Supplementary File S1: Summary of Key Findings in Fire Spotting Research

Table S1. 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 S2. 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 S3. 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 S4. 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 ≥ 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 S5. 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 S6. Summary of studies published between 2000 and 2023 examining the integration of spotting in existing or new fire spread models.

Authors & References	Title	Year	Country	Model type/ Approach	New Model/ Approach	Main findings
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 [52]	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 [53]	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 [54]	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. [55]	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. [56]	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. [57]	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 [58]	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 [59]	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. [60]	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. [61]	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. [62]	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. [63]	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. [64]	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. [65]	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. [66]	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. [67]	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. [68]	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. [69]	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. [70]	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. [71]	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. [72]	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 [73]	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 S7. 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 [74]	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. [75]	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. [76]	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 [77]	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. [78]	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 [79]	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. [80]	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. [81]	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. [82]	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. [83]	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 [84]	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. [85]	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. [86]	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. [87]	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. [88]	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. [89]	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 [90]	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. [91]	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. [92]	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. [93]	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. [94]	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. [95]	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. [96]	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. [97]	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. [98]	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 S8. 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 [99]	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. [100]	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. [101]	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. [102]	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

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