-2000).

				Analyzes the evolution and complexity of these calculation systems in parallel with advancements in technology.		
Wadhwani et al. [5]	2022	Australia	Empirical models Numerical Model (Computational Fluid Dynamics (CFD))	Review of empirical and numerical models to develop accurate predictive models for firebrand transport (parametric studies) using CFD, incorporating environmental factors such as wind and turbulence.	Literature review	Review of firebrand studies on generation and transport, analyzing the role of firebrands in wildfire propagation.
Rego et al. [6]	2021	Portugal	Case-based analysis using documented examples of large fires. Development of interactive spreadsheets to visualize factors influencing crown fire spread and spotting distances, supporting understanding and prediction.	Defines extreme fires by their uncontrollable behavior and significant impacts. Applies fire science principles to explore driving mechanisms through conceptual analysis, illustration of key conditions, and the use of interactive modeling tools.	Literature review	Reviews fire spotting dynamics to improve management strategies, covering all phases and assessing wind and fuel moisture effects on wildfire propagation.

Table A10. Summary of studies on firebrand generation modeling (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Wickramasinghe et al. [7]	2022	Australia	• Physics-based model • Experimental observation (data) • Inverse analysis Fire Dynamics Simulator (FDS)	Conducted a physics-based model to simulate firebrand transport and generation using inverse analysis to match experimental data, applying interpolation techniques to calibrate the effects of wind velocity, relative humidity, and vegetation species.	Semi-empirical	Semi-physical
Tohidi et al. [8]	2015	United States	• Monte Carlo simulations • Experimental test • Statistical analysis (nonlinear regression model)	A mechanical failure model was developed to simulate the firebrand break-off process. Virtual firebrands were generated based on their surface area and aspect ratio using Monte Carlo simulations. Statistical analysis validated simulation results with experimental data.	Semi-empirical	Statistical-empirical
Caton-Kerr et al. [9]	2019	United States	• Experimental study • Observational research	Cylindrical wooden dowels were subjected to various heating conditions to simulate breakage mechanisms. Three-point bending tests were used to evaluate their mechanical response and ultimate strength,	Semi-empirical	Semi-physical

			• Analytical method (mathematical modelling, dimensional analysis and mechanical analysis)	while dimensional analysis clarified the relationships between the observed parameters.		
Thomson et al. [10]	2022	Canada	• Observational research (utilizes right-censored or current status observations) • Stochastic fire spread growth model (generates data from a simulation study mimicking real wildfire conditions) • Statistical model • Spot fire production model. • Firebrand rate model	Develop a simulator to model the generation and lofting of burning embers from wildfires, estimating spot fire development rates and significant covariates. Use a Poisson process for firebrand generation and a logistic function for spot fire probability, incorporating an indicator for burning states. The simulator employs a stochastic wildfire growth model based on the Canadian Forest Fire Behavior Prediction (FBP) System, incorporating a barrier, to generate simulated data. This data is then used to estimate parameters via maximum likelihood, utilizing right-censored or current status observations.	Hybrid model	Combination of stochastic methods (to handle randomness), probabilistic method (new ignition), and semi-empirical techniques (to incorporate observed data (empirical data) and physical principles)
Jha & Zhou [11]	2022	United States	• Observational research (historical fire data analysis) • Machine learning (ML) models: K-Nearest Neighbors (KNN) model, a non-linear Support Vector Machine (SVM)	Firebrand data was collected from full-scale laboratory experiments with various fuel types and wind speeds. This data was used to train and assess two non-parametric ML models to predict the number and landing mass distribution of the firebrands.	Empirical	Statistical-empirical

Table A11. Summary of studies on firebrand transport modeling (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Ellis [12]	2010	Australia	• Observational research (drop test) • Statistical analysis (correlation, ANOVA, standard t-test and linear regression) • Models for terminal velocity	Investigated jarrah's aerodynamic characteristics and firebrand yield (E. marginata) and karri (E. diversicolor) eucalypt barks dropped from a 22.7 m mobile tower to record fall times for calculating terminal velocity. Additionally, parameters such as gliding and spin behavior of bark flakes were examined. The bark samples (22 karri and 27 jarrah)	Empirical	Statistical-empirical

				were collected based on specific criteria to ensure representation (to capture variation). Linear regression and correlation analyses were conducted to evaluate the relationships between terminal velocity, surface density (mass/projected area) and spin behavior of the samples.		
Tohidi & Kaye [13]	2017a	United States	• Physics-based model • Observational research (free-fall test using image processing techniques) • Statistical analysis (Metropolis Monte-Carlo simulations)	Developing and validating a comprehensive 3D deterministic 6-Degrees-of-Freedom (DOF) transport model for rod-like debris, including lift and rotational forces. Additionally, a statistical approach was employed to validate the results of the free-fall experiments (with non-combusting model firebrands) against numerical simulations.	Semi-empirical	Semi-physical
Almeida et al. [14]	2011	Portugal	• Experimental research (controlled laboratory experiments (vertical combustion tunnel)) • Software: LAB Fit and Statistica (for data analysis) • Empirical model	Conducted laboratory experiments with firebrand materials from Pinus pinaster and Eucalyptus globulus (two representative species in Portugal), varying particle orientation (±90℃) and airflow velocity (0 to 6.5 m/s) on combustion (flaming or glowing regime) under both wind and no-wind conditions. Measure mass loss, residual mass, flaming duration, and burnout times. Develop empirical models to predict trends and illustrate their importance.	Empirical	Statistical-empirical
Song et al. [15]	2017	China	• Experimental model (wind tunnel experiment) • Simplified theoretical analysis (heat transfer analysis)	Experiments were conducted in a wind tunnel using disc-shaped wood particles of varying sizes (about 1 g), which were heated to create smoldering and then blown by horizontal winds of 5 or 7 m/s. The transport distance and mass loss of the firebrands were measured.	Semi-empirical	Semi-physical
Oliveira et al. [16]	2014	Portugal	• Physics-based model (mathematical model) • Observational research (firebrand drop test and combustion)	Develop a mathematical model to predict cylindrical wind-driven firebrands' trajectory, mass, temperature, and size evolution. Validate with tests comparing experimental measurements of non-burning particles in still air and burning particles in airflow with existing data.	Semi-empirical	Semi-physical
Page et al. [17]	2019	United States	• Observational research (National Infrared Operations Program (NIROPS) data collection) • Statistical analysis	Utilized broad-scale infrared data from the 2017 Northern Rockies, USA, fire season to assess environmental and fire-related factors. Correlations were examined between the maximum observed spot fire distance and geo-referenced data on wind speed, vegetation, terrain, and fire	Empirical	Statistical-empirical

			• Evaluation of Albini's model (1979) - (theoretical model)	characteristics. A comparison was conducted between the observed maximum spotting distance for each unique fire day and the predicted theoretical maximum spot fire distance from Albini's (1979) model.		
Storey et al. [18]	2020	Australia	• Observation research (optical line scans of wildfires) • Statistical analysis and models (Gamma generalized linear model and Negative Binomial Regression) • Maximum-distance model • Spot-number model	Analyzed 338 aircraft-acquired observations from south-east Australian wildfires (2002-2018). Used statistical analysis to identify key predictors of maximum spotting distance and number of long-distance spot fires.	Empirical	Statistical-empirical
Thurston et al. [19]	2017	Australia	• UK Met Office Unified Model (UM) • Large-Eddy Model (LEM) (turbulent plume dynamics) • Lagrangian particle transport model	Couple LES of bushfire plumes with an offline Lagrangian particle transport model to calculate the firebrand trajectories and evaluate the impact of turbulent plume dynamics.	Semi-empirical	Physical-mechanistic
Koo et al. [20]	2012	United States	• Physics-based model (firebrand transport and firebrand combustion model) • HIGRAD/FIRETEC model (coupled-physics fire model for wind field generation)	Simulate disc and cylindrical firebrand combustion and transport using a coupled-physics model, assessing trajectories with/without terminal velocity assumptions. Conduct eight surface fire simulations and four with combined surface and canopy fuels.	Semi-empirical	Physical-mechanistic
Mendez & Farazmand [21]	2022	United States	• Physics-based firebrand transport model • Crude Monte Carlo Simulations (CMCS) • Importance Sampling (IS) • Large Deviation Theory (LDT)	Examine methods for quantifying the landing distribution of firebrands and propose a method for predicting low-probability spot fire events, such as spot fires that occur far from the original burn unit. The estimated landing distribution (providing probability density function (PDF)) quantifies the proportion of the firebrands landing at a distance l, regardless of size or mass. Numerical findings were demonstrated using two analytically prescribed wind fields (logarithmic and hyperbolic tangent wind profiles).	Semi-empirical	Statistical-mechanistic
Tohidi & Kaye [22]	2017c	United States	• Physics-based stochastic model • Experimental test (wind tunnel)	A stochastic model for firebrand transport was developed and evaluated using wind tunnel data. Coupled the LES-resolved velocity field with a	Stochastic model	Semi-physical

				3D deterministic firebrand flight model using Monte Carlo simulations. Conducted sensitivity analysis to assess the impact of initial conditions on trajectories.		
Albini et al. [23]	2012	United States	• Mathematical Model • Physics-based model (analytical trajectory calculations) • Physics-based model for active crown fire (source) • Observational research (empirical data integration)	A mathematical model was developed to incorporate wind-blown flame front height and tilt, a two-dimensional wind-blown buoyant plume model, logarithmic wind speed variation, and an empirical model for firebrand burning rate. The firebrand's trajectory was analytically expressed from the plume's lower boundary to the canopy top. The combined horizontal flight distance and the point where the plume flow can no longer carry the firebrand determine the spotting range based on its final diameter.	Semi-empirical	Physical-mechanistic
Cruz et al. [24]	2022	Australia	• Observational research • Statistical analysis (logistic and non-linear regression analysis) • Functional forms	Developed fire spread models for three fire behavior phases using logistic and non-linear regression with datasets from experimental fires and wildfires. Modelled effects of wind speed, fine dead fuel moisture, understory fuel structure, long-term landscape dryness, and slope steepness. The fire spotting effect was incorporated in the high-intensity phase (Phase III). Evaluated model performance using statistical analysis for reliability.	Empirical	Statistical-empirical
Himoto & Tanaka [25]	2008	Japan	• Physics-based urban fire spread model • Observational research (historical fire data analysis) • Firebrand spotting model (probabilistic approach) • Hamada model	Fire spread was simulated by predicting the behavior of individual building fires under the thermal influence of neighboring fires. A one-layer zone model was used, considering thermal radiation, wind-blown fire plumes, and firebrand spotting. The model was validated using a hypothetical urban area with 2,500 buildings and a past urban fire in the city of Sakata in 1976.	Semi-empirical	Physical-mechanistic
Pereira et al. [26]	2015	Portugal	• Large Eddy Simulation (LES) with equivalent volumetric heat source. • Mathematical and Numerical models • Coupled fire-atmosphere model	Conducted LES of wind above vegetation using a volumetric heat source. Predicted distances for spherical firebrands as Lagrangian points. Solved particle momentum, heat, and mass transfer equations in	Theoretical	Physical-mechanistic

			• Physics-based model (firebrand transport and combustion model) • Albini model	an unsteady 3D wind field. Compare distances for grass fires and burning trees to the Albini model.		
Sardoy et al. [27]	2007	France	• Physics-based model (three-dimensional - 3D) • Firebrand thermal and combustion model • Numerical model	The 3D physics-based model includes precomputing gas flow and thermal fields induced by a crown fire (allowing the localization of firebrands in the plume). It investigates the thermal degradation and combustion of fuel particles and calculates the trajectories and burning rates of disc-shaped firebrands (of varying sizes and densities) under various conditions.	Theoretical	Physical-mechanistic
Anthenien et al. [28]	2006	United States	• Observational research (experimental test) • Numerical Model (Runge–Kutta method) • Mathematical model (firebrand combustion and transport model)	This study employs a numerical model to investigate firebrand behavior, with a focus on the dynamics of burning and transport. Coupled ordinary differential equations are solved with a Runge–Kutta method to simulate trajectories of spherical, cylindrical, and disc geometries launched from specific heights or lofted by a buoyant plume (from a small-scale ground fire plume). The impact of initial mass, surface burning temperatures, and wind conditions on propagation distances is systematically assessed.	Theoretical	Physical-mechanistic
Bhutia et al. [29]	2010	Canada	• Large Eddy Simulation (LES) • Classical plume model • Coupled fire-atmosphere model • Physics-based model (firebrand transport and combustion model)	Classical plume modelling examined firebrand lofting under restrictive conditions. The coupled fire/atmosphere LES approach connected firebrand lofting, propagation, and deposition processes. It analyzed the behavior of firebrands from a moving grass fire in a 3D, time-varying coupled atmosphere-wildfire circulation. The study conducted a sensitivity analysis of the propagation to the release height and compared the results from the coupled LES with those from the empirically derived 2D plume model approach.	Theoretical	Physical-mechanistic

Table A12. Summary of studies on firebrand ignition modeling (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Fang et al. [30]	2021	China	• Physics-based model (Theoretical study) • Experimental test	The heated spherical stainless-steel particle was prepared at a temperature in a ceramic tube furnace. The particle was then released onto a pine needle fuel bed to study ignition behavior. The effects of particle temperature and radiation heat flux on ignition probability and ignition delay time were assessed. Multiple trials were conducted to ensure the reliability and consistency of the data.	Semi-empirical	Semi-physical
Fernandez-Pello et al. [31]	2015	United States	• Experimental model • Physics-based model (Semi-empirical analytical and numerical model approaches)	The study combines experimental and theoretical modelling to understand the ignition mechanisms of natural combustible material (fuel beds) by hot metal particles and embers. Heated metal particles and embers were dropped onto a cellulose-based fuel bed. Additionally, a 2D computational model was developed to simulate the ignition process using coupled algebraic equations, which were solved numerically.	Semi-empirical	Semi-physical
Hadden et al. [32]	2011	United Kingdom	• Physics-based model (hot spot ignition) • Experimental tests	The study employs experimental and theoretical analysis to investigate the ignition process in homogeneous fuel beds using hot (500-1300℃) spherical steel particles (0.8-19.1 mm), with a focus on the relationships between particle size and temperature.	Semi-empirical	Semi-physical
Yang et al. [33]	2022	China	• Experimental tests • Statistical analysis • Logistic regression model (a mathematical model to predict ignition probabilities)	Conduct ignition experiments with larch fuel beds at varying moisture levels and packing ratios, using wind speeds and firebrands (such as cones and twigs). Established two empirical models linking ignition probability with fuel properties and wind speed.	Empirical	Statistical-empirical
Scott et al. [34]	2011	United State	• Physics-based model (based on Hot Spot Ignition Theory) • Experimental test	Conducted experimental (laboratory and real-life fire fuel bed) and theoretical analysis of ignition of fuel beds with hot spherical steel particles. The experiment involved particle diameters ranging from 0.8 to 19.1 mm and temperatures between 500 °C and 1300°C, focusing on the ignition behavior of different fuel beds.	Semi-empirical	Semi-physical
Ganteaume et al. [35]	2009	France	• Observation research	Various tests were conducted under laboratory conditions to assess the ability of several fuel beds to be ignited by firebrands and to sustain a fire (fuel bed tests). In	Empirical	Statistical-empirical

			• Experimental tests (laboratory conditions) • Statistical analysis (including Linear Regression, Logistic Regression, ANOVA (Analysis of Variance), Chi-square tests, and Hierarchical Cluster Analysis)	addition, the ability of different firebrands to ignite fuel beds was analyzed (firebrand tests). Common fuel beds and firebrands from southern Europe were selected. Logistic regression models were developed to predict the probability of fuel bed ignition.		
Urban et al. [36]	2017	United States	• Experimental tests • Observational research • Physics-based model (analytical study)	Conduct an experimental and analytical study using hot metal particles (aluminum and stainless steel) with diameters ranging from 1.6 to 8 mm. These particles were heated to temperatures between 500 and 1100℃ and then dropped onto a powder grass blend fuel bed (natural fuel beds).	Semi-empirical	Semi-physical
Urban et al. [37]	2019	United States	• Experimental test • Observational research (recorded the smoldering ignition or no ignition) • Statistical models (logistic regression model) • Physics-based model (energy model - ignition dynamics)	Conducted small-scale wind tunnel experiments by dropping glowing firebrands onto a porous fuel bed made of coastal redwood sawdust at varying moisture levels to observe ignition outcomes. The results were analyzed using logistic regression to establish ignition boundaries based on firebrand size and fuel moisture content.	Semi-empirical	Semi-physical
Álvarez et al. [38]	2023	Chile	• Physics-based model (ignition delay times) • Experimental test (Idealized-Firebrand Ignition Test (I-FIT)) • Linear regression model	An electric heater was used to simulate firebrands and expose Eucalyptus globulus leaves to a controlled heat flux. Ignition delay times were evaluated for fuel beds with volume fractions ranging from 0.03 to 0.07 and moisture contents found in real Chilean forests.	Semi-empirical	Semi-physical
Viegas et al. [39]	2014	Portugal	• Experimental test (laboratory conditions) • Observational research	Measured ignition time delay and tested ignition probability for 11 pairs of burning firebrands (eucalyptus bark and pine cones) dropped from 50 cm on fuel beds of species common in Mediterranean forests with varying moisture contents.	Empirical	Statistical-empirical

Yin et al. [40]	2014	China	• Physics-based model (theoretical consideration of the heat transfer process) • Experimental test • Observational research (Observed and recorded the ignition behavior) • Linear regression models	Ignition experiments involved placing glowing firebrands on a pine needle fuel bed with varying moisture contents. A heat transfer analysis theory for firebrand ignition was conducted and validated by correlating the theoretical results with experimental data.	Semi-empirical	Semi-physical
Lin et al. [41]	2022	China	• Physics-based 2-D computational model • Experimental observations	Created a 2-D computational model integrating heat and mass transfer with heterogeneous chemical reactions to simulate smoldering ignition behavior under various conditions, focusing on irradiation spot size and radiant heat flux of typical solid fuels.	Theoretical	Physical-mechanistic
Matvienko et al. [42]	2018	Russia	• 3-D Mathematical model (Physics-based model) • Experimental model • Observation research	Develop a 3-D mathematical model to simulate the ignition of fuel bed (FB) by firebrands. Conducted experiments to verify and test the model and to determine the FB ignition time by a single pine bark and twig firebrand (Pinus sylvestris).	Theoretical	Physical-mechanistic
Zhu & Urban [43]	2023	United States	• Experimental test • Observational research • Numerical model (2D model) • Logistic regression function (ignition results) • Sensitivity analysis	Electric cartridge heaters (7.5 mm and 15 mm) were used as idealized firebrands to simulate conditions up to 60 kW/m^2. A second heater was added to study thermal interactions under critical conditions. Numerical modelling was used to analyze various firebrand sizes and separation distances.	Semi-empirical	Semi-physical
Valenzuela et al. [44]	2023	Chile	• Experimental tests (combustion tests) • Analytical model (based on thermal ignition theory)	Utilized a customized Idealized-Firebrand Ignition Test (I-FIT) instrument with radiant heaters to simulate the effect of decreasing incident heat flux on the ignition delay times of dry pine needles, measuring ignition delay times, mass loss, radial temperatures, and radiative heat flux. Developed an analytical model based on thermal ignition theory using an integral approach, comparing predicted ignition temperatures with actual measurements to evaluate delay times.	Semi-empirical	Semi-physical

Table A13. Summary of studies on physics-based fire spotting models (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Hillen et al. [45]	2015	Canada	• Birth-jump models (using random walk and two-compartmental reaction-diffusion approaches)	Birth-jump models were formulated as nonlinear integro-differential equations using random walk and reaction-diffusion approaches to describe coupled growth and spatial spread, particularly in scenarios where these processes cannot be decoupled. The model introduced key parameters, including spotting intensity (rate σ) and spotting spread (variance ds), to analyze the impact of fire spotting on fire spread in homogeneous terrain under both no-wind and constant wind conditions.	Theoretical	Physical-mechanistic
Martin & Hillen [46]	2016	Canada	• Modelling approach (Physics-based and statistical) • Observational research (experimental data) • Numerical simulation	Develop a physics-based model for firebrand transport and combustion, incorporating detailed spotting processes and statistical modelling techniques like regression analysis and non-linear regression to analyze firebrand mass distribution. Utilize experimental data from laboratory and field experiments to measure ignition probabilities and validate the model. Employ numerical simulations to demonstrate the impact of various model components on the spotting distribution.	Semi-empirical	Physical-mechanistic
Masoudvaziri et al. [47]	2021	United States	• Observational research • Hamada model SWUIFT model (based on the Cellular Automata model)	A new quasi-empirical model was proposed to replicate the characteristics of modern wildland-urban interface (WUI) fires, focusing on key mechanisms such as thermal radiation and fire spotting. This model was validated using spread rates from nine major North American wildfires, specifically the 2007 Witch and Guejito fires and the 2017 Tubbs fire.	Semi-empirical	Semi-physical
Sardoy et al. [48]	2008	France	• Physics-Based model • Numerical simulation • Dimensional analysis • Statistical model	The transport of 10,000 disc-shaped firebrands was analyzed with different aspect ratios under moderate- to high-intensity surface wildfire scenarios, including partial to full-crown involvement. Firebrand properties and initial locations were randomly generated. The study calculates the normalized mass of firebrands in both flaming and charring states and examines their spatial distribution on the ground.	Theoretical	Statistical-mechanistic

Table A14. Summary of studies on the integration of spotting into fire spread models (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Trucchia et al. [49]	2019	Spain	• Statistical models • Global sensitivity analysis • Sparse surrogate models: generalized Polynomial Chaos (gPC) and Gaussian Process (GP) • LSFire+ model • Numerical simulations	The study utilizes a stochastic representation of the fireline and surrogate models (gPC and GP) to identify key parameters affecting the topology and size of the burnt area. It calculates Sobol's sensitivity indices and tests various truncation and projection strategies for gPC surrogates. It performs best with a sparse least-angle regression (LAR) strategy and a low-discrepancy Halton's sequence. The training data set was from Monte Carlo random Sampling, quasi-random Halton's sequence, and the quadrature rule.	Semi-empirical	Semi-physical
Pagnini & Mentrelli [50]	2016	Spain	• **Randomized Level Set method *** • Probability Density Function (PDF) • Numerical simulation	The study employs randomized level set contours and a reaction-diffusion evolution equation to simulate front propagation, incorporating random effects such as turbulent heat convection and fire spotting. It includes criteria for marking burned areas, accounts for fuel ignition delays, and calculates heat accumulation over time. Numerical simulations analyze the forefront's evolution with and without firebreak zones using the LSM and current modelling approach.	Semi-empirical	Semi-physical
Pagnini & Mentrelli [51]	2014	Spain	• **Level Set Method** (**LSM ***) • Reaction-Diffusion equation • Randomized (generalized) Level Set Method • Physical Random Fluctuations (PDF of spotting and turbulence effects) • Numerical simulation	The modelling and simulation of wildfire propagation using level-set and reaction-diffusion equations as complementary and reconciled methods to create a smooth representation of the fire front contour. This approach considers deterministic positions driven by the rate of spread (ROS) and incorporates random effects, such as turbulent hot air and fire spotting, using the probability density function (PDF). Numerical simulations of a simple case study examined the model's behavior, taking into account fire-break effects, pre-heating, and ignition delays.	Semi-empirical	Semi-physical
Mentrelli & Pagnini [129]	2016	Italy	• Randomized (generalized) Level Set Method • Numerical simulation	The modified level set method incorporates random effects due to turbulent hot-air transport and fire spotting using a probability density function (PDF) approach. This enhances the deterministic rate of spread (ROS) through the	Semi-empirical	Semi-physical

				convolution of the PDF, improving the classic level set approach for practical test cases.		
Pagnini [52]	2014	Spain	• Generalized Level Set Method • Probability Density Function (PDF) • Numerical simulation: Total Variation Diminishing (TVD) Runge–Kutta scheme	Tracked the fire front using the deterministic rate of spread (ROS) equation with random effects from turbulence and fire spotting (using the probability density function (PDF)) and marked burned points with a 0-1 threshold and ignition delay due to hot air and landing firebrands. Used the generalized LSM to analyze differences between windward (turbulence only) and leeward (turbulence and fire spotting) sectors, focusing on ember jump-length and wind direction variability.	Hybrid model	Semi-physical
Nishino [53]	2019	Japan	• Physics-based fire plume model • Stochastic modelling • Observation research (historical fire damage data) • Monte Carlo simulations	The development and validation of a physics-based urban fire spread simulation incorporating the stochastic occurrence of spot fires, specifically for Japan's densely built wooden residential areas. Validated using Monte Carlo simulations based on the Itoigawa fire data, comparing results with the 2016 incident fire damage without considering fire suppression and ignition delays of adjacent buildings.	Hybrid model	Semi-physical
Alexandridis et al. [54]	20008	Greece	• CA model • Observational research • GIS • Non-linear optimization technique (Black-box)	Developed a Cellular Automata (CA) model to simulate the dynamics of forest fire spread on a mountainous landscape, considering vegetation type, density, wind speed, direction, and the spotting phenomenon (characterized by the transport of firebrands like pinecones). The model simulated the 1990 Spetses wildfire, fine-tuning parameters with black-box optimization techniques and GIS data. Validation was performed using actual fire data.	CA2 - Random chance of fire spread model	Other Models
Alexandridis et al. [55]	2011	Greece	• CA model • GIS • Lattice-based dynamic model • Wildfire-spread model • Sensitivity analysis	The formulated CA-GIS model presents a lattice-based dynamic system incorporating various factors, including landscape statistics, vegetation attributes, wind field data, fuel humidity, and spotting transfer mechanisms. The model also incorporates fire suppression tactics based on the operational capabilities of air tankers. The developed model is evaluated by simulating the dynamics of a large-scale fire in the Greek National Park of	CA2 - Random chance of fire spread model	Other Models

				Parnitha Mountain (June 2007) and comparing the results with actual fire-spread characteristics.		
Perryman et al. [56]	2013	United States	• CA model • Submodels (statistical model and mathematical models (for fire spread and firebrand behavior) • Spotting mechanism (stochastic and probabilistic integration approaches for firebrand lift-off and dispersion) • Sensitivity analysis • Observational research (Simulations using real fire events)	A CA model was developed that combines fire spread and firebrand landing patterns. Simulated wildfire in a Pinus ponderosa ecosystem with varying conditions. Conducted 2500 stochastic simulations to study spot fire ignition beyond fuel breaks and their impact on fire spread.	Hybrid CA: Physics-based + spotting parametrization + CA3 (with stochastic model and probabilistic rules)	Other Models
McDanold & Malik [57]	2023	Unite States	• SERF (Spatially extended radiant heat fire) model • Observational research (prescribed fires performed outside of a laboratory) • CA model • Coupled map lattice (CML) model • Modified Newton's law of cooling • Kernel distribution	A fine-scale fire behavior model was developed using infrared temperature data from the New Jersey Pine Barrens (2017-2020), defining five stages based on parameters like radiant temperature. The model incorporated a coupled map lattice (CML) model into a CA framework for accurate metrics. One hundred simulations were conducted with fuel moisture and spotting ignitions (incorporated as an initial condition not represented in the dataset, with multiple ignition points placed randomly), validating the results against observational data from prescribed fires.	Hybrid CA3: Basic Physical Principles (radiant heat transfer and fire spread), similar to percolation models (random thresholds)	Other Models
Zhao [58]	2011	China	• Observational research (historical fire data) • Irregular coarse CA model • GIS • Fire spread analysis: Radiative, convective, and long fire spread (non-local interaction) using	Development of a fire-spread model (GIS-CA-fire tool) based on irregular coarse CA integrated with GIS to simulate fire behavior and assess its damage in densely built urban areas. Two sub-processes were analyzed: (I) fire development in a single building and (II) fire spread among buildings (short fire spread due to direct flame contact, radiative and convective spread and long fire spread due to firebrand spotting). The model is verified	Hybrid CA: Physics-based (deterministic and stochastic approaches) + spotting parametrization +	Other Models

			simplified physics-based parametrization for firebrand transport, stochastic firebrand generation, and probabilistic ignition upon landing) • Loss Assessment Model	through 100 random simulations for a real site fire spread in Kobe City (1995, Japan), comparing simulation results with local observations.	CA3 (with stochastic model and probabilistic rules)	
Boychuk et al. [131]	2009	Canada	• Stochastic fire growth model • Observational research	Developed a stochastic model using a continuous-time Markov chain to predict fire behavior, including average growth and variability. Implemented for probability contour plots, burn size distributions, and event time distributions, with an incorporated spotting mechanism.	CA3 - stochastic model with continuous-time Markov Chain Model	Other Models
Krougly et al. [130]	2009	Canada	• Stochastic fire growth model • GIS • Observational research	Developed a stochastic model with a space-time Markov process on a lattice, implemented in C++ as "TDsimulator". Generates disturbance patterns based on user inputs, predicts changes in landscape cover with GIS routines and simulates forest fire behavior.	CA3 - stochastic model with continuous-time Markov Chain Model	Other Models
Masoudvaziri et al. [132]	2023	Unite States	• SWUIFT (Streamlined Wildland–Urban Interface Fire Tracing) model (CA framework) • Monte Carlo simulation • Sensitivity Analysis	Integrates stochastic modelling to track firebrand dispersion and conduct sensitivity analyses on critical variables. It employs Monte Carlo simulations with Latin hypercube sampling to capture uncertainties in fire spotting, wind speed and ignition criteria, optimizing computational efficiency. The framework combines historical wildfire hazard data with cumulative distribution functions to assess the number of ignited buildings over time. It was tested on two real wildfire events in California (Trails and Fountain Grove communities) to demonstrate variations in community fire spread.	CA3 - stochastic model and probabilistic rules	Other Models
Egorova et al. [133]	2020	Spain	• WRF-SFIRE model (Level-Set Method (LSM))	The study splits the motion of the fire front into a drifting part (based on the level-set method) and a fluctuating part (parametrized for the turbulence of hot-air transport and firebrand landing distance (jump-length distribution	Hybrid model	Semi-physical

			• Statistical model (physical parametrization of firebrand landing distribution) • Numerical simulation • Simplified Firebrand model (RandomFront parametrization)	of firebrand)). The model highlights the net effects of turbulence and firebrand flying without fire-atmosphere coupling.		
Egorova et al. [134]	2021	Spain	• Physics-based fire plume model • Rothermel's ROS model • Fire spotting model • Numerical simulations	The study develops a formula that links flame geometry and fireline intensity, based on the energy conservation principle and the energy flow rate in the convection column above the fireline in wildfires, for both steady and unsteady cases. This formula is incorporated into Rothermel's Rate of Spread (ROS) model to account for the effects of wind and slope on flame geometry. Flame geometry is then integrated into firebrand landing distribution, and numerical simulations are used to demonstrate the significant contribution of flame geometry to generating secondary fires.	Hybrid model	Semi-physical
Egorova et al. [136]	2022	Spain	• Level-Set Method (LSM) • Albini Model (theoretical model) • Extension of RandomFront parametrization • Numerical simulation	The study develops an alternative Albini formulation based on the energy conservation principle and extends the RandomFront parametrization to include flame geometry and slope. The analysis examines the flame geometry on flat terrain and compares it with the effects of slope. Numerical simulations and post-processing evaluate the impact of these parameters on fire behavior.	Hybrid model	Semi-physical
Kaur et al. [59]	2016	Spain	• Level Set Method (LSM) (for Eulerian moving interface method) • Discrete Event System Specification (DEVS) (using Lagrangian front tracking technique) • Probability Density Function (PDF) (embodied random effects) • Numerical simulation	The fire-front propagation is modelled as a combination of drifting and fluctuating components, with random effects (turbulence and fire spotting) represented by a PDF, including fuel ignition delay. The performance of these effects is evaluated using both Eulerian (LSM) and Lagrangian (DEVS) methods through numerical simulations with identical setups, accounting for wind effects and fire-break zones. In addition, a sensitivity analysis is conducted to assess the impact of changes in the lognormal distribution shape on firebrand landing distances.	Hybrid model	Semi-physical

			• Sensitivity analysis			
Asensio et al. [60]	2021	Spain	• PhyFire model and HDWind model (integrated in online GIS) • Spotting model • Numerical method	The PhyFire model is a simplified physical wildfire spread model developed by the research group on Numerical Simulation and Scientific Computation at the University of Salamanca. It has been integrated into an online **GIS** interface, incorporating the effects of fire spotting as a random heat contribution to enhance usability and accuracy.	Semi-empirical	Semi-physical
Trucchia et al. [61]	2019	Spain	• RandomFront 2.3 (physical parameterization of fire spotting) in a coupled fire-atmosphere model (WRF-SFIRE) • Numerical simulation using LSFire+ model (based on level set method)	The RandomFront 2.3 model was updated by integrating it into the WRF-SFIRE coupled fire-atmosphere model to simulate fire behavior. The model also considered the turbulent effect of the heat fluxes and included the ignition delay of fuel, which accounted for the combined impacts of firebrand landing and hot air exposure. Numerical simulations performed using the LSFire+ model evaluated fire behavior under various conditions, with a focus on the probabilistic modeling of firebrand transport and ignition.	Hybrid model	Semi-physical
Loepfe et al. [62]	2011	Spain	• FIRE LADY (FIre REgime and LAndscape DYnamics) model • Canadian Forest Fire Weather Index System (FWI) • Statistical analysis	Developed FIRE LADY, using weather, topography, vegetation growth, fire behavior, suppression, and land use changes. Modeled fire behavior with Rothermel equations, including crown fire and spotting (with a stochastic percolation approach). Calibrated for three NE Spain regions to reproduce fire regimes, land cover changes, and tree biomass.	Semi-empirical	Semi-physical
Hargrove et al. [135]	2000	Unite States	• EMBYR model (Probabilistic model) • Cellular Automata (CA) model • Bond percolation process (connectivity of burning cells) • Fire spread simulation • SPOT subroutine of the Rothermel-derived BEHAVE fire prediction model	The EMBYR model simulates fire ignition and spread in a gridded heterogeneous landscape. It evaluates fire spread probability (I) to eight neighboring cells based on local conditions (fuel type, moisture, wind) and incorporates fire spotting by distributing firebrands to downwind sites. Simulations assessed various weather and fuel conditions on the subalpine plateau of Yellowstone National Park to analyze fire behavior and landscape-scale fuel heterogeneity.	CA2 - Random chance of fire spread model similar to percolation models (random thresholds)	Other Models

Porterie et al. [63]	2007	France	• Fire spread model using the small world network (SWN) model to simulate fire propagation • Percolation transition criterion (to establish thresholds for fire spread in heterogeneous media) • Observational research (laboratory experiments) • Statistical analysis	The forest is modelled as a network comprising of flammable sites (nodes) and potential fire paths (edges), incorporating a weighting procedure based on the characteristic times of thermal degradation and combustion. This model accounts for both short-range (radiative, convective) and long-range spotting effects of firebrands. Validation is conducted through laboratory experiments, focusing on fire front propagation thresholds and analyzing the fractal dimensions of burned areas to assess model accuracy.	Theoretical	Physical-mechanistic
Zigner et al. [64]	2020	United States	• Fire Area Simulator (FARSITE) model • High-resolution fuel maps and hourly wind data • FlamMap simulations • Sensitivity analysis	Used FARSITE within FlamMap to simulate two wildfires under Sundowner winds in Santa Barbara, focusing on fire spread rates and perimeters. Conducted sensitivity tests on ignition timing, location, and spotting impact. Aimed to evaluate model performance under extreme wind conditions for wildfire management.	Semi-empirical	Semi-physical
Zohd [65]	2020	United States	• Machine-Learning Algorithms (MLA's) • Observational research • Physics-based model	A framework was developed with submodels for ember trajectory, topography, and machine learning, enabling real-time simulations for first responders. It simulates hot ember-driven fire propagation and debris distribution.	Hybrid model	Machine learning (data-driven) with digital twin technology (system-based modelling).

* CA—Cellular Automata; LSM—Level Set Method; Randomized Level Set method - reaction-diffusion equation is associated with the LSM; GIS—Geographical Information Systems.

Table A15. Summary of empirical research on fire spotting (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Filkov & Prohanov [66]	2019	Australia	• Observational research (empirical data from thermal imaging)	They developed custom software to analyze short-distance spotting dynamics by detecting and tracking flying firebrands in thermal images. The software consists of two main modules: a detector and a tracker. The detector determines	Empirical analysis based on	Observed data to analyze and characterize firebrands, contributing

			• Mathematical model (image processing and tracking algorithms)	the location, and the tracker compares the firebrand in different frames and determines the identification number of each firebrand. This process enables the determination of firebrand temperature, size, and velocity. The results were compared with the data obtained by independent experts and experimental data.	observational research	to both theoretical models (firebrand transport in wildland and structural fires) and improving empirical models.
Adusumilli et al. [67]	2021	United States	• Experimental observation • Computer algorithm (used to process the images and extract firebrand characteristics) • First-order extrapolation method	Estimate the total number of hot firebrands from 71 burning trees/shrubs (Douglas fir, ponderosa pine, and sagebrush) with heights ranging from 1.4 to 6.2 meters. A network of 65 fire-resistant fabric stations strategically placed at different radii and angles in the wind direction measured the released firebrands. With this data, a first-order extrapolation method was developed to estimate the source terms (total number of hot firebrands released).	Empirical analysis based on observational research	Observing, collecting data, and measuring firebrand generation rates during experiments with trees or shrubs torching helps implement detailed physics-based wildfire propagation models more accurately.
Almeida et al. [68]	2014	Portugal	• Observational and Experimental Research (controlled laboratory experiments) • Particle image velocimetry system (PIV) • Dynamic Studio software of Dantec (identify and characterize particles)	The firebrands released from burning eucalyptus trees were analyzed through four burning tests (T1 to T4) involving eucalyptus barks and shrubs. The design of the tests incorporated variations in the location (suspended and on a fuel bed) and orientation (vertical and horizontal) of the eucalyptus barks. An additional test was performed with a shrub fuel bed. Measurements of convective upflow velocity and temperature (2 meters above the tree), weight loss, and firebrand release via Particle Image Velocimetry (PIV) were conducted. The number and size distribution of firebrands released were analyzed under different scenarios.	Empirical analysis based on observational research.	Descriptive, controlled, quantitative analysis of firebrands released from torching trees (laboratory experiments).
Hudson & Blunck [69]	2019	United States	• Experimental model (Vertical tunnel experiment)	Samples of 125 mm length, 2 and 6 mm diameters, and moisture content of 0.5% and 15% from different species (douglas fir, western juniper, ponderosa pine, and white oak) were burned in a heated wind tunnel to simulate controlled	Empirical analysis based on observation research.	Collect empirical data to create models and parameters to estimate

			• Observational research (DSLR camera) • Statistical analysis (Factorial analysis of variance - ANOVA)	conditions. Ember formation time was measured with a DSLR camera. A factorial analysis of variance was conducted to assess the sensitivity of ember formation time to various factors, including species (dowel vs. natural sample), diameter, moisture content, fuel condition, crossflow temperature, and crossflow velocity.		the rate of ember generation under different conditions.
Ganteaume et al. [70]	2011	France	• Observational research • Experimental tests (laboratory conditions) • Flammability measurement method • Statistical analysis	Experimental tests were conducted under laboratory conditions to analyze the effect of fuel moisture content on ignition and combustion for eight types of firebrands commonly generated by wildfires in Southern Europe. The firebrands studied included various parts of trees and different shapes, such as pine twigs, pine bark plates, eucalyptus bark, leaves, pine cone scales, pine cones, acorns, and bark cubes.	Empirical analysis based on observation research.	Describe and characterize firebrand properties for use as inputs in models that predict their behavior within a convective plume and their potential to cause spot fires.
Suzuki & Manzello [71]	2018	Japan	Experimental and observational research	Firebrands were collected from an urban fire in Itoigawa-city, Niigata, on December 22, 2016. They were analyzed for size and mass, characterized using image analysis software to determine projected areas, and compared with available literature data and (National Institute of Standards and Technology) NIST firebrand generators.	Empirical analysis based on observation research.	Collecting and characterizing firebrand properties from a recent urban fire, comparing them with literature findings and those generated using a firebrand generator.
Thompson et al. [72]	2022	Canada	• Observational research (experimental canopy fire) • Acoustic analysis (monitoR package)	Audio data from cameras housed within fire-proof steel boxes were used to detect and quantify firebrand impacts. Distinct acoustic signatures of firebrands hitting the steel boxes were correlated with fire location and intensity to measure firebrand travel distance and quantify the number of firebrands per second (rate of impacts). An experimental crown fire served as a proof of concept to validate the technique's viability.	Semi-empirical	Semi-physical

			Analytical firebrand travel distance model (Albini model)			
Filkov et al. [73]	2020	Australia	• Observation research Expert elicitation approach through Structured Surveys	Surveyed Australian fire management experts on dynamic fire behaviors in more than 1000 ha fires from 2006 to 2016. Analyzed DFB frequency and quantity observed in each fire.	Empirical analysis based on observation research	Quantitative data on the frequency of dynamic fire behaviors (DFBs) is collected through expert surveys and observational studies, with direct observations regarded as the most representative. This data serves as a foundation for developing predictive models.
Donovan et al. [74]	2023	United States	• Observational research (prescribed fires and wildfire data) • Fuel model BehavePlus fire modelling software v. 5.0.5 (SPOT module based on models developed by Albini for both surface fire and torching trees).	Calculated spot-fire distances within the Loess Canyons Experimental Landscape, Nebraska, U.S.A., using BehavePlus (using SPOT module to calculate the maximum distance), comparing scenarios of grasslands, encroached grasslands, and Juniperus woodlands under prescribed fire and wildfire conditions to assess wildfire risk.	Empirical analysis based on observational research.	Utilizing observational data and simulations to quantify and analyze the impact of vegetation on the spread of fire spots (secondary fires).
Storey et al. [75]	2020	Australia	• Observational research (real-world observational data) • Statistical tests	Analyzed spotting patterns from 251 wildfires using over 8000 **aerial line scan images** from southeast Australia (2002-2018) to quantify spot fire numbers, describe spotting distance ranges (short, medium, and long) and compare	Empirical analysis based on observation research.	Analysed aerial line scan images of wildfires to examine spotting

				patterns across regions. These patterns were associated with broad rainfall measures, elevation and fuel type.		patterns, measure spotting distances, and assess the distributions of spot fires.
Tohidi & Kaye [76]	2017b	United States	• Experimental tests (controlled wind tunnel experiments) • Observational research • Trajectory analysis (Image processing algorithms) Statistical analysis (correlation and probability density function (PDF) analysis)	Conducted wind tunnel experiments, coupled with lofting and downwind transport of non-combusting rod-like firebrands during firebrand shower scenarios. Using image processing algorithms to solve firebrand trajectories. Analyzed the correlation between maximum rise height (z_{max}) and landing location (x_l) and examined PDFs of x_l/z_{max} across different firebrand aspect ratios (firebrand model).	Empirical analysis based on observation research	Observations from controlled laboratory experiments, analysis, and data collection for modelling firebrand transport in wildfires contribute to predictions of spot fire risk and a better understanding of fire spotting phenomena.
Hernández et al. [77]	2018	Chile	• Experimental test Statistical error analysis	The relationship between time to ignition and incident radiative heat flux on forest fuel layers was analyzed by experimental studies of spontaneous ignition using idealized firebrands under controlled conditions. A bench-scale apparatus was utilized to measure ignition time, mass loss, radial temperatures, and radiative heat flux on Radiata Pine needle samples. The firebrand was simulated using a cylindrical electric heater that produced a heat flux of up to 26.7 $\mathrm{kW/m^2}$.	Empirical analysis based on observation research.	Collection of empirical data to understand the ignition of forest fuels by idealized firebrands for use in existing or new thermal models.
Cruz et al. [78]	2012	Australia	Observational research (real-world fire data), "retrospective analysis and reconstruction of an event" using existing models.	The study analyzed the weather conditions, fuels, and propagation of the Kilmore East fire, including tracking fire spotting to understand high-intensity fire behavior in eucalypt forests. Data sources, including infrared line scans, digital photographs, video footage, witness statements, and interviews with fire suppression personnel, were used to reconstruct the fire's propagation and behavior (physical processes).	Empirical analysis based on observational research.	Use existing models for detailed description (physical processes) and reconstruction of real-world events (retrospective empirical analysis).

Beverly et al. [79]	2010	Canada	• Fire ignition and spread • Predictive models: FireWise and FireSmart programs. • Empirical data: Historical fire and vegetation type. • Albini's (1979) • Predictive model: Spotting distances and fire spread.	The study analyzed ignition processes from burning vegetation, including radiant heat, short-range spotting, and long-range spotting. Using GIS, it mapped wildland-urban interface boundaries and identified potential wildfire entry points, suggesting specific mitigation strategies for each community.	Empirical analysis based on observation research	The evaluation method is standardized to map and classify exposure to ignition based on observational data using existing Albini's models.
McCaw et al.[80]	2012	Australia	• Prescribed fire (field experiments) • Observation research Statistical analysis	High-intensity experimental fires were conducted in dry eucalypt forests under high fire danger summer conditions. Fires were ignited simultaneously at two locations with differing understory and fuel structures developed over 2-22 years post-prescribed burning. Fuels were sampled, and per cent cover and hazard scores were assessed for five fuel layers. Fuel and wind data were correlated with fire spread, flame height, firebrand density, and spotting distance.	Empirical analysis based on observation research.	Collection of empirical data describing and understanding fire behavior and its relationship with vegetation characteristics.
Sharples et al. [81]	2012	Australia	• Observational research (line-scan images) • Wind-terrain interaction theory Simple terrain filter model	The interaction between wind, terrain, and multispectral fire data collected during the January 2003 alpine fires over south-eastern Australia was analyzed. A terrain-filter model was used to identify terrain features that contributed to fire channelling, characterized by intense lateral and downwind spotting and extensive flaming zones.	Semi-empirical	Semi-physical
Sullivan [82]	2017	Australia	• Review of Heat Transfer and Interaction Mechanisms	Reviewed research on wildland fire behavior, focusing on heat transfer processes like advection, radiation, flame contact, and burning material transport (spotting). Explored thermal degradation reactions and environmental interactions. Identified knowledge gaps for further study.	Literature review	Reviewing and analyzing existing research on heat transfer processes and interactions in wildland fires.

Peace et al. [83]	2022	Australia	• ACCESS-Fire model • Dry Eucalypt Forest Fire (Vesta) fire spread model • Observational research	Utilized the ACCESS-Fire model (existing model), integrating the Dry Eucalypt Forest Fire (Vesta) fire spread component with the Australian Community Climate and Earth System Simulator (ACCESS) to simulate the behavior of the surface fire spread and fire-atmosphere interaction, focusing on the development of pyrocumulonimbus (pyroCb) clouds and ember transport.	Computational modelling study	Numerical simulation to replicate and analyze the behavior of past fires.
Toivanen et al. [84]	2019	Australia	• U.K. Met Office Unified Model (UM) • Fire model • Observational research	Developed a wildfire model using the UM with four nests with horizontal grid spacings of 4 km, 1.5 km, 444 m, and 144 m. Simulated the Kilmore East fire with and without fire-atmosphere coupling, adding ignitions for long-range spotting. Compared results to observed fire behavior.	Semi-empirical	Physical-mechanistic
Thurston et al. [85]	2016	Australia	• Observational research • UK Met Office Unified Model (UM) (Numerical simulation) Australian Community Climate and Earth-System Simulator (ACCESS) • Sensitivity tests	Evaluated the numerical weather prediction (NWP) systems, such as the UK Met Office Unified Model (UM) within ACCESS, through high-resolution (explicitly resolve shallow convective circulations) numerical simulations at horizontal grid spacings of 400 m and 1.2 km, with multiple vertical levels to capture boundary-layer rolls. Model outputs were validated against observed temperature and wind profiles during Black Saturday bushfires. The analysis assessed the impact of boundary-layer rolls on fire danger through wind variability and ember lofting.	Semi-empirical	Physical-mechanistic
Lareau et al. [86]	2022	United States	• Observational research (satellite and airborne infrared observations) • Fire-perimeter tracking method	Developed and validated a radar-based fire-perimeter tracking tool to track wildfire progression at high spatial and temporal resolution, especially for those affecting communities in the wildland-urban interface. Conducted detailed analyses of radar-derived perimeters for the Bear Fire and Camp Fire to evaluate rapid growth patterns and spotting behavior.	Empirical	Statistical-empirical
Díaz-Delgado et al. [87]	2004	Spain	• Observational research (Remote sensing imagery) • Visual and analytical approaches • Geographic Information Systems (GIS)	Employed fire scar maps generated from remote sensing imagery (30-60 m resolution) using several visual or analytical approaches to identify and document burned areas across the study region accurately. Overlaid geographical layers with burned area maps enable the extraction of crucial spatial fire parameters, such as fire size, frequency distribution, and patterns of fire occurrence. Recorded and analyzed data on fire spots and residual	Empirical analysis based on observational research	Empirical observational analysis using mixed methods (visual and analytical approaches) to quantify and describe spatial and temporal fire

			• Digital Elevation Model • Fractal Dimension • Statistical model	vegetation islands to examine their relationships with fire characteristics and environmental factors.		patterns, their relationships with environmental and human factors, and the effects influencing fire spread and spotting behavior.
Shennan et al. [88]	2023	United States	• Observational research (airborne thermal infrared (ATIR) imagery • United States National Agriculture Imagery Program (NAIP) • Geovisualization tools	Developed geovisualization tools integrating ATIR (Airborne Thermal Infrared imagery) and topographic data to analyze wildfire behavior, including the rate of spread and spotting. These tools were tested and evaluated through user feedback and applied to the Thomas and Detwiler wildfire events in California in 2017.	Empirical	Statistical-empirical
Storey et al. [89]	2021	Australia	• Experimental test (using combustion wind tunnel in laboratory conditions from Forest Fire Research Laboratory of ADAI in Lousã, Portugal) • Observational research (FLIR ThermaCam SC640 infrared camera and color video cameras) • Statistical analysis	Conducted 30 laboratory fire experiments on a 3 m × 4 m fuel bed made of dead mature Pinus pinaster needles, incorporating 0, 1, or 2 manually ignited spot fires, with variations including the presence or absence of a model hill. The combined rate of spread (ROS) of the main fire and any merged spot fires was analyzed using appropriate statistical methods.	Empirical analysis based on observation research	Investigating the interaction between spot fires and topography through laboratory experiments.
Hart et all. [90]	2021	Canada	• Observational research • Photogrammetric monoplotting technique	Georeferenced oblique aerial wildfire photographs from airtanker response in the early stages of fire growth were used to locate fire front positions in photo	Empirical analysis based on	Empirical data collection based on actual wildfire observations to validate

			• software program WSL Monoplotting Tool (MPT) • Canadian Fire Behavior Prediction System	pairs from five fires, taking 31 to 118 minutes apart. Head fire spread distance and head fire rate of spread (HROS) were then calculated to assess fire behavior.	observational research	fire spread models or develop a new empirical relationship.

Table A16. Summary of studies on integration of spotting into operational fire spread models (2000–2023).

Authors & References	Year	Country	Method	Methodology	Model Type/ Approach	New Model/ Approach
Andrews [91]	2014	United States	Review and description of the system's development and updates.	BehavePlus is based on mathematical models for fire behavior, fire effects, and fire environment. It is designed to encourage examination of the impact of a range of conditions through tables and graphs. In BehavePlus, the CROWN module models the generation of firebrands, the SPOT module handles firebrand lofting and wind-driven transportation, and the IGNITE module evaluates firebrand ignition upon landing.	Semi-empirical	Semi-physical
Asensio et al. [92]	2023	Spain	• PhyFire model (2D physical forest fire spread model) • Continuous Partial Differential Equations (PDE) formulations • Numerical methods • Computational model • Random heat contribution of fire spotting using spotting parametrization (based on the ideas of the RandomFront 2.3) • GIS	The historical analysis of the PhyFire model provides details of the mathematical and numerical methods applied in its development for forest fire spread. These methods include finite differences, mixed, classical, and adaptive finite elements, data assimilation, sensitivity analysis, parameter adjustment, and parallel computation.	Semi-empirical	Semi-physical
Moreno et al. [93]	2014	Spain	• Virtual Reality operational tool • Fire spread model (Algorithms based on a Physics-based model	Provides real-time fire spread algorithms for both forest and urban environments at interactive rates using a cellular automata model. Algorithms handle user-initiated actions (agents), natural and artificial	Hybrid Model (CA3+Physics-based algorithms + Agent-	Other Models

			(for urban fire) and Achtemeir's Rabbit model (simple rules and autonomous agents to simulate fire evolution (dynamic variables and complex interactions)) • GIS • CA model (managing spatial aspects and local interactions)	firebreaks, variable wind conditions, and non-contiguous fire propagation (including embers and fire spotting). An object-oriented approach is employed for architecture in efficient computation for mixed forest-urban environments, with validation conducted against established models (such as FARSITE) and expert feedback to ensure accuracy and realism in the training scenarios.	Based Model (ABM) + empirical data)	
Plucinski et al. [94]	2017	Australia	• Bushfire behavior models - Amicus (operational model and decision support system) • Observational research (empirical data, expert judgement, and local knowledge)	The development of Amicus, a decision support system for the Australian bushfire context, integrates bushfire behavior models with expert judgment and local knowledge. It uses statistical relationships from field and laboratory experiments to predict fire behavior (rate of spread, flame height, fireline intensity, spotting distance). It analyzes temporal trends and uncertainties to provide reliable predictions.	Semi-empirical	Semi-physical

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