# Supplementary File S2: Classification of spotting models and Approaches

**Table S9.** 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 |
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| **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)<br>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. Analyzes the evolution and complexity of these calculation systems in parallel with advancements in technology. | Literature review | Provides a comprehensive review of the most important work in wildland fire mathematical modelling (1940-2000). |
| **Wadhwani et al.** [5] | 2022 | Australia | Empirical models<br>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. |

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| **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 S10.** 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<br>• Experimental observation (data)<br>• Inverse analysis<br>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<br>• Experimental test<br>• 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<br>• Observational research<br>• Analytical method (mathematical modelling, dimensional analysis and mechanical analysis) | 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, while dimensional analysis clarified the relationships between the observed parameters. | Semi-empirical | Semi-physical |
| **Thomson et al.** [10] | 2022 | Canada | • Observational research (utilizes right-censored or current status observations)<br>• Stochastic fire spread growth model (generates data from a simulation study mimicking real wildfire conditions)<br>• Statistical model<br>• Spot fire production 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 | Hybrid model | Combination of stochastic methods (to handle randomness), probabilistic method (new ignition), and semi-empirical techniques (to incorporate observed |

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| | | | • Firebrand rate model | maximum likelihood, utilizing right-censored or current status observations. | | data (empirical data) and physical principles) |
| **Jha & Zhou** [11] | 2022 | United States | • Observational research (historical fire data analysis)<br>• 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 S11.** 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)<br>• Statistical analysis (correlation, ANOVA, standard t-test and linear regression)<br>• 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) 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. | Empirical | Statistical-empirical |
| **Tohidi & Kaye** [13] | 2017a | United States | • Physics-based model<br>• Observational research (free-fall test using image processing techniques)<br>• 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))<br>• Software: LAB Fit and Statistica (for data analysis)<br>• Empirical model | Conducted laboratory experiments with firebrand materials from Pinus pinaster and Eucalyptus globulus (two representative species in Portugal), varying particle orientation (±90°C) 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 |

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| **Song et al.** [15] | 2017 | China | • Experimental model (wind tunnel experiment)<br>• 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)<br>• 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)<br>• Statistical analysis<br>• Evaluation of Albini's model (1979) - (theoretical model) | 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 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. | Empirical | Statistical-empirical |
| **Storey et al.** [18] | 2020 | Australia | • Observation research (optical line scans of wildfires)<br>• Statistical analysis and models (Gamma generalized linear model and Negative Binomial Regression)<br>• Maximum-distance model<br>• 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)<br>• Large-Eddy Model (LEM) (turbulent plume dynamics)<br>• 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)<br>• 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<br>• Crude Monte Carlo Simulations (CMCS)<br>• Importance Sampling (IS)<br>• 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 | Semi-empirical | Statistical-mechanistic |

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| | | | | demonstrated using two analytically prescribed wind fields (logarithmic and hyperbolic tangent wind profiles). | | |
| **Tohidi & Kaye** [22] | 2017c | United States | • Physics-based stochastic model<br>• 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 3D deterministic firebrand flight model using Monte Carlo simulations. Conducted sensitivity analysis to assess the impact of initial conditions on trajectories. | Stochastic model | Semi-physical |
| **Albini et al.** [23] | 2012 | United States | • Mathematical Model<br>• Physics-based model (analytical trajectory calculations)<br>• Physics-based model for active crown fire (source)<br>• 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<br>• Statistical analysis (logistic and non-linear regression analysis)<br>• 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<br>• Observational research (historical fire data analysis)<br>• Firebrand spotting model (probabilistic approach)<br>• 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.<br>• Mathematical and Numerical models<br>• Coupled fire-atmosphere model<br>• Physics-based model (firebrand transport and combustion model)<br>• Albini 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 an unsteady 3D wind field. Compare distances for grass fires and burning trees to the Albini model. | Theoretical | Physical-mechanistic |
| **Sardoy et al.** [27] | 2007 | France | • Physics-based model (three-dimensional - 3D)<br>• Firebrand thermal and combustion model<br>• 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 | Theoretical | Physical-mechanistic |

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| | | | | burning rates of disc-shaped firebrands (of varying sizes and densities) under various conditions. | | |
| **Anthenien et al.** [28] | 2006 | United States | • Observational research (experimental test)<br>• Numerical Model (Runge–Kutta method)<br>• 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**)<br>• Classical plume model<br>• Coupled fire-atmosphere model<br>• 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 S12.** 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)<br>• 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<br>• 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.<br>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 |

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| **Hadden et al.** [32] | 2011 | United Kingdom | • Physics-based model (hot spot ignition)<br>• 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<br>• Statistical analysis<br>• 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)<br>• 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<br>• Experimental tests (laboratory conditions)<br>• Statistical analysis (including Linear Regression, Logistic Regression, ANOVA (Analysis of Variance), Chi-square tests, and Hierarchical Cluster Analysis) | 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 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. | Empirical | Statistical-empirical |
| **Urban et al.** [36] | 2017 | United States | • Experimental tests<br>• Observational research<br>• 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<br>• Observational research (recorded the smoldering ignition or no ignition)<br>• Statistical models (logistic regression model)<br>• 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)<br>• Experimental test (Idealized-Firebrand Ignition Test (I-FIT))<br>• 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 |

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| **Viegas et al.** [39] | 2014 | Portugal | • Experimental test (laboratory conditions)<br>• 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)<br>• Experimental test<br>• Observational research (Observed and recorded the ignition behavior)<br>• 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<br>• 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)<br>• Experimental model<br>• 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<br>• Observational research<br>• Numerical model (2D model)<br>• Logistic regression function (ignition results)<br>• 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)<br>• 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 S13.** 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)<br>• Observational research (experimental data)<br>• 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<br>• 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<br>• Numerical simulation<br>• Dimensional analysis<br>• 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 S14.** 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 |
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| **Trucchia et al.** [49] | 2019 | Spain | • Statistical models<br>• Global sensitivity analysis | The study utilizes a stochastic representation of the fireline and surrogate models (gPC and GP) to identify key parameters affecting the topology and | Semi-empirical | Semi-physical |

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| | | | • Sparse surrogate models: generalized Polynomial Chaos (gPC) and Gaussian Process (GP)<br>• LSFire+ model<br>• Numerical simulations | 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. | | |
| **Pagnini & Mentrelli** [50] | 2016 | Spain | • **Randomized Level Set method***<br>• Probability Density Function (PDF)<br>• 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***)<br>• Reaction-Diffusion equation<br>• Randomized (generalized) Level Set Method<br>• Physical Random Fluctuations (PDF of spotting and turbulence effects)<br>• 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** [52] | 2016 | Italy | • Randomized (generalized) Level Set Method<br>• 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 convolution of the PDF, improving the classic level set approach for practical test cases. | Semi-empirical | Semi-physical |
| **Pagnini** [53] | 2014 | Spain | • Generalized Level Set Method<br>• Probability Density Function (PDF)<br>• 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** [54] | 2019 | Japan | • Physics-based fire plume model<br>• Stochastic modelling<br>• Observation research (historical fire damage data)<br>• 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 |

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| **Alexandridis et al.** [55] | 20008 | Greece | • CA model<br>• Observational research<br>• GIS<br>• 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.** [56] | 2011 | Greece | • CA model<br>• GIS<br>• Lattice-based dynamic model<br>• Wildfire-spread model<br>• 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 Parnitha Mountain (June 2007) and comparing the results with actual fire-spread characteristics. | CA2 - Random chance of fire spread model | Other Models |
| **Perryman et al.** [57] | 2013 | United States | • CA model<br>• Submodels (statistical model and mathematical models (for fire spread and firebrand behavior)<br>• Spotting mechanism (stochastic and probabilistic integration approaches for firebrand lift-off and dispersion)<br>• Sensitivity analysis<br>• 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** [58] | 2023 | Unite States | • SERF (Spatially extended radiant heat fire) model<br>• Observational research (prescribed fires performed outside of a laboratory)<br>• CA model<br>• Coupled map lattice (CML) model<br>• Modified Newton's law of cooling<br>• 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** [59] | 2011 | China | • Observational research (historical fire data)<br>• Irregular coarse CA model<br>• GIS | 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 | Hybrid CA: Physics-based (deterministic and stochastic approaches) + | Other Models |

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| | | | • Fire spread analysis: Radiative, convective, and long fire spread (non-local interaction) using simplified physics-based parametrization for firebrand transport, stochastic firebrand generation, and probabilistic ignition upon landing)<br>• Loss Assessment Model | spread and long fire spread due to firebrand spotting). The model is verified through 100 random simulations for a real site fire spread in Kobe City (1995, Japan), comparing simulation results with local observations. | spotting parametrization + CA3 (with stochastic model and probabilistic rules) | |
| **Boychuk et al.** [60] | 2009 | Canada | • Stochastic fire growth model<br>• 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.** [61] | 2009 | Canada | • Stochastic fire growth model<br>• GIS<br>• 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.** [62] | 2023 | Unite States | • SWUIFT (Streamlined Wildland–Urban Interface Fire Tracing) model (CA framework)<br>• Monte Carlo simulation<br>• 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.** [63] | 2020 | Spain | • WRF-SFIRE model (Level-Set Method (LSM))<br>• Statistical model (physical parametrization of firebrand landing distribution)<br>• Numerical simulation<br>• Simplified Firebrand model (RandomFront parametrization) | 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 of firebrand)). The model highlights the net effects of turbulence and firebrand flying without fire-atmosphere coupling. | Hybrid model | Semi-physical |
| **Egorova et al.** [64] | 2021 | Spain | • Physics-based fire plume model<br>• Rothermel's ROS model<br>• Fire spotting model | 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 | Hybrid model | Semi-physical |

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| | | | • Numerical simulations | 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. | | |
| **Egorova et al.** [65] | 2022 | Spain | • Level-Set Method (LSM)<br>• Albini Model (theoretical model)<br>• Extension of RandomFront parametrization<br>• 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.** [66] | 2016 | Spain | • Level Set Method (LSM) (for Eulerian moving interface method)<br>• Discrete Event System Specification (DEVS) (using Lagrangian front tracking technique)<br>• Probability Density Function (PDF) (embodied random effects)<br>• Numerical simulation<br>• Sensitivity analysis | 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 |
| **Asensio et al.** [67] | 2021 | Spain | • PhyFire model and HDWind model (integrated in online GIS)<br>• Spotting model<br>• 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.** [68] | 2019 | Spain | • RandomFront 2.3 (physical parameterization of fire spotting) in a coupled fire-atmosphere model (WRF-SFIRE)<br>• 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.** [69] | 2011 | Spain | • FIRE LADY (FIre REgime and LAndscape DYnamics) model<br>• Canadian Forest Fire Weather Index System (FWI)<br>• 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 |

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| **Hargrove et al.** [70] | 2000 | Unite States | • EMBYR model (Probabilistic model)<br>• Cellular Automata (CA) model<br>• Bond percolation process (connectivity of burning cells)<br>• Fire spread simulation<br>• 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.** [71] | 2007 | France | • Fire spread model using the small world network (SWN) model to simulate fire propagation<br>• Percolation transition criterion (to establish thresholds for fire spread in heterogeneous media)<br>• Observational research (laboratory experiments)<br>• 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.** [72] | 2020 | United States | • Fire Area Simulator (FARSITE) model<br>• High-resolution fuel maps and hourly wind data<br>• FlamMap simulations<br>• 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** [73] | 2020 | United States | • Machine-Learning Algorithms (MLA's)<br>• Observational research<br>• 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 S15.** Summary of **empirical research** on fire spotting (2000-2023).

| Authors & References | Year | Country | Method | Methodology | Model type/ Approach | New Model/ Approach |
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| **Filkov & Prohanov** [74] | 2019 | Australia | • Observational research (empirical data from thermal imaging)<br>• Mathematical model (image processing and tracking algorithms) | 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 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. | Empirical analysis based on observational research | Observed data to analyze and characterize firebrands, contributing to both theoretical models (firebrand transport in wildland and structural fires) and improving empirical models. |
| **Adusumilli et al.** [75] | 2021 | United States | • Experimental observation<br>• Computer algorithm (used to process the images and extract firebrand characteristics)<br>• 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.** [76] | 2014 | Portugal | • Observational and Experimental Research (controlled laboratory experiments)<br>• Particle image velocimetry system (PIV)<br>• 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** [77] | 2019 | United States | • Experimental model (Vertical tunnel experiment)<br>• Observational research (DSLR camera) | 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 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 | Empirical analysis based on observation research. | Collect empirical data to create models and parameters to estimate the rate of ember generation under different conditions. |

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| | | | • Statistical analysis (Factorial analysis of variance - ANOVA) | sample), diameter, moisture content, fuel condition, crossflow temperature, and crossflow velocity. | | |
| **Ganteaume et al.** [78] | 2011 | France | • Observational research<br>• Experimental tests (laboratory conditions)<br>• Flammability measurement method<br>• 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** [79] | 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.** [80] | 2022 | Canada | • Observational research (experimental canopy fire)<br>• Acoustic analysis (monitoR package)<br>Analytical firebrand travel distance model (Albini model) | 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 |
| **Filkov et al.** [81] | 2020 | Australia | • Observation research<br>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. |

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| **Donovan et al.** [82] | 2023 | United States | • Observational research (prescribed fires and wildfire data)<br>• 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.** [83] | 2020 | Australia | • Observational research (real-world observational data)<br>• 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 patterns across regions. These patterns were associated with broad rainfall measures, elevation and fuel type. | Empirical analysis based on observation research. | Analysed aerial line scan images of wildfires to examine spotting patterns, measure spotting distances, and assess the distributions of spot fires. |
| **Tohidi & Kaye** [84] | 2017b | United States | • Experimental tests (controlled wind tunnel experiments)<br>• Observational research<br>• 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.** [85] | 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 $kW/m^2$. | 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.** [86] | 2012 | Australia | Observational research (real-world fire data), "retrospective analysis and | 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 | Empirical analysis based on observational research. | Use existing models for detailed description (physical processes) and reconstruction of real- |

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| | | | reconstruction of an event" using existing models. | fire suppression personnel, were used to reconstruct the fire's propagation and behavior (physical processes). | | | world events (retrospective empirical analysis). |
| **Beverly et al.** [87] | 2010 | Canada | • Fire ignition and spread<br>• Predictive models: FireWise and FireSmart programs.<br>• Empirical data: Historical fire and vegetation type.<br>• Albini's (1979)<br>• 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.**[88] | 2012 | Australia | • Prescribed fire (field experiments)<br>• Observation research<br>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.** [89] | 2012 | Australia | • Observational research (line-scan images)<br>• Wind-terrain interaction theory<br>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** [90] | 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.** [91] | 2022 | Australia | • ACCESS-Fire model<br>• Dry Eucalypt Forest Fire (Vesta) fire spread model<br>• 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.** [92] | 2019 | Australia | • U.K. Met Office Unified Model (UM)<br>• Fire model<br>• 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 |

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| **Thurston et al.** [93] | 2016 | Australia | • Observational research<br>• UK Met Office Unified Model (UM) (Numerical simulation) Australian Community Climate and Earth-System Simulator (ACCESS)<br>• 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.** [94] | 2022 | United States | • Observational research (satellite and airborne infrared observations)<br>• 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.** [95] | 2004 | Spain | • Observational research (Remote sensing imagery)<br>• Visual and analytical approaches<br>• Geographic Information Systems (GIS)<br>• Digital Elevation Model<br>• Fractal Dimension<br>• Statistical model | 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 vegetation islands to examine their relationships with fire characteristics and environmental factors. | Empirical analysis based on observational research | Empirical observational analysis using mixed methods (visual and analytical approaches) to quantify and describe spatial and temporal fire patterns, their relationships with environmental and human factors, and the effects influencing fire spread and spotting behavior. |
| **Shennan et al.** [96] | 2023 | United States | • Observational research (airborne thermal infrared (ATIR) imagery<br>• United States National Agriculture Imagery Program (NAIP)<br>• 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.** [97] | 2021 | Australia | • Experimental test (using combustion wind tunnel in laboratory conditions from Forest Fire Research Laboratory of ADAI in Lousã, Portugal) | 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. |

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| | | | • Observational research (FLIR ThermaCam SC640 infrared camera and color video cameras)<br>• Statistical analysis | | | |
| **Hart et all.** [98] | 2021 | Canada | • Observational research<br>• Photogrammetric monoplotting technique<br>• software program WSL Monoplotting Tool (MPT)<br>• Canadian Fire Behavior Prediction System | Georeferenced oblique aerial wildfire photographs from airtanker response in the early stages of fire growth were used to locate fire front positions in photo 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. | Empirical analysis based on observational research | Empirical data collection based on actual wildfire observations to validate fire spread models or develop a new empirical relationship. |

**Table S16.** 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** [99] | 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.** [100] | 2023 | Spain | • PhyFire model (2D physical forest fire spread model)<br>• Continuous Partial Differential Equations (PDE) formulations<br>• Numerical methods<br>• Computational model<br>• Random heat contribution of fire spotting using spotting parametrization (based on the ideas of the RandomFront 2.3)<br>• 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.** [101] | 2014 | Spain | • Virtual Reality operational tool<br>• 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 |

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| | | | (for urban fire) and Achtemeir's Rabbit model (simple rules and autonomous agents to simulate fire evolution (dynamic variables and complex interactions))<br>• GIS<br>• 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.** [102] | 2017 | Australia | • Bushfire behavior models - Amicus (operational model and decision support system)<br>• 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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