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REVIEW ARTICLE

Trending and emerging prospects of physics-based and ML-based wildfire spread models: a comprehensive review

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Abstract The significant threat of wildfires to forest ecology and biodiversity, particularly in tropical and subtropical regions, underscores the necessity for advanced predictive models amidst shifting climate patterns. There is a need to evaluate and enhance wildfire prediction methods, focusing on their application during extended periods of intense heat and drought. This study reviews various wildfire modelling approaches, including traditional physical, semi-empirical, numerical, and emerging machine learning (ML)-based models. We critically assess these models' capabilities in predicting fire susceptibility and post-ignition spread, highlighting their strengths and limitations. Our findings indicate that while traditional models provide foundational insights, they often fall short in dynamically estimating parameters and predicting ignition events. Cellular automata models, despite their potential, face challenges in data integration and computational demands. Conversely, ML models demonstrate superior efficiency and accuracy by leveraging diverse datasets, though they encounter interpretability issues. This review recommends hybrid modelling approaches that integrate multiple methods to harness their combined strengths. By incorporating data assimilation techniques with dynamic forecasting models, the predictive capabilities of ML-based predictions can be significantly enhanced. This review underscores the necessity for continued refinement of these models to ensure their reliability in real-world applications, ultimately contributing to more effective wildfire mitigation and management strategies. Future research should focus on improving hybrid models and exploring new data integration methods to advance predictive capabilities.

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Introduction

Wildfires are one of the most pervasive threats in a forested environment. In many forest ecosystems, fire has long been an important component and has influenced flora and fauna both favourably and unfavourably (Halofsky et al. 2020; González et al. 2022). Moreover, the destruction caused by wildfires has considerable consequences to societies (Moritz et al. 2014) and the atmosphere, e.g., changes in air quality (Yao et al. 2018; Singh et al. 2022). Conditions conducive to wildfire spread are magnified because of climatic changes in recent decades leading to rising average temperatures and prolonged drier and hotter periods (Jolly et al. 2015). Although forests are not evenly dispersed over the world, the total area is approximately 4.06 billion hectares, equivalent to around 5000 square metres for each person on the planet (The State of the World's Forests 2020). According to a global analysis of forest loss from 2003 to 2012, an average of 67 million ha of land was burned yearly (van Lierop et al. 2015). In 2015, around 98 million ha of forest was impacted by wildfires (FAO 2020). Between 2002 and 2023, Global Forest Watch recorded a substantial loss of 76.3 million ha of humid primary forest worldwide. This accounted for 16% of the total tree cover loss during the same period. The global area covered by humid primary forests diminished by 7.4% over this timeframe (Global Forest Watch 2014).

Understanding wildfire spread is crucial because of its pervasive threat in forested environments. Fire has long influenced flora and fauna, but recent trends show an alarming increase in wildfires, exacerbated by climate change. Rising temperatures, shifting weather patterns, and increased carbon dioxide emissions contribute to the global acceleration of devastating wildfires, posing imminent threats to.biodiversity and ecosystem stability (Flannigan et al. 2006, 2009; Knorr et al. 2016; Stott 2016). Given these challenges, robust strategies for risk mitigation are imperative. By studying fire behaviour, we can develop insights into the dynamics of wildfires and anticipate their potential impacts on ecosystems, human settlements, and infrastructure. Additionally, the necessity of modelling arises from the complexity and unpredictability of wildfire behaviour, especially under changing environmental conditions driven by climate change. Models provide a systematic framework for simulating and predicting fire spread, aiding in decision-making processes for wildfire management and emergency response planning. Moreover, they enable us to assess the effectiveness of different mitigation strategies and prioritise resources for maximum impact. This article examines various models for predicting wildfire spread, acknowledging the importance of studying fire behaviour, the necessity of modelling, and the associated needs and challenges.

Various approaches, such as hazard reduction burning, fuel management, fire suppression, and the development of fire-resistant housing, are being implemented to mitigate the risks and impacts of wildfires. Hazard-reduction burning reduces the amount of fuel available and lowers fire intensity. In contrast, fuel management involves reducing the amount of fuel available to the fire by removing or reducing the amount of combustible material in an area. Fire suppression involves using resources to contain and control fire, while fire-resistant housing helps protect people and property from the effects of a wildfire.

Predictive models play a pivotal role in the pursuit of effective wildfire risk mitigation. Wildfires can cause considerable destruction, and for their effective control, it is essential to quickly identify the source and understand their spread. Accurate prediction of fire spread is crucial for forecasting their location and managing them effectively.

Statistical models, including logistic regression, decision trees, and random forests, utilise historical data to establish relationships between factors such as wind speed, temperature, and fuel moisture levels (Bamdale et al. 2021; Naser 2021; Nur et al. 2022; Do et al. 2023; Noroozi et al. 2024). Logistic regression is particularly effective in predicting the probability of fire spreading to specific areas, providing valuable insights (Guo et al. 2016). Decision trees (Sachdeva et al. 2018) and random forests (Noroozi et al. 2024), on the other hand, excel at identifying and ranking the most significant factors that influence fire spread, thus enhancing our understanding of wildfire dynamics. These predictive models, which draw on both statistical patterns and physical principles from existing fire behaviour data, are essential for accurately forecasting the likelihood and behaviour of wildfire spread. They provide crucial information for proactive wildfire management and mitigation strategies by integrating diverse datasets and sophisticated analytical techniques.

At the same time, physical models simulate the processes governing fire spread, incorporating mathematical equations to account for elements like wind speed and fuel moisture levels, especially in complex terrains (Sullivan 2009a). By combining the strengths of both statistical and physical models, researchers can enhance the accuracy and predictive capabilities of wildfire spread models, ultimately contributing to more effective wildfire management and mitigation strategies.

Advanced technologies, such as ML, computer vision, artificial intelligence, and space application technologies intelligence (Kansal et al. 2015; O'Connor et al. 2017; Bui et al. 2018; Eden et al. 2020) and remote sensing offer efficient methods for detecting and monitoring active fires, reducing potential damage and firefighting costs (Scarth et al. 2015). These technological innovations are instrumental in mitigating the impact of wildfires, aiming not only to enhance detection capabilities but also to optimise the allocation of resources.

ML models, a subset of artificial intelligence, harness the power of data and algorithms to learn from past experiences (Dogan and Birant 2021). In the context of wildfire management, these models are invaluable by analysing historical data and leveraging it to create predictive models capable of forecasting the spread of future fires. Although more complex than their statistical and physical counterparts, these models stand out for their ability to incorporate a broad array of variables. Understanding the requirements of ML models is crucial, particularly in terms of the variables they depend on for accurate predictions.

In addition to ML, remote sensing technology has emerged as an advanced tool in recent decades, proving invaluable for monitoring and understanding wildfire behaviour. Using diverse sensor systems and software, it facilitates an enhanced understanding of the relationship between fires and their environment, the causes and effects of various fire events, and the influence of weather on fire dynamics (Anderson 1969). Both the spatial distribution of fires and the weather conditions that affect fire activities have been mapped using remote sensing data. It shows how fire fronts spread and how the atmosphere affects fire behaviour. In addition, remote sensing data is used to create spatial maps encompassing components such as fuel types, moisture content, wind direction and speed, topography, and terrain, all essential components for wildfire spread modelling. This data collection is valuable for updating fuel and fire behaviour models and plays a significant role in fire detection and monitoring (Sunar and Özkan 2001; Babushka et al. 2021). These models are instrumental in predicting the environmental impact of fires and simulating their movement through space and time. By incorporating remote sensing data, they provide accurate forecasts of fire behaviour, aiding firefighters in planning better fire suppression strategies.

This review compares and evaluates different fire spread models based on their requirements, model structures, and limitations. By examining the variables required by each model, assessing their limitations, and scrutinising the overall model structure, this addresses key research questions surrounding the effectiveness and applicability of various wildfire spread prediction methods. Ultimately, this evaluation will address the challenges of wildfire management by identifying the most effective and applicable models, thereby aiding in the development of more accurate and reliable prediction tools.

Methods for literature review

This wildfire spread model review analysed research published in peer-reviewed journals or in conference proceedings from 1946–2022. The studies were classified according to topic (e.g., fire spread, fire behaviour, fire dynamics). A thematic analysis was carried out on the literature to systematically identify and code key patterns and themes. This qualitative approach allowed for the determination of the most used fire spread models and their applications. This review also included an analysis of current research trends in the field, as well as a discussion of the strengths and weaknesses of different fire spread models. Additionally, it also provides an assessment of the future directions for research.

Weather and wildfire monitoring, analysis, and forecasting have been revolutionised with recent technological developments such as advanced satellite imaging providing high-resolution images, ML algorithms, and real-time data analytics. In addition, such developments have shifted our emphasis to more mechanistically comprehensive models of wildfire combustion and heat transmission, indicators such as heat flux and aerosol can be observed using remote sensing methods (Jiang et al. 2004; Reid et al. 2013; Bei et al. 2020). Subsequent findings have provided specifics on the weather around the fire front and its relationship to weather phenomena operating at wider geographic extent. Understanding the spread of fire in urban interface regions, where wildland fuels and manmade structures coexist, has contributed to this shift. The various models utilised to predict the spread of a fire in various locations around the world are outlined in Table 1.

To summarise, wildfire spread models developed worldwide vary according to their origin of development, model type, variables used, the algorithm used, and fuel type (Table 1). Classifying model types based on their characteristics can provide valuable information about the dynamics of fire spread and thereby helping researchers to develop better models. The literature identifies advantages, disadvantages and specific requirements of different models.

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Table 1 List of wildfire spread model from 1946

Model type	Model name	Origin	Variables	Algorithms	Fuel type	References
Theoretical	Fons fire spread model	United States	Fuel type, fire intensity, wind speed, slope, fuel moisture, air temperature, relative humidity, fire size	In Heterogeneous Bed, $R = \frac{\frac{W_a}{A_a\gamma_a}+\frac{W_b}{A_b\gamma_b}+\frac{W_c}{A_c\gamma_c}+\ldots+\frac{W_n}{A_n\gamma_n}}{\frac{W_a}{A_a\gamma_a R_a}+\frac{W_b}{A_b\gamma_b R_b}+\frac{W_c}{A_c\gamma_c R_c}+\cdots+\frac{W_n}{A_n\gamma_n R_n}}$ In the context provided, "*R*" represents the rate of spread in a heterogeneous bed composed of particle types *a, b, c, …, n* *Wa, Wb, Wc,…. Wn* is the fuel bed's dry particle weight per unit area. In the given scenario, "*A*" represents the cross-sectional area, and "γ" denotes the density of dry particles In natural homogeneous fuel bed, $R = \frac{(f_c+f_r)\sigma L}{\gamma C_p ln((t_f-t_1)/(t_f-t_i))}$ where R is the rate of spread, t_i is ignition temperature, t_f is the uniform temperature of flame surrounding the particle, C_p is the specific heat of the moist particle, γ is the density of the moist particle, *fc* and *fr*, are the coefficients of heat transfer for convection and radiation energy, L is the distance between particles, σ is the surface volume ratio of the particle	Light forest fuel, specifically pine needles, twigs and small branche	(Fons 1946)
Empirical	Mk 3/4 grassland fire spread meter	Australia	Wind speed, slope, fuel type, humidity, temperature, firebreaks	Grassland Fire Danger Meter $(GFDI) = 2exp(-23.6 + 5.01ln(C) + 0{,}0281\ T - 0.226\sqrt{RH} + 0.633\sqrt{U_{10}})$ In the given context, C is the degree of curing (%), T is Temperature, RH is relative humidity and U_{10} is wind speed measured at 10 m height	Grasslands	(McArthur 1966)
Theoretical	Van Wagner's forest fire spread model	Canada	Flame length, angle between flame front and unburned surface, flame emitted radiation intensity	$(wV)^{\frac{1}{3}} = \frac{200Ee(1+cosA)}{(6.2M+98)}$ where w is the weight of fuel consumed, V is speed, A is the flame angle, E is radiation intensity, e is fuel absorptivity	Red pine needles	(Van Wagner 1967)
Theoretical	The Thomas model of fire growth and spread in the open	United Kingdom	Moisture content, temperature, thermal conductivity	Rate of spread in thick fuels, $R = (\frac{Q''_n}{2\theta_i})^2(I + \sigma\lambda)/Kp_s c_\omega \sigma$ where R is the rate of spread, Q''_n is the net forward flux allowing for cooling losses, c_ω is the adequate specific heat of the moist wood, θ_i is the rise in temperature causing ignition, K is the thermal conductivity, p_s is solid fuel, λ is the volume of voids in the fuel bed per surface area of solid in the fuel bed Rate of spread in light fuels $R = \frac{Q''_n}{p_h C_w \theta_i}$ where p_h is the mass of ignitable wood per unit volume of the fuel bed	Open fires are typically wood, charcoal, or other combustible materials	(Thomas 1967)
Empirical	Mk 5 Forest Fire Danger Meter	Australia	Air temperature, relative humidity, wind speed	Forest Fire Danger Meter $(FFDI) = 2exp(-0.45 + 0.987ln(D) + 0.0345RH - 0.0338\ T + 0.0234\ U_{10})$ In this equation, "*D*" represents the Drought Factor ($0 < D \leq 10$), "*RH*" denotes relative humidity (%), "*T*" represents air temperature (°C), and U_{10} represents the average 10-m open wind speed (km/h)	Eucalypt forests	(McArthur 1967)

Table 1 (continued)

Model type	Model name	Origin	Variables	Algorithms	Fuel type	References
Theoretical		United States	Moisture content, radiant heat, convective heat, bulk density of fuel bed, ambient temperature	$R = \frac{\sigma\lambda}{\rho_f Q_{ig}}[\sigma\varepsilon_c T_c^4(\int_0^\infty F_{12}dx) + \sigma\varepsilon_F T_F^4(\int_0^\infty F_{12}dx) + nh_c(T_c - T_1)$ In the context, R is a steady rate of spread, Tc is combustion zone temperature, T_1 is ambient air Temperature, λ is the void volume per total surface area, ρ_f is fuel particle density, Q_{ig} is the amount of moisture in the fuel, $\sigma\varepsilon_c T_c^4 = E_c$ (combustion zone emissive power), $\sigma\varepsilon_F T_F^4 = E_f$(flame emissive power)	Ponderosa pine, white pine, lodgepole pine	(Anderson 1969)
Semiempirical		United States	Heat flux, wind and slope	$-R = \frac{I_P}{\varphi_{ig}} - R = \frac{I_P}{\varphi_{ig}}$ In the context, R represents the rate of spread of fire, φ is net heat absorbed per unit volume above the ambient state, φ_{ig} is the value at φ at an ignition	Porous fuel	(Frandsen 1971)
Semiempirical	Rothermel Model	United States	Wind velocity, slope, fuel model, fire line intensity, fireline length	$F = (I_R\, \xi(1 + \phi_w + \phi_s))/\rho_b\varepsilon Q_{ig}$ where, "F" represents heading fire spread rate (m/min) "I_R" denotes reaction intensity (kJ/m min m^2) "ξ" stands for propagating flux ratio "ρb" represents oven dry bulk density (kg/m^3) "ε" signifies effective heating number (dimensionless) "Qig" denotes heat of pre-ignition (kJ/kg) Here, in the Eq. (2) of fire spread ϕw is the coefficient of windspeed and ϕs is the coefficient of slope from the Rothermel fire spread equation (Rothermel 1972): $\phi w = 5.275\beta^{-0\cdot 3} tan\phi^2$ $\phi s = C(3.281U)^B\left(\frac{\beta}{\beta op}\right)^{-E}$	Grass, coniferous trees or deciduous trees	(Rothermel 1972)
Theoretical		United States	Ambient flow, fuel moisture, topography, endothermic pyrolysis	$\Delta_v = \frac{\Delta_c\left[\Delta_{CT}+\Delta_W+\Delta_{CI}+\Delta_{w}^{\frac{4}{5}}\Delta_{CS}\right]+(\Delta_{RF}+\Delta_{RB})+\Delta_K}{1+\Delta_M+\Delta_{PYR}}$ Here all are dimensionless energy-transfer parameters where Δ_v is the flame spread velocity, Δ_c is convective coefficient, Δ_{CT} is turbulent diffusion, Δ_W is wind velocity, Δ_{CI} is interior convection, Δ_{CS} is surface convection, Δ_{RF} is flame radiation, Δ_{RB} is ember radiation, Δ_K is gas conduction, Δ_M is evaporation energy, Δ_{PYR} is pyrolysis energy	Pine needles	(Pagni and Peterson 1973)
Theoretical		Russia	Moisture content, radiant heat, bulk density of fuel bed, ambient temperature	$\varepsilon_f = 1 - e^{-xd}$ where ε_f is the emissivity of the flame, d is the depth of the flame in the fuel bed		(Telisin 1974)

Table 1 (continued)

Model type	Model name	Origin	Variables	Algorithms	Fuel type	References
Theoretical		Russia	Temperature, radiation measurement	$u = l/(\tau_s + \tau_d)$ In the given context: "u" represents the flame spread rate over a fuel bed "l" denotes the mean distance between points of contact of particles "τ_s" represents the average time of flame spread along the distance "τ_d" signifies the average time of passage from one particle to another	Pinus sylvestris	(Konev and Sukhinin 1977)
Theoretical	FIRECON	United States	Wind speed and direction, fuel moisture, and topography	$S = (\sum_{k=1}^{K} q_k)/\rho h q_k$ where K is the number of heat transfer mechanisms, q_k is the heat that comes or leaves a unit width of fuel bed in unit time due to the kth heat transfer mechanism, this is the specific weight of the fuel, h is the height of the flame		(Cekirge 1978)
Semiempirical	Central Australia Spinifex model	Australia	Ambient temperature (C), relative humidity (%), 2-m wind speed (km/h), bare ground cover (%), spinifex cover (%), MC (%) live and dead patchiness	$ROS = -0.419 + 1.125 * 3\sqrt{(fuelfactor * weatherfactor)}$	Grasslands	(Griffin and Allan 1984)
Semiempirical	Red book; forest fire behaviour tables	Australia	Fuel load (T/ha), dead fuel, MC (%), 2-m wind speed (km/h)	$R = Y + A\ exp(U_{1.5}N)$ where R is the rate of headfire spread $Y\ function = 21.37 - 3.42MC + 0.085\ M\ C^2$ $A\ function = 48.09\ MC\ exp(-0.60MC) + 11.90$ $N\ function = 0.44 - 0.0096\ M\ C^{1.05}$ where MC is moisture content	Eucalypt forests	(Sneeuwjagt and Peet 1985)
Theoretical		Australia		$R = \frac{E_f + E_c}{Q}$ where $E_f + E_c$ is total heat input into the unburnt surface fuel		(De Mestre et al. 1989)
Theoretical		Australia		$R = ((A - B_{\tau_i})/\propto)/pc\tau_i$ where R is the rate of spread, A is the heat output of the flame, B_{τ_i} is heat lost by cooling, $\propto$ its absorption coefficient, p is density, c is combustion interface, τ is the temperature above ambient, i is ignition		(Weber 1989)
Empirical		Canada	Fuel moisture, wind speed, type of fuels, fuel loading, topography	$ROS = A * B * T^{(B-1)}$ $B = 1.204 + 0.740 * (1 - e^{(-0.319*WS)})$ $A = 0.324 * ROSeq^{0.637}(Needless)$ $A = 0.628 * ROSeq^{1.188}(Excelsior)$ In the context, ROS denotes the rate of spread at time T (m/min) of head fire, A and B is Allometric equation coefficient, T is elapsed time since ignition(min), WS is wind speed(km/h), $ROSeq$ is Equilibrium ROS (m/min)		(McAlpine and Wakimoto 1991)

Table 1 (continued)

Model type	Model name	Origin	Variables	Algorithms	Fuel type	References
Empirical	Spinifex model	Australia	Topography, wind speed, temperature, moisture content	$ROS = 3.90(wind^2) - 82.08(FMC) + 5826.36(cover) + 43.5(temp) - 4935.29$ In the equation, *ROS* denotes spread rate, wind = wind speed at 2 m, *FMC* = fuel moisture content, *cover* = % spinifex cover/% bare ground, *temp* = air Temperature	Spinifex	(Burrows et al. 1991)
Empirical		Canada	Foliar moisture content	Conifer plantation spread rate $ROS = RSS + CFB * (RSC - RSS)$ $RSI = 30 * (1 - e^{-0.08*ISI})^{3.0}$ $RSS = RSI * BE$ $RSC = 60 * (1 - e^{-0.0497*ISI})^{1.00} * \frac{FME}{FMEavg}$ In the given context: "*ROS*" represents the spread rate in a conifer plantation "*RSI*" refers to the intermediate surface fire spread rate "*ISI*" signifies the initial spread index "*CFB*" denotes the crown fraction burned "*RSS*" represents the surface fire spread rate "*BE*" stands for the built-up index effect "*RSC*" signifies the crown fire spread rate "*FME*" represents the foliar moisture content "*FMEavg*" is a specific value of 0.778	Coniferous, Deciduous, mixed wood, Slash	(Canadian Department of Forestry 1992)
Semiempirical	Button grass model	Australia	Soil, fuel age, land cover	$\text{Fuel Loading} = a_i(AGE * COVER)^{b_i}$ where a_i and b_i are constants that depend on-site productivity	Monocots and dicots	(Marsden-Smedley and Catchpole 1995)
Theoretical		France	Slope, temperature, turbulent	$V = V_0(1 + \theta_s)$ where V = rate of spread, V_0 is rate of spread under windless and slope less conditions and θ_s is slope factor	Pinus pinaster litter	(Santoni and Balbi 1998)
Semiempirical		Australia	Windspeed, ambient temperature and humidity	$R = \frac{(l+mU^n)e^{-\frac{347}{s}}\beta^{-0.499}e^{-kM}}{\rho_P(Q_P+MQ_w)}$ where R is the rate of spread, U is wind speed, ρ_P is Particle density, β is packing ratio, s is surface-area-to-volume-ratio, Qp is heat of pyrolysis, Q_w is the heat of desiccation, M is moisture content	Pine needle litter and grassland	(Catchpole et al. 1998a)
Semiempirical	Heathland Model	Australia	Wind speed, vegetation height	$R_P = aU_2^bH^c$ where R_P is the predicted spread rate (m/min), $U2$ is the wind speed measured at 2 m (km/hr), and H is the vegetation height (m), The fitted values were a = 0.801 (standard error 0.221), b = 1.10 (s.e. 0.10), and c = 0.49 (s.e. 0.08)	Heathlands and Shrublands	(Catchpole et al. 1998b)

Table 1 (continued)

Model type	Model name	Origin	Variables	Algorithms	Fuel type	References
Semiempirical		Portugal	Wind speed, dead fuel moisture content and fuel-complex structure	$R = aU^b exp(-cM_d)$ where R is the spread rate in m/min U is the wind speed M_d is the moisture content % The estimates obtained for a, b and c were 3.258 (standard error (S.E.) = 1.929), 0.958 (S.E. = 0.216) and 0.111 (S.E. = 0.026)	Portuguese shrubland	(Fernandes 1998)
Empirical	CSIRO Grassland Meter	Australia	Wind speed, fuel moisture, grass curing, pasture type	$U_{10} < 5kmh^{-1}$ $R_n = \left[0.054 + 0.269U_{10}\right].\varnothing M.\varnothing C$ $R_{cu} == \left[0.054 + 0.209U_{10}\right].\varnothing M.\varnothing C$ when $U_{10} > 5kmh^{-1}$ $R_n = [1.4 + 0.838(U_{10} - 5)^{.844}].\varnothing M.\varnothing C$ $R_{cu} = [1.1 + 0.715(U_{10} - 5)^{.844}].\varnothing M.\varnothing C$ $R_e = [0.55 + 0.3547(U_{10} - 5)^{.844}].\varnothing M.\varnothing C$ where R_n is the quasi-steady rate of spread in undisturbed natural pastures (km h^{-1}), R_{cu} is the quasi-steady rate of spread in cut, grazed, or partially trampled pastures (km h^{-1}), R_e is the quasi-steady rate of spread in eaten-out pasture conditions (km h^{-1}), U_{10} is 10 m wind speed in the open (km h^{-1}) application bounds (0–80 km h^{-1}), $\varnothing M$ is the moisture coefficient and $\varnothing C$ is the curing coefficient	Grasslands	(Cheney et al. 1998)
Empirical	EMBYR	United States	Fuel moisture, wind speed, wind direction, time	$S_{av} = \sum S^2/(n_p \sum S)$ where S_{av} is the area-weighted average cluster size. S is the size of individual p patches and n_p is the total number of patches	Subalpine conifers	(Hargrove et al. 2000)
Semiempirical	FARSITE: Fire Area Simulator-model development and evaluation	United States	Weather conditions, fuel type and characteristics topography, fire size, rate of spread and fire behaviour	The FARSITE model uses a two-dimensional CA algorithm to simulate fire spread	Grass, shrubs, trees, or scrub	(Finney 1998)
Empirical		Finland	Surface fuel moisture content, mid-flame wind speed	Canadian Forest Fire Weather Index System (FWI System) (Canadian Forest Service 1992) and Finnish Fire Risk Index (FFI) (Venäläinen and Heikinheimo 2003) were used to evaluate burning conditions	Pinus sylvestris and Picea abies	(Tanskanen et al. 2007)
Semiempirical	Wildfire Dynamics Simulator (WFDS)	Australia	Wind speed, ignition line fire length, temperature, and fuel moisture content	$R_0 = (0.165 + U_2)exp\left(\frac{[-0.859-2.036U_2]}{W}\right)exp(-0.108M)$ where R_0 is the observed head fire spread rate, U_2 is the measured wind speed, W is the head fire width and M is the fuel moisture content	Grasslands	(Mell et al. 2007)

Table 1 (continued)

Model type	Model name	Origin	Variables	Algorithms	Fuel type	References
Theoretical	ForeFire/Meso-NH	France	Radiant factor, flame thickness speed factor, flame gas velocity, slope	$R = R_0 + A\frac{R}{1+(R/r_0)cos\gamma}(1 + \sin\gamma - \cos\gamma)$ where R is the speed of the front, R_0 is the propagation speed in case of null wind and no slope, r_0 is the radiant coefficient and γ is the flame tilt angle relative to ground normal $tan\gamma = tan\alpha + \frac{U}{u_0}$ Here U is the wind effect, u_0 is the buoyancy effect and α is slope	High large eddy simulation (LES) box with open boundary condition	(Filippi et al. 2011)
Empirical	ARPS/DEVS-Fire	Japan	Oven-dry fuel loading, fuel depth, fuel particle surface area to volume ratio, fuel particle moisture content, total mineral content, wind velocity, wind direction, slope, aspect	POD (Probability of detection) = $\frac{H}{H+M}$ where H is the number hits and M is the number of misses FAR (False alarm rate) = $\frac{F}{F+N}$ where F is number of false alarm and N is number of true negatives HSS (Heidke skill score) = $\frac{H+N-E}{H+M+F+N-E}$ where $E = \frac{(H+M)(H+F)+(M+N)(F+N)}{(H+M+F+N)}$		(Dahl et al. 2015)
Semiempirical		Australia	Slope, ignition length, dead fuel moisture content, wind speed and direction	$R = \sum\left[R_0 + 0.2(5.67(WF)^{0.91} - R_0\right)U_{10}]H^{0.22}exp(-0.076MC), U_{10} < 5$ $R = 5.67\left(\omega FU_{10}\right)^{0.91}H^{0.22}exp(-0.076MC), U_{10} \geq 5$ where R is rate of the fire spread model, R_0 is rate of fire spread at wind zero taken as 5 m/min, WF is wind adjustment factor (0.67 for heath-shrublands and 0.35 for woodlands, U_{10} is 10 m open wind speed, H is average vegetation height, MC is moisture content of dead fuel $MC = 4.37 + 0.16, RH - 0.1(T - 25) - \Delta 0.027RH27RH$ RH is relative humidity	Heathland and shrubland	(Anderson et al. 2015)

Table 2 Studies collectively demonstrate the efficacy of CA models in understanding and predicting wildfire spread dynamics

Dataset used	Methods	Result	Inferences	References
Existing vegetation data, topographic data such as aspect, elevation and slope, past burned data, meteorological data	Extreme learning machine (ELM)	Simulation accuracy of prediction is 58.45% to 82.08%	ML methods like extreme learning machine (ELM) show promise in calculating cell ignition probabilities with high accuracy, requiring fewer training samples compared to traditional modelling approaches	Zheng et al. (2017)
Weather station data, ASTER GDEM version 2, Landsat TM and ETM +	1) Maximum likelihood method used for classification 2) Two-step method for reducing error	A mean kappa coefficient = 0.6352 and mean accuracy = 87.89%	Efficient, accurate forest fire simulation; meteorological data enhances accuracy	Rui et al. (2018)
DEM, vegetation data, wind direction and speed data, actual fire map	CA-based model	Total accuracy = 0.88. Kappa coefficient = 0.74	CA model predicts Hyrcanian forest fires with 0.88 accuracy, suggesting enhancements	Eskandari (2016)
Remote sensing image data of wildfires, slope, slope direction, vegetation type, vegetation height, vegetation coverage, elevation data, resolution of the remote sensing image was 30 m	LSTM, S-LSTM, ELM	Mean squared errors were less than 1, maximum mean squared errors were 2.73, Kappa Coefficient of LSTM-CA = 0.76 to 0.92 and ELM-CA = 0.65 to 0.81	Accurate fire spread prediction vital; S-LSTM outperforms LSTM for ROS. Integration of CA, vegetation correction, ML enhances simulation accuracy	Li et al. (2022)
Combustible factor, slope factor, wind speed factor data	MD-CA	Area error rate is 9.42%–15.63% and the perimeter error is 4.21%– 8.99%. The Errors are less than in the CA model	Enhancing forest fire spread accuracy: MD-CA surpasses traditional CA model. Integration of slope, moisture, wind enhances simulation realism	Zhang et al. (2021)
Forest raster data (including fuel type, elevation, slope, degree of curing), fuel type, ignition points, and weather stream (including wind speed/direction, temperature, and relative humidity, etc.)	Wave propagation and Cellular Automata	Above 90% of accuracy	Cell2Fire: Accurate fire growth prediction tool for landscape management. Decision-makers can use this tool to identify critical areas prone to wildfires and adjust management plans accordingly. By incorporating stochastic weather scenarios and parallel processing capabilities	Pais et al. (2021)
Hypothetical data was created	Cellular Automata	This algorithm's output of hypothetical wildfire fronts was found to be in good accord with knowledge of how fires spread in existing forests	Efficient CA model predicts forest fire spread effectively. Valuable for real-time fire management and decision support	Karafyllidis and Thanailakis (1997)

and weaknesses of different fire spread models. Additionally, it also provides an assessment of the future directions for research.

Weather and wildfire monitoring, analysis, and forecasting have been revolutionised with recent technological developments such as advanced satellite imaging providing high-resolution images, ML algorithms, and real-time data analytics. In addition, such developments have shifted our emphasis to more mechanistically comprehensive models of wildfire combustion and heat transmission, indicators such as heat flux and aerosol can be observed using remote sensing methods (Jiang et al. 2004; Reid et al. 2013; Bei et al. 2020). Subsequent findings have provided specifics on the weather around the fire front and its relationship to weather phenomena operating at wider geographic extent. Understanding the spread of fire in urban interface regions, where wildland fuels and manmade structures coexist, has contributed to this shift. The various models utilised to predict the spread of a fire in various locations around the world are outlined in Table 1.

To summarise, wildfire spread models developed worldwide vary according to their origin of development, model type, variables used, the algorithm used, and fuel type (Table 1). Classifying model types based on their characteristics can provide valuable information about the dynamics of fire spread and thereby helping researchers to develop better models. The literature identifies advantages, disadvantages and specific requirements of different models.

Models for wildfire spread prediction

Wildfire spread prediction models are valuable tools in managing and mitigating the impacts of wildfires. These models are designed to forecast the progression of fires by incorporating factors that influence fire behaviour. The primary categories of wildfire spread prediction models include traditional models, such as semi-empirical and numerical models (Pastor et al. 2003), cellular automata models, and modern ML models. Traditional models rely on physical principles and empirical data to simulate fire spread but struggle with the dynamic nature of environmental conditions and the precise estimation of ignition events. The first mathematical model of fire propagation was developed by Fons (1946), marking a significant advancement in wildfire modelling. This section reviews the most advanced models for predicting wildfire spread, examining their structures, strengths, and limitations to provide a comprehensive understanding of current and emerging methods in wildfire prediction.

Table 3 A summary of studies focused on a wildfire spread based on the Rothermel model

Methods and dataset	Result/Accuracy	Inference	Reference
Pre- and post-fire fynbos biofuel was estimated. Rothermel's model analyses fire behaviour 1976–1984 experimental fire data was used	The model accurately predicted the spread rate and flame length. However, it overestimated fire intensity in high-biomass locations	Fire danger indices and predictions based on Rothermel's approach may boost the utility of fynbos fire data	Van Wilgen et al. (1985)
Meteorological and topographical data	The Kappa coefficient was 0.7398 and the Sørensen coefficient was 0.7419	The Rothermel model-based simulation programme might predict fire propagation in windthrow zones	Yin et al. (2018)
Conducted 276 combustion tests, adjusted Rothermel model, analysed forecast accuracy	Original Rothermel: MAE (Mean absolute error) 0.03–4.04 m/min, MRE (Mean relative error) 4.28%–105.59%. Modified: MAE 0.03–2.16 m/min, MRE 4.40%–53.99%	The study enhanced Pinus koraiensis fire spread prediction by modifying the Rothermel model, reducing MAE and MRE, crucial for fire research and safety	Geng et al. (2024)
Integrated Rothermel model with Albini modifications for fire spread prediction	Results showed high accuracy in predicting fire growth patterns, F1-scores 0.56–0.97, precision/recall 0.43–0.86/0.80–0.89	Study integrated Rothermel model into hybrid raster–vector framework, accurately predicting fire growth patterns. High F1-score indicates agreement between observed and simulated patterns, promising operational fire management applications	Zhang and Tian (2023)
Applied Rothermel model to re-estimate SAV ratio, mineral, and heat content parameters for improved prediction accuracy. Conducted indoor burning experiments	R2 model improved Rate of spread prediction over R1 model and direct Rothermel model, lower MAE/MRE, acceptable tree species errors	Study aimed to enhance forest fire spread prediction using Rothermel model and reformulated models R1 and R2. Results favoured R2, improving accuracy	Zhang and Tian (2023)

Cellular automata (CA) model

The cellular automaton (CA) concept is a prominent theoretical framework for understanding the behaviour of complex systems, and it has been used extensively in various research fields. The advantage of CA models is their adaptable evolution rules and significant computational efficiency (Tian et al. 2021). Cellular automata (CA) is a collection of cells on a grid of a particular shape that changes over time according to a set of rules provided by the state of the surrounding cells, as defined by Neumann (1951) and Singh and Gu (2012). In CA, cells have discrete states and evolve by spatially discrete-time update rules (Hanson 2009). Cellular automata (CAs) are arrays of precisely programmed cells in one, two, or three dimensions. CA models were proposed by John Von Neumann in "Theory of Self-reproducing Automata" (Neumann 1966).

The most significant characteristic of a CA is that the array's automata interface with neighbours. Changes in a cell's state depend not just on its current state but also on the conditions of adjacent cells. This has made CAs a popular approach for researching the evolution of features in integrated applications. CA models are a common technique in the case of fire spread prediction and are a physical system where time and place are distinct and interactions are local. The potential of CAs to model wildfire spread prediction is based on the premise that past fires influence future spread behaviour through local interactions among land covers. The interest in CA-based models for wildfire spread simulation is due to their simplicity, intuitiveness, flexibility, and transparency.

Numerous CA models (Karafyllidis and Thanailakis 1997; Eskandari 2016; Zheng et al. 2017; Rui et al. 2018; Pais et al. 2021; Zhang et al. 2021; Li et al. 2022) have been used into systems for predicting wildfires (Table 2). For example, Zheng et al. (2017) simulated the complex mechanisms of fire spread with a new method of CA modelling. This was developed by integrating the extreme learning machine (ELM) algorithm and the conventional CA framework for modelling wildfires. According to their findings, the ELM successfully predicted the possibility of ignition for each cell. Using the proposed modelling approach, the effect of wind speed on the pattern of fire spread can be precisely described. ELM output is calculated with L nodes in the hidden layer, represented by Eq. 1:

$$f_L = \sum\nolimits_{i=1}^{L} \beta_i g_i(x) = \sum_{i=1}^{L} \beta_i g\left(\omega_I * x_j + b_i\right), j = 1, to, N \tag{1}$$

where, f_L is igniting probability, considered the ELM model's output and x an input vector. L denotes the number of hidden nodes, N the number of training samples, β_i the weight vector between the jth hidden layer and output, g an activation function of mapping the model from the input, ω and b are the vias vectors. A radial basis function (RBF) network was used in this research. Validation against actual fire behaviour observations indicates that the simulation's performance is satisfactory and, in most situations, superior to that of previously reported studies.

Li et al. (2022) integrated the long short-term memory model (LSTM) with the CA framework for modelling wildfire spread prediction. The LSTM is the most prevalent in the time series domain and falls into the category of recurrent neural networks. Both ML and neurocomputing have been influenced by the development of LSTM. A type of neural network known as a recurrent neural network (RNN) is one that was developed primarily for the processing of temporal inputs. The neurons that make up a RNN contain a cell state or memory, and the information is processed based on this internal state. This is performed using loops inside the neural network to achieve the desired result. According to this research, the simulation and analysis of three natural wildfires in the United States with the ELM-CA model showed that the LSTM-CA model was more accurate and practicable for simulating wildfire spread. The first attempt at the CA model for wildfire spread prediction was made by (Karafyllidis and Thanailakis 1997). This research involved the development and implementation of an algorithm based on the CA model to identify fire fronts in a variety of hypothetical forests. The results were in reasonable conformity with the experience of fire spreading in actual forests.

Rothermel model

The mathematical Rothermel model (Rothermel 1972) is the most used for predicting the spread of wildfires (Pastor et al. 2003), particularly in European countries (Sullivan 2009b). It computes the fire spread rate (m min^{-1}) in a plane with the ground surface at every vertex:

$$F = (I_R \xi (1 + \phi_w + \phi_s)) / \rho_b \varepsilon Q_{ig} \tag{2}$$

where, F is fire spread rate (m/min). I_R is reaction intensity (kJ m min^{-1} m^{-2}). ξ is the propagating flux ratio. ρb is the oven-dry bulk density (kg m^{-3}). ε is the effective heating number, (dimensionless). Q_{ig} is the heat of pre-ignition, (kJ Kg^{-1}).

In Eq. (2), $_w$ is the coefficient of windspeed and ϕ_s the coefficient of slope from the Rothermel fire spread equation (Rothermel 1972):

$$\phi_w = 5.275 \beta^{-0.3} tan\phi^2 \tag{3}$$

Table 4 Summary of studies on a wildfire spread based on the FIRETEC model

Methods and dataset	Result/Accuracy	Inference	Reference
Comparing FIRETEC and WFDS models. Using the Topography dataset and important fuel type observations including ambient temperature (°C), relative humidity (%), effective fine fuel moisture (%), canopy bulk density (kg m^{-3}) (CBD), and 10 m open wind speed (km h^{-1})	WFDS and FIRETEC predicted 87.5% and 84.2% of crown fire spread rates, respectively	The authors assumed a steady, no-shear wind profile. This assumption led to higher near-surface and within-canopy wind speeds than predicted, which may explain the increased spread predictions	Hoffman et al. (2016)
Six simulations were done with the coupled fire/atmosphere model FIRETEC to investigate bark-beetle-induced pinyon tree mortality on fire behaviour in pinyon-juniper forests. Field data, fuel bed with high density and mortality, wind speed, and fuel moisture	This study suggests that 4.5 m/s winds at 7.5 m height were adequate to conduct the fire across the discontinuous forest stands without mortality	Above-canopy winds affected the simulated fire spread. Moderate winds put out the fire in the living pinyon woods, while severe winds spread it	Linn et al. (2013)
The study used FIRETEC simulations, detailed fuel structures, ignition data, wind profiles, and firebrand specs	The study accurately revealed fire behaviour and fuel treatment impacts, using comprehensive, relevant methods and datasets aligned with research objectives	The study underscores fuel treatments' role in fire behaviour, aiding strategy development for community protection by showing how treatments affect fire spread and intensity	Marshall et al. (2020)
The study used IGRAD/FIRETEC for uniform grassland fires, compared against Urbanski data, with a physics-based particulate emission model and zonal adaptation	Wind-velocity-correlated emission factors, model predictions matched field data within a single standard deviation, confirming model accuracy	The physics-chemistry model in IGRAD/FIRETEC accurately predicted wildland fire emissions, showing promise for diverse ecosystems, pending further validation and refinement	Josephson et al. (2021)
HIGRAD/FIRETEC model utilised for weather-wildfire simulation. CPDbio data used to establish correlations for sooting potential	HIGRAD/FIRETEC matched field data for emission factors, simulations within one standard deviation	The HIGRAD/FIRETEC model effectively predicted soot emissions across ecosystems, closely matching field data within one standard deviation, capturing trends	Frangieh et al. (2020)

Table 5 A summary of studies focused on a wildfire spread based on the CAWFE model

Methods and dataset	Result/Accuracy	Inference	Reference
Clark's atmospheric fluid dynamics model coupled with BEHAVE's fire spread algorithm and BURNUP's heat release model	After BURNUP, a rate of mass loss therapy was introduced to the five-atmosphere sensible and latent heat exchange treatment	Fixed wind uncoupled test reveals novel tracer approach mimics known fire behaviour	Clark et al. (2004)
The Big Elk Fire model's coupled atmospheric fire simulation was used to collect pertinent wildlife fire parameters, such as fire parameter length	The formation of slope winds due to sun heating of mountain slopes and valley ignition caused the surface fire to dry out and the canopy to ignite owing to strong burning and surface fuel loading	The study concludes that the atmosphere-fire coupling, which impacts winds at least 5 km away from the fire and determines the evolution of all fire parameters, is a significant force that must be taken into account	Coen et al. (2013)
The Me'so-NH mesoscale numerical model has coupled to the point functional fore fire simplified physical front-tracking wildfire model to examine the changes in propagation speed and behaviour brought about by atmospheric feedback	It can be seen from simulations of typical experimental setups that the numerical atmospheric model can faithfully capture the fire's convective effects of heat	The numerical results are equivalent to the estimated values for the wind induced by fire, and they exhibit behaviour that is consistent with other numerical methods already in use	Filippi et al. (2009)
Physical model, numerical techniques, and software architecture of a model composed of the Fire Spread Model (SFIRE) module integrated with the Weather Research and Forecasting (WRF) model	Even with fine resolution in decametres, the coupled model can operate on a cluster quickly than in real-time. Additionally, the results demonstrate that WRF and SFIRE can realistically portray the rate of fire spread, temperature, upward velocities, and horizontal wind speed associated with a steady fire front passage (unaffected directly by the ignition)	The FireFlux is more relevant since it gives information gathered when a real fire was burning, as opposed to the Meteotron experiment, which concentrated on the dynamics of a stationary plume produced by a group of burners	Mandel et al. (2011)
Studied models such as linked atmosphere-fire models, WRF, CAWFE, and fire models for numerical weather forecasting	The advantage of models based on convective-scale NWP models is that the underlying NWP model was built to mimic weather on steep, complex terrain and retain sharp changeable gradients	However, some of the concepts provided here may also be novel to those working in the atmospheric modelling community. To use, configure, and comprehend simulations using coupled models, users from fields apart from the physical sciences may seek out novel information	Coen (2018)

$$\phi_s = C(3.281U)^B \left(\frac{\beta}{\beta op}\right)^{-E} \quad (4)$$

where β is the packing ratio of the fuel bed, ϕ the slope angle, U is the wind speed (ms^{-1}), and C, B and E are coefficients of the fuel particle sizes in the fuel bed.

The Rothermel model considers the topography and meteorological conditions (speed and direction of the wind) while simulating the burning of forest fuels such as trees, grass, and shrubs. According to Weise and Biging (1997), this model performs well except in the case of an upslope spread with an opposing flow; it is also sensitive to the rate of spread in fuel beds with moisture content higher than 35% (Table 3).

FIRETEC model

FIRETEC (Linn 1997) is a coupled atmospheric transport/wildfire behaviour model developed at the Los Alamos National Laboratory, New Mexico, USA, which relies on mass, momentum and energy conservation principles. In FIRETEC, the wildland fire's complex combustion reactions are simplified using wood pyrolysis, char burning, hydrocarbon combustion, and soot combustion in the presence of oxygen. The most recent enhancement to FIRETEC consists of an additional chemistry model (Linn et al. 2002). The interactions between wildfires and the atmosphere are promising in the current state of research with a complex three-dimensional structure using hypothetical and historical fire situations that are more realistic than previous (Reisner et al. 2000). The model was integrated into HIGRAD to simulate wildfires with a 3D Landscape. HIGRAD is a 3D computer model of fluid dynamics that inherently illustrates the airflow and its changes in response to the terrain and different types of fuel. Thus, the FIRETEC predictions are more persuasive for fire authorities to understand how wildfires will behave in rough terrain and different weather conditions. Additional empirical fire models can also integrate with the existing framework to produce better prediction accuracy.

Running FIRETEC requires a significant amount of computer resources. As a result, the model has a high computational cost and can only be applied temporally and spatially at a micro level. Because the model does not consider interactions on larger scales of atmospheric motion, it cannot be used to simulate conditions that last more than a few hours, or that cover an area larger than one kilometre.

Several studies (Linn and Cunningham 2005; Colman and Linn 2007; Pimont et al. 2009; Hoffman et al. 2016) have been used for wildfire prediction and validation of the FIRETEC model. According to Hoffman et al. (2016) study on crown fires using an extensive empirical crown fire dataset, FIRETEC could accurately estimate the spread rate. Interestingly, 80% of FIRETEC projections for crown fire spread rate were within the 95% prediction bands based on open wind speed estimates (Table 4).

Coupled atmosphere–wildland fire environment (CAWFE) model

The National Centre for Atmospheric Research (NCAR), Boulder, CO., USA, developed the coupled atmosphere-wildland fire-environment (CAWFE) model (Clark et al. 2004; Coen 2005) as the initial attempt to pair atmospheric and fire models. The Clark-Hall mesoscale atmospheric model and a tracer-based fire spread model make up the first-generation CAWFE, where the front-tracking system is known as a tracer (Clark et al. 2004). Four moving dots, known as tracers, are present in each fuel cell to depict the boundary between burning and non-burning regions. The position of tracers is described by fluxes such as sensible and latent heat on both the fuel and air grids. The three-dimensional CAWFE was built using basic thermodynamic and motion equations that depict the fine-scale dynamics of convective processes ranging from millimetres to mega metres in horizontal length and capture prevailing meteorological conditions. The latest CAWFE (Coen et al. 2013) version includes a fire behaviour module and a numerical weather forecast model.

Fire model component: this includes heat fluxes, water vapour, smoke released into the atmosphere, and surface and crown fires that slowly consume fuel after they catch fire. Applying the Rothermel (1972) fire spread rate formula, or, for Australian fuel complexes, those proposed by Noble et al. (1980), local fire rates depend on the predicted wind components. The consumption of fuel mass overtime at the surface is categorised using a BURNUP algorithm, separating each atmospheric grid cell into fuel cells. A quadrilateral created by four tracers, one for each fuel cell, identifies the burning regions of fuel cells and the fire front, the point where burning fuel and unignitable fuel meet.

Numerical model: this model from NCAR is described in Clark et al. (2004). For the sensible and heat fluxes from the fire to feed back into the atmosphere and affect the temperature, pressure, and, ultimately, the winds around the fire, which drive the fire propagation, an atmospheric prediction model has been coupled with the empirical fire spread model. Thus, the complex relationship between fire and regional winds can be represented in this wildlife simulation model.

While wildland fire activities take place at several orders of magnitude smaller than the atmospheric grid size, the semi-physical fire module is fully connected to the atmospheric model (for example, 0.1 mm). Consequently, CAWFE does not replicate combustion chemistry, oxygen

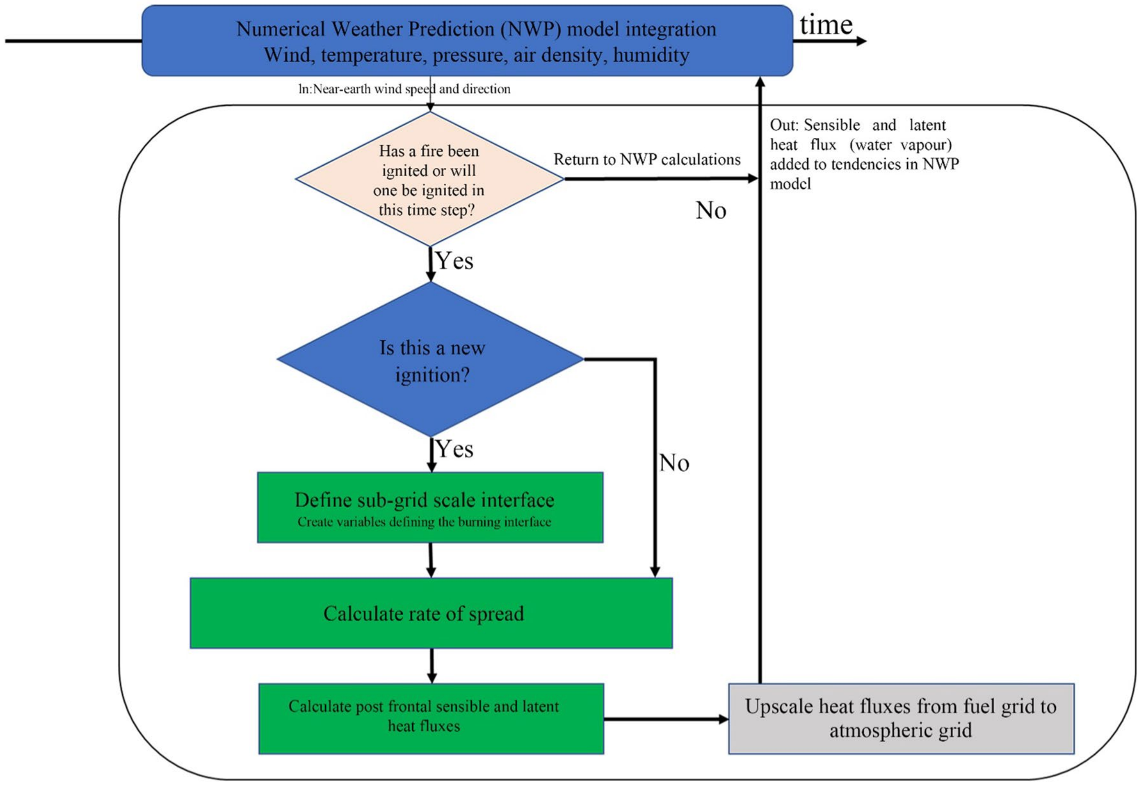

Fig. 1 Components of the WRF coupled weather–fire mode. Adapted from: Coen et al. (2013)

consumption, or flames. To show the interaction of a minor fire with eddies in the atmospheric boundary layer at high resolution, the model has simulated small flames in large eddy simulation (LES) mode. CAWFE has a multi-nesting capability that refines the grid spacing to the most acceptable resolution modelling domain in which fire growth is studied to simulate larger fires. The model replicates the remaining period of interacting weather and fire behaviour in all nests after the simulation ignites a fire in the most acceptable domain. Although CAWFE can simulate mesoscale wildfires, there is currently no evidence that it is quick enough for a real-time application (Table 5).

Weather research and forecasting numerical weather prediction system (WRF-FIRE)

An operational strategy that can be applied to wildfire model development is provided by a numerical weather prediction (NWP) model. The scaled physics, dynamic parameterisation, and data assimilation of NWP models make them useful for prediction or projection. The weather research forecast (WRF) model can logically incorporate wildfire by only including a physics option (Coen et al. 2013; Mandel et al. 2014). The fifth generation NCAR/Penn State mesoscale model (MM5) has been upgraded to WRF. The key advantages of utilising WRF are that it is an open and widely accessible model and that a sizable community of scientists from across the world (approximately 6000 registered users) actively develops it, resulting in ongoing model improvements. The advanced research WRF (ARW) modelling system is currently maintained and supported by NCAR's Mesoscale and Microscale Meteorology Division for use in a variety of applications at various scales, including real-time forecast, research, coupled-model applications, regional climate research, and data assimilation. None of the previous models has been used as real-time forecasting tools for wildland fires since simulations can execute more quickly than in real-time. WRF became a rapidly expanding community model due to separating scientific codes from computing parallelisation and other designs. It supports a wide variety of physics modules and dynamics solvers. The WRF pre-processing system (WPS), WRF data assimilation (WRF-DA), and ARW or NMM dynamics solver are the main programs that make up the WRF model. Meteorological data from other sources, such as global models, can be imported into the WRF simulation domain with the help of WPS, which performs data conversion, projection, and interpolation. Among these are the steps of constructing simulation domains and interpolating terrestrial data such as topography, soil types, and land use. Since the WRF model

Table 6 A summary of several studies focused on a wildfire spread based on the WRF-Fire/SFire model

Methods and dataset	Result/Accuracy	Inference	Reference
With an idealised domain of 6400 m × 6400 m × 3000 m (length, width, and height), WRF-Fire was employed. Its horizontal resolution was 20 m (atmospheric grid), while its vertical resolution was 2 m. (fire grid). With 61 levels, a stretched vertical coordinate was utilised. The levels were spaced approximately 4 m apart at the surface, 70 m apart at 1 km AGL, and 140 m apart at the model's top	The front quickly accelerated at first, and then the spread slowed; qualitatively, the model's output was in accord with the experimental results. Considering many scales precluded the possibility of a quantitative comparison; not a sentence	The result of the WRF-Fire model clearly illustrates a relationship between fireline geometry and rate of spread, even though a correlation between local fireline curvature and immediate local rate of spread was not found	Thomas et al. (2017)
Examined the most recent WRF-SFIRE operational testing development. In addition, a fuel-moisture model and a system for assimilating fuel-moisture data based on observations from remote automated weather stations (RAWS) are being developed. The WRF-Chem model was also used	Modelling the spread of fire while accounting for dynamic changes in the fuel characteristics brought on by weather conditions is possible by the coupling between the atmospheric component of the system and the fuel moisture model. In its present iteration, the model also forecasts the weather and fuel moisture, which the system's fire component uses to mimic fire behaviour	WRF-SFIRE is now an "all-in-one model," with the ability to predict air quality, plume ascent, plume dispersion, and fire spread within a single integrated framework thanks to the newly added capabilities for predicting smoke and fire emissions	Mandel et al. (2014)
The WRF-Fire coupled atmosphere-fire model is used to investigate the relationship between the fire-to-atmosphere coupling and the sensitivity of resolving VLS to both the horizontal and vertical grid spacing from inside the model framework	From the ignition area to the ridge line, the fire front moves up slope. The rate of lateral fire spread across the leeward slope exceeds the base rate of spread. This can happen when the upslope fire spreads. The rate of spread of the fire's lateral extensions is sporadic and is greatest on the leeward slope and near to the ridge line	The results show that, to represent VLS using WRF-Fire, great spatial resolution and two-way atmosphere-fire coupling are necessary	Simpson et al. (2014)
FireFlux field data is used to evaluate and enhance the performance of the coupled atmosphere-fire model WRF-SFIRE	The experimental burn simulation using WRF-SFIRE demonstrates that WRF-SFIRE can simulate the head-fire rate of spread, the vertical temperature structure of the fire plume, and the fire-induced surface flow and vertical velocities inside the plume up to 10 m above ground	Future field campaigns to evaluate delicate linked atmosphere fire models might take advantage of the study's advice for the most effective experimental pre-planning, design, and execution strategies	Kochanski et al. (2013)
National Fire Danger Rating System (NFDRS) and Fosberg fire-weather indices for June 2005 are constructed using WRF model simulations and observations from interior Alaska	The evaluation shows that WRF is highly suited for fire weather prediction in a boreal forest scenario. Forecast lead is only modestly associated with weather and fire data inaccuracies. WRF's interior Alaska precipitation performance is comparable to other mid latitude mesoscale models	WRF can accurately predict daily temperature extremes, relative humidity, air and dewpoint temperatures, and shortwave radiation. It is inferred from indirect examination of observed fires that the NFDRS indices produced by WRF capture the variability of fire activity	Mölders (2008)

Table 7 A summary of studies on wildfire spread based on McArthur wildfire danger metre

Methods and dataset	Result/Accuracy	Inference	Reference
The long-term trend of extreme McArthur wildfire Danger Index (FFDI) values is illustrated spatially. This fire weather indicator was evaluated by calculating the return period of its extreme values and fitting extreme value distributions to FFDI data sets from 78 stations in Australia	Combining the RF and IDW interpolation algorithms will yield the best interpolation results for the FFDI. The seasonal FFDI return period's spatial distribution reveals that the summer months are when the majority of southern Australia's FFDI is at its peak, while spring is when it is at its maximum in northern Australia	The possibility of intense fire weather in the region is evaluated in this study. The method described in this paper is easily adaptable to use with high-resolution models of the current climate and climate change scenarios	Sanabria et al. (2013)
Several fire risk indices for various fuel types utilised in an operational scenario in Australia and the US are compared to a straightforward fire danger index F that is intuitive and simple to calculate	The comparisons imply that F offers a reasonable indicator of fire danger rating and that it might be an effective educational tool when discussing fire danger and fire weather	The comparison of various fire measurement indices was successful	Sharples et al. (2009)
MFFDI's original drought factor, the Keetch-Byram Drought Index (KBDI), and the Mount's Soil Dryness Index's original drought factor are all compared (MDSI)	The most appropriate method to construct the wildfire hazard index in Indonesia is the McArthur calculation method using the KBDI of the drought component	Given that wildfires have previously been accurately forecasted twice, MFFDI views the drought factor from KBDI as the most promising formulation choice for inclusion in the early warning system of wildfires	Hadisuwito and Hassan (2021)
Changes in daily maximum FFDI and hourly varying FFDI values were compared to five binary fire activity statistics in six forest areas (including the use of several soil moisture deficit indices)	The current anticipated hourly maximum FFDI is appropriate, and there is the minimal advantage to adopting other methods to calculate the Drought Factor	The hourly FFDI distribution did not seem to affect the fire activity rates, which were comparable on days with both wide and narrow distributions, with the exception of one study site, where more fires occurred on days with large distributions	Plucinski et al. (2020)
Meteorological factors are employed solely in the McArthur FFDI. This indicator is developed into fire hazard categories to warn the public and estimate firefighting difficulty	A quantile map created using the method described here can be used as a geographically variable fire danger threshold	A spatially variable threshold may assist in conveying a high fire threat, and a regional modification is recommended	Stephenson et al. (2015)

Table 8 A summary of several studies focused on a wildfire spread based on WFDS Simulation is provided

Methods and dataset	Result/Accuracy	Inference	Reference
Through comparison to laboratory tests, the WFDS capacity to simulate the shift from surface to crown fire was assessed. The experiments were carried out at the USFS wildfire Laboratory in Riverside, California	The research monitored the ignition of chamise fuel (*Adenostoma fasciculatum*) above a surface excelsior fire. WFDS wind speed profiles matched experimental readings. Fire simulations were used to determine the rate of spread using only surface fuel and varying substrate parameters and fuel moisture content	Results from WFDS models mirrored the patterns observed in laboratory trials regarding both surface fire spread and elevated fuel bed igniting	Castle et al. (2013)
Using cutting-edge computational approaches for wind and combustion physics, researchers modelled wildland and wildland-urban interface fires	These "physics-based" models offer a more comprehensive understanding of fire behaviour under a wider range of environmental variables than empirically based models. Physics-based models help us understand their flaws and how to improve them, not replace simpler and faster models	These physics-based models must be considered when implemented with heterogeneous fuels and fire-induced winds	Mell et al. (2010)
wildfire spread prediction using several techniques: Control Variate Monte Carlo (MC) and Multilayer MC approaches achieve 100 × speedups over a normal MC method	Multifidly estimators were 100 × faster than Monte Carlo approaches. Due to low bias and moderate variability, the multilevel approach performed significantly better than the control variates	Other fire behaviour factors, such as heat transfer, fuel consumption, and smoke production, may also be examined for uncertainty	Valero et al. (2021)
WFDS modelling of fire propagation and comparison with experimental and modelling outcomes	There were inconsistencies in the data (such as maximum temperature, mass loss, ignition temperature, and time to ignition), but analyses of temporal variation in temperature and mass loss showed branch-scale fire spread modelling was possible as long as the branches' fuel-moisture content stayed below 25%	Both trials and modelling emphasised similar groups of species, which ranked species according to their branch flammability	Terrei et al. (2019)

operates in cycling (updating at a given frequency) mode, it can also be used to update the model's initial conditions. The modelling system's main component is the ARW solver, which includes several simulation initialisation programmes and a numerical integration programme encompassing physics schemes and numeric and dynamics options. Prognostic spatiotemporal discrete variables can be integrated throughout time with the help of the ARW solver. There is also a refresh of the diagnostic variables and internal and external forces at each grid node. In addition to radiation, clouds, and fire, ARW also uses forces including buoyancy, advection, the Coriolis effect, and mixing. To manage turbulence, the ARW solver uses several formulations for turbulent mixing and filtering.

The weather research forecast model includes the fire module as an additional physics option. The CAWFE model serves as a template for the module (physics package). The lowest WRF level is subject to change depending on how the vertical levels are set, coupled with the fire module through the passage of winds, temperature, and moisture. The fire module will use these winds to forecast the spread of the fire and consequent heat and water vapour emissions. The heat and water vapour emissions are returned to WRF and dispersed vertically through an extinction depth that is postulated. WRF-FIRE (Mandel et al. 2014) computes heat fluxes based on an exponential decay function and distributes the sensible heat flow vertically to account for radiation. No PBL model is employed because the WRF-FIRE module operates in LES mode. The grid and some sub-grid-scale calculations for unresolved momentum, heat, water vapour fluxes, and other diagnostics were used to resolve turbulence. The exact amounts of heat and water vapour fluxes then would be added to the top level of integration by user selected WRF land surface models (LSM) (Fig. 1).

Weather research and forecast-spread fire (WRF-SFIRE) model

WRF-SFIRE is an embedded atmosphere-wildfire approach that integrates the weather research and forecasting model (WRF) and a level-set fire-spread simulation. WR-Sfire (Mandel et al. 2011) is a semi-empirical or empirical modelling approach for wildland fire spreading. It is used for wildland fire simulations, simulation of smoke emissions, dispersion and impact on air quality.

The performance of WRF SFIRE is evaluated using data from the FireFlux experiment and field observations from the authors' previous work (Kochanski et al. 2013). The results show that WRF-SFIRE can accurately simulate the spread of fire up to 10 m in the air, as well as the temperature structure of the fire plume at various heights. Vertical wind speeds were overestimated by the model, whereas horizontal wind speeds were underestimated for tower heights of more than 10 m. According to Giannaros et al. (2019), the WRF-SFire model accuracy of coupled atmosphere-fire model predictions is often assessed qualitatively. It is impossible to evaluate the usefulness of coupled models as operational fire spread forecast tools when considering only single event (Table 6).

McArthur's wildfire danger metre

The development of McArthur's wildfire danger metre, first developed in Australia in 1967, over the past ten years has been crucial for predicting fire danger and interpreting fire behaviour. Data were gathered from the fire danger meter by measuring displacements along the scales from the tables on the back of the meter, or from McArthur's hand-drawn graphs. Derived functions described the links between these data and climatic variables. Most operations were straightforward, easily linearised, and provided a near-perfect fit for the data. Combining the different parts created a single equation linking the meteorological factors to the Fire Danger Index and the fire characteristics displayed on the meter. The metric system was used for all calculations. However, all equations utilise metric units even though the drought index on the wildfire danger meter is represented in values comparable to points of rainfall. The equations are aimed to characterise the meters as accurately as possible, even if no conclusions concerning the precision of the meters are intended. Australia still makes extensive use of McArthur's meters for predicting fire risk. The likelihood of a fire starting, the speed at which it spreads, and the difficulty of putting it out are all intimately correlated with the indices obtained from the meters. The indexes have been applied to other geographical areas despite being developed for certain forest and grassland types. They are a crucial component of forecasting and offer a framework for analysing fire behaviour in the target plant communities. The meters claim to provide "acceptable accuracy" in the forest meter and are for "average" pastures in the case of the grassland metre MK 3. They also feature several approximations. Additionally, the equations permit the automatic calculation of fire-danger indices or prospective spread rates from weather data using computer systems. They can also be applied to historical examinations of weather data regarding fire occurrences and have been utilised in models of the long-term dynamics of forests subject to wildfire and controlled burns (Table 7).

Wildland–urban interface fire dynamics simulator (WFDS) model

The fire dynamics simulator (FDS) was developed at the National Institute of Standards and Technology in the United States. The wildland–urban interface fire dynamics simulator (WFDS) is an extension of the FDS. To approximate

Table 9 Summary of studies focused on a wildfire spread model based on the Heathland model

Methods and dataset	Result/Accuracy	Inference	Reference
This study combines the Discrete Factor Method Generalised Negative Binomial (DFM-GNB) model with a specific finite mixture model, incorporating a joint preference (RP)-stated preference (SP) strategy. The information utilised in this study was obtained from a survey conducted among visitors to a heathland area in Belgium's Hoge Kempen National Park (hereafter referred to as HKNP)	The definition of the model yields reliable estimations for the hypothetical quality change and travel cost parameters. Employing a probability ratio test, we can dismiss the possibility of consistency between the exposed and asserted preference parameters	The relatively minor difference in visiting rates between a grass-encroached area and the current situation suggests that recreational value alone may not entirely justify expenditure on restoration management following wildfires	Nobel et al. (2020)
After experimentally studying soil carbon dynamics in a raised peat bog and a Calluna heathland following varying fire severities, the simulation of dryness in 2 m plots resulted in the creation of a gradient of fire severity	The CH4 flux from the raised bog increased because of burning. In the summer, when it constituted 79% of the CO_2-equivalent emission, the flux rose from 1.16 to 25.3 $nmolm^2s^{-1}$. The soil water was not significantly affected by the burning	In Calluna heathlands and peatlands, greater fire severity within the range achieved in our experimental burns had no impact on the short-term soil carbon dynamics	Grau-Andrés et al. (2019)
The research analyses a 14-year time series from a network of fixed plots. Fifty-metre-radius plots were established at 61 randomly chosen grid nodes. During each visit, observations were made regarding indications of recent fires that had burned more than 30% of the plot area and whether mowing had occurred (yes or no)	The findings indicate that rapid vegetation growth poses management challenges for the Vauda and southern European lowland heathlands	The most effective method to control heathland scrub vegetation may involve combining the impacts of various treatments, such as fire and herbivores, as they might have the most potential	Borghesio (2014)

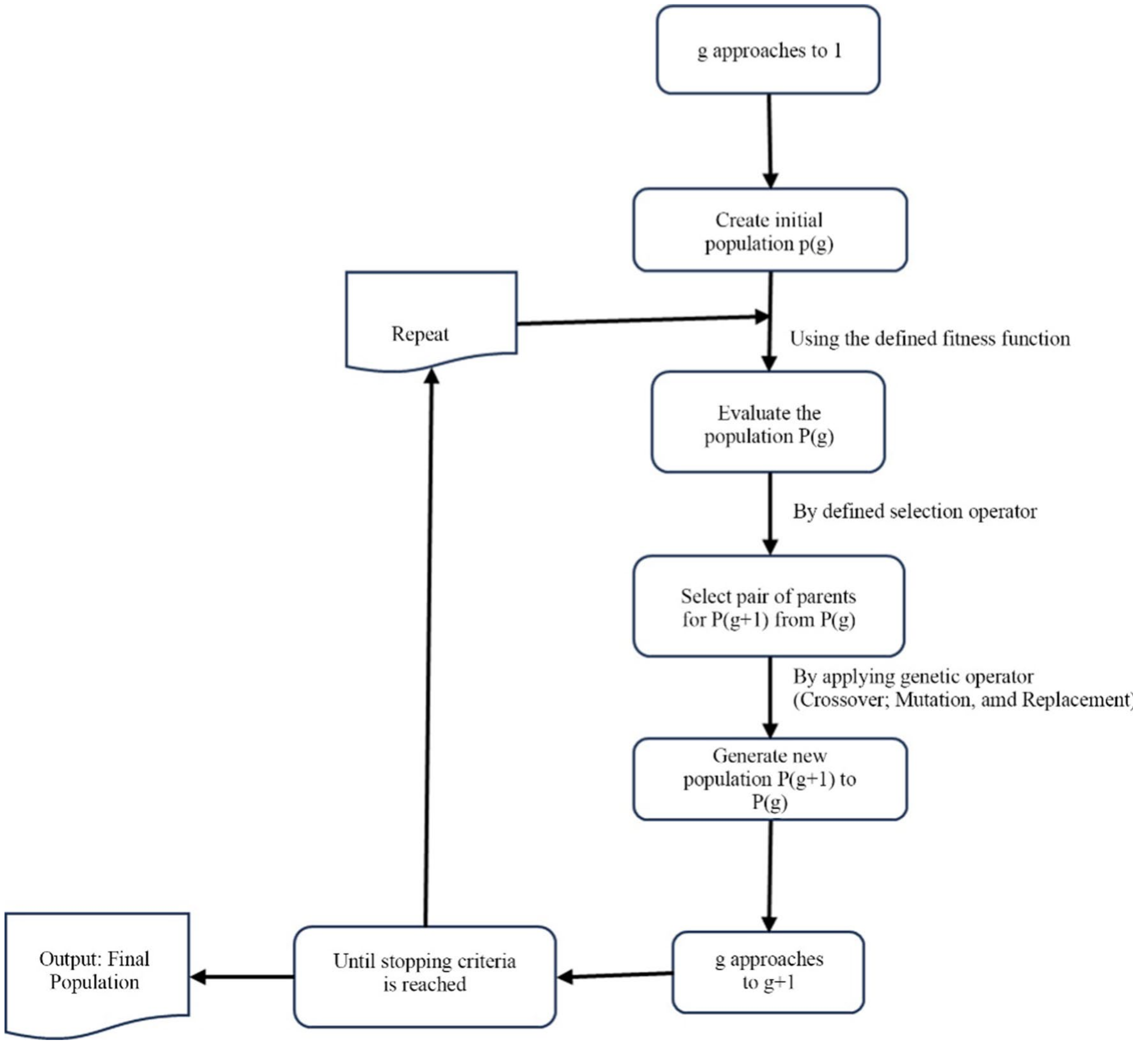

Fig. 2 General genetic algorithm steps

the governing equations for fluid dynamics, emissions, and the thermal diminishment of solid fuel, WFDS uses a semi-coupled, physics-based, three-dimensional model of a fire and its atmosphere. The combustion process is where FIRETEC and WFDS diverge significantly. Being temperature independent, WFDS implies that combustion only occurs when fuel gas and oxygen are mixed. In contrast, WFDS maintains enthalpy, the measure of energy in a thermodynamic system, and FIRETEC preserves potential temperatures. As it is widely acknowledged that the time scale of chemical reactions is considerably shorter than the time scale of mixing, the model does not account for the energy released because of chemical processes. A low Mach number approximation, the ratio of the speed of a body to the speed of sound, is included in the large eddy simulation (LES) model FDS extension, WFDS, to eliminate acoustic wave propagation from the dynamics. It also has a rapid and direct pressure solver, which helps to reduce the amount of time spent computing. To increase computing efficiency further, WFDS employs a multi-mesh to rectify the LES equations for a sub-grid inner volume of 1.5 km^2 and 200 m height with separation as small as 1.6 m. Although the multi-mesh serves the model in LES mode, it lacks multi-nest characteristics. Because information is only transmitted at the outside boundaries, overlaying meshes has no benefit. While the model can seamlessly mimic the LES scale, updates to the outer boundary conditions and coarse resolution values cannot be applied simultaneously via the inner mesh feedback. There is no contact between the cells of the overlay mesh. Since a catastrophic wildfire is a multi-scale occurrence, this can be a significant concern in simulation (Table 8).

Heathland model for wildfires

A few tree species and herbaceous plants are usually less common grow in heathlands, which are characterised by

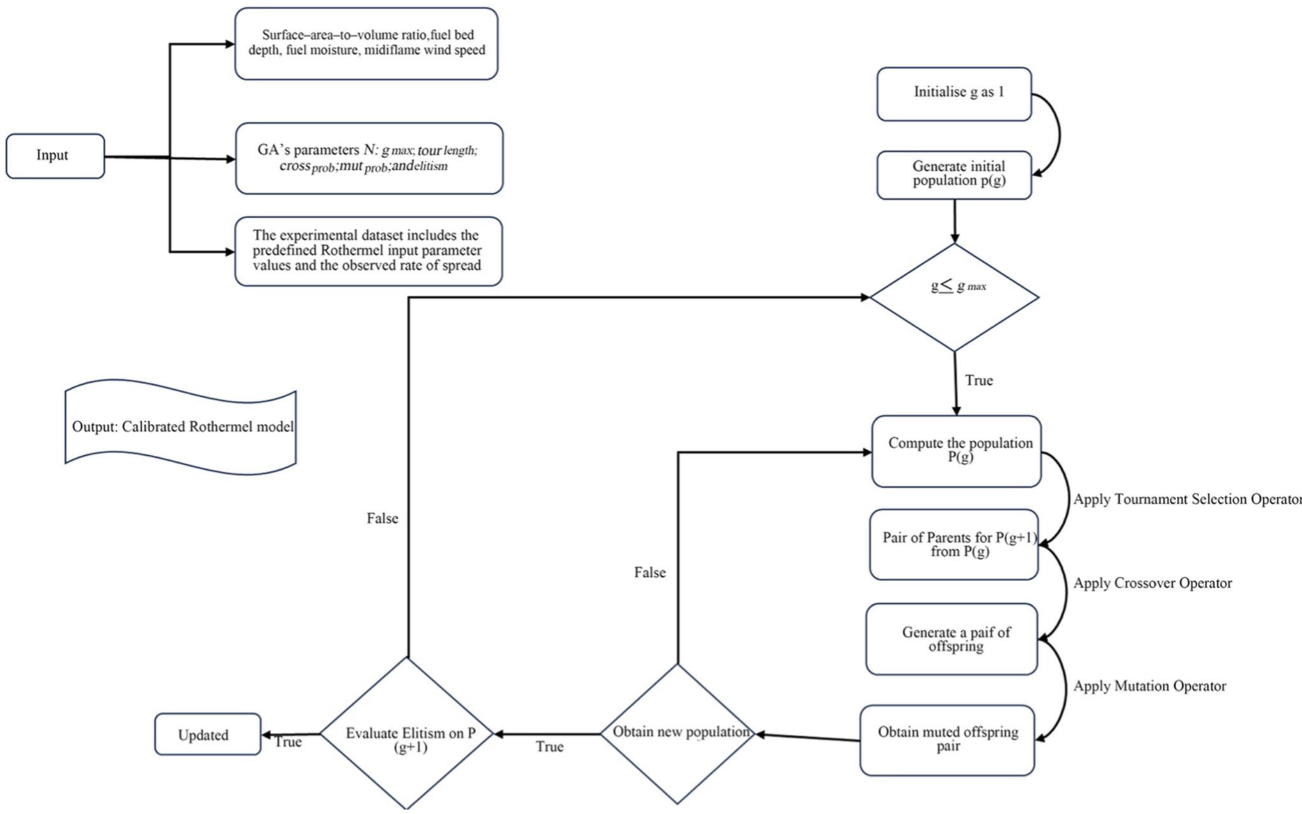

Fig. 3 Calibration methodology using genetic algorithm

vast open spaces with low-growing plants, including gorse and heather, that give the area its name (Anderson et al. 2015). Research on atmospheric fire variables and behaviour in shrubland fuels were by several research programs. Case studies of wildfire documentation were assembled in databases from Australasia, Europe, and Africa. Data were gathered by land management and research organisations for specific objectives, (e.g., creation of fire danger rating systems, design of controlled burning standards, and examination of the effects of fire on biodiversity). As a result, there was a wide range in information of fuel characteristics. Important climatic factors and fire behaviour characteristics were seen by researchers. Based on this information, particularly the fuel description subset, the dataset was divided into two main groups.

Model development subset: This consisted of data from 79 fires collected across a wide range of fuel designs, fire environment factors, and fire behaviour features. The high quality of the fuel data and the presumption that fires were expanding at or near their quasi-steady pace of advance were the key characteristics of this data subset. To ensure that this premise was valid, the data were subjected to three key constraints. These restrictions covered slope steepness, the length of the ignition line, and fuel moisture. The behaviour of fires on slopes is particularly complex due to differences in fuel structure and moisture content, issues with the interplay of wind and slope, and other factors. To minimise these effects, the data selected for analysis were restricted to slopes of less than five degrees. There was no attempt to statistically parameterise the relationship between the steepness of a slope and the rate at which a fire spread across a shrubland. It is well-established that head-fire widths and ignition line lengths have an impact on how quickly a fire spreads, with narrower fire widths unable to spread at the same rates as free-burning fires. To account for this potential confounding factor, the data utilised for modelling were restricted to ignition line lengths larger than or equal to 50 m. The effect of the length of the ignition line was also examined in the analysis. The authors used fewer wildfires with reduced ignition lines to construct an ignition line length adjustment (Table 9).

Genetic algorithm approach for wildfire spread

(Figure. 2) Numerous search and optimisation issues have been successfully solved by genetic algorithms (GAs) (Mendes et al. 2012). GAs are stochastic search techniques first developed in 1975 and motivated by genetics and natural selection. A set of components from a specific search area or a broad domain with numerous potential

Table 10 A summary of studies on a wildfire spread model based on genetic algorithm (GA)

Methods and dataset	Result/Accuracy	Inference	Reference
A dynamic data-driven application system (DDAS) using a Genetic Algorithm is introduced. The algorithm calculates fire records. The simulator calculus used by the analytical method allows for the optimisation of wind values for each individual	Comparing the two-stage approach to conventional prediction demonstrates that pre-searching increases simulation accuracy. This reduces the impact of uncertain input parameters on prediction results. The offered steering approaches converge on quality search candidates	Master/worker programming was used to develop DDDGA for wildfire spread prediction. Operation requires a high-resolution topographic map	Denham et al. (2012)
A decision-making aid that used CA and Genetic Algorithms to design a parallel processor to predict wildfires	The main result was a continuous-state space CA representing a local system or process. Find a CA with discrete state space that delivers equivalent outcomes to the CA with continuous state space using a (number of CA states/CA lattice size) grid. Specialised CPUs can model physical systems	These new computational resources simulate and model physical processes dynamically. Modelling and simulating locally interacting systems without Partial differential equations and general-purpose hardware	Karafyllidis (2004)
Wildfire susceptibility map involved using a Support Vector Machine (SVM) and Random Forest (RF). A total of thirteen variables, topographical and meteorological, were examined along with historical wildfires	The optimised RF model performed best (0.8495), followed by the original RF (0.8169). The optimised SVM model produced lower (0.7456) but higher (0.7148) outcomes than the RF	The study emphasises feature selection approaches in determining a wildfire's susceptibility, while data mining approaches can simulate it	Hong et al. (2018)
Using a population string, study how fire spreads using "Fire propagation on homogenous terrain" and "Wind-slope correction."	Because the velocity of fire propagation is not constant in all directions, a flexible fireline form, such as an ellipse or circle, is likely to yield superior outcomes	Simulation–optimization techniques can be applied to fire propagation models, novel information-gathering systems, and weather forecast models	Chaudhary et al. (2013)
For wildfire susceptibility modelling, the Genetic Algorithm for Rule-set Production (GARP) and 10 environmental layers were created	Environmental factors such as "distance to the next road, land cover, precipitation, distance to the nearest settlement, aspect, relative humidity, elevation, wind speed, and temperature" influence fire susceptibility. According to the results, these parameters were below 0.05	Future research will use weather data to evaluate and enhance the model	Zheng et al. (2022)

Table 11 Recent studies on Machine Learning Techniques in Wildfire Spread Prediction

ML methods employed	Key finding	Reference
DNN regression model with a hybrid architecture	Created a neural network for forecasting wildfire spread up to 5 days ahead, emphasising wind direction and land cover. Attained F1-score 0.64–0.68. Integrating high-res data vital near water bodies boosts accuracy	Shadrin et al. (2024)
CNN, Bidirectional Long Short-Term Memory (BiLSTM)	The CNN-BiLSTM model excels in wildfire prediction, emphasising model setup, threshold values, time steps. Positive correlation was found between soil moisture and spread	Marjani et al. (2024)
ANN, LR, K Nearest Neighbours, Support Vector Machine, and Random Forest classifiers	PCA extracted key variables for fire risk prediction. SHAP technique emphasised feature importance. ANN exhibited superior accuracy and stability. RH, DC, ISI crucial predictors. tenfold stratified cross-validation was used	Zaidi (2023)
Support Vector Regression (SVR), Gaussian Process Regression (GPR), Regression Trees, and Neural Networks	SVR, GPR, NN, and other ML models surpassed (Cheney et al. 1998) in Australian grassfire prediction. ML models offered improved accuracy and variable identification. Independent dataset testing crucial for performance enhancement	Khanmohammadi et al. (2022)
Small-scale multilayer perception neural network	The study's main focused on the learning-based method accurately predicts short-term wildfire spread without relying on empirical Rate of Spread (RoS) models	Zhai et al. (2020)
Decision tree	Multi-core architectures and OpenMP reduce forest fire prediction model execution time, enhancing parameter calibration, accuracy, and prediction speed	Artés et al. (2016)

solutions to a problem are processed by GAs (Table 10). This group is known as the population, and each member is an individual. Individuals, also considered as chromosomes, are made up of genes and represent the potential solutions to the optimisation problem. The core components of each solution are genes. Depending on the issue, an individual may be expressed in various ways, such as binary sequences of zeros and ones, complex numbers, vectors, and more (Fig. 3). After the chromosomes have been encoded, the population is typically randomly initialised. The capacity of a solution (individual) to optimise the fitness function that is particular to the problem being solved is measured using a defined fitness function applied to all individuals. The selection procedure occurs where fresh people are selected to be parents based on the fitness values of everyone. The parents are subjected to crossover, mutation, and replacement reproduction operators to breed the children and create the next generation. The GA operators are repeated until a particular requirement is met.

Calibration methodology using genetic algorithms for wildfire

The genetic algorithm begins by randomly producing an initial population of N individuals to calibrate a model of wildfire behaviour. Genes, which serve as calibrated input parameters in this work, make up each individual. The GA operators were chosen as follows:

- The selection operator involves creating a tournament by randomly choosing a certain number of wildfire simulations from the existing population. The simulation that produces the most desirable outcome (e.g., the least amount of damage) wins the competition and is selected to be a parent to the following generation. Once more, this procedure is carried out to produce a pair of parent simulations.
- The selection operator creates a tournament by randomly selecting a certain number of participants from a population of wildfires. The fire that exhibits the best firefighting performance triumphs in the contest and is chosen to be a parent to the succeeding generation. To create a pair of parent fires, this process is repeated.
- The uniform operator serves as the mutation operator for wildfire simulations. This operator involves randomly selecting a gene from the offspring and changing its value to fit the gene's specific search space at a predetermined probability of mutation (mut prob). This allows for the simulation to explore different combinations of parameters and increases the chances of finding an optimal solution.
- A few of the most incredible people from the previous generation replace random people in the new population, applying elitism to the whole population.

For every generation g ($g = 1$, g (max)), the new population is assessed and the cycle is continued until *gmax* generations have been produced. The person from the final population who has the best fitness is the final solution when the algorithm is finished. This is the final calibrated algorithm for the wildfire spread calibration.

Cutting-edge machine learning methods for wildfire spread

Recent advancements in machine learning (ML) have shown promising prospects for enhancing wildfire spread prediction. Techniques such as deep learning (Radke et al. 2019), ensemble methods (Srivas et al. 2016), and reinforcement learning (Ganapathi Subramanian and Crowley 2018) are gaining attention for their ability to handle complex and nonlinear relationships within wildfire data. Deep learning models, particularly convolutional neural networks (CNNs) (Marjani et al. 2023) and recurrent neural networks (RNNs) (Perumal and van Zyl 2020) excel in capturing spatial and temporal patterns in wildfire dynamics, enabling more accurate predictions of fire behaviour. Ensemble methods, such as random forests and gradient boosting, leverage the collective intelligence of multiple models to improve prediction robustness and mitigate overfitting (Huot et al. 2022; Koh 2023). Additionally, reinforcement learning algorithms are being explored for optimising wildfire management strategies by dynamically adapting firefighting tactics based on real-time feedback. These cutting-edge ML methods offer exciting opportunities to revolutionise wildfire prediction and management, paving the way for more effective strategies to mitigate the devastating impacts of wildfires on ecosystems and communities (Table 11).

Discussion

The purpose of wildfire modelling is to make a thorough process to simulate fire occurrences and an inclusive analysis of archive fire records which can assist wildfire managers in making decisions related to early warning and arrange for necessary actions during prevention. Modelling wildfires can be used to create preventive measures, such as studying fire behaviour and the daily operations of wildfire personnel. The critical evaluation of current wildfire prediction models reveals both advancements and challenges. While existing models offer valuable insights, incorporating further international research findings will enhance the robustness and applicability of wildfire prediction strategies. This review of wildfire spread prediction models illuminates the evolution, strengths, and limitations of existing methods. By synthesising findings from various studies from 1946 to the present, this review offers important insights into the current landscape of wildfire prediction and identifies areas for future research and development.

One notable challenge lies in the variability of fire behaviour across different regions, necessitating adaptable models that can accommodate diverse climatic and vegetation characteristics. From empirical and semi-empirical models to theoretical and ML-based techniques, researchers have explored a wide array of methods to forecast fire behaviour (Khanmohammadi et al. 2022; Zaker Esteghamati et al. 2023; Qayyum et al. 2024). Each model presents unique advantages and challenges, emphasising the importance of selecting an approach based on the specific requirements of the application. Integrating findings from international studies can provide a more comprehensive understanding of these variations, enabling model refinement for global applicability.

In addition, this review highlights the crucial role of data in wildfire prediction. ML models in particular, leverage diverse datasets to create predictive models capable of forecasting the spread of future fires. By analysing historical data and incorporating a broad array of variables, ML models offer enhanced predictive capabilities compared to traditional statistical and physical models (O'Connor et al. 2017; Sayad et al. 2019).

Remote sensing technology emerges as another crucial component in wildfire prediction and monitoring. By providing spatial maps encompassing factors such as fuel types, moisture content, wind direction, and topography, remote sensing data enhances the accuracy of wildfire spread models (Carta et al. 2023; Kanwal et al. 2023). Incorporating remote sensing data not only improves the understanding of fire dynamics but also aids in updating fuel and fire behaviour models for more accurate predictions.

The models discussed in this review are the most advanced models available for predicting the spread of wildfires. The CA model is a simple but powerful tool for predicting the spread of fire in a highly heterogeneous environment (Khalaf et al. 2024). The CA model has been widely used in the prediction of wildfire spread with good results. It is a computer-based simulation of physical processes on a grid and is useful for predicting fire spread in complex terrain. The Rothermel model is also commonly used for predicting fire spread. It is based on mathematical equations that simulate the physical processes that drive fire spread such as wind speed and fuel moisture levels. The FIRETEC model is a semi-empirical model that considers the effects of ambient conditions, fuel characteristics, and terrain on fire spread (Or et al. 2023). The CAWFE model is a coupled atmosphere wildland fire environment model that provides accurate predictions of fire spread based on the interaction of atmosphere and land surface processes (Moody et al. 2023).

The WRF-FIRE and WRF-SFIRE models are numerical weather prediction systems that use fuel characteristics and environmental conditions to predict fire spread (Shamsaei et al. 2023). The McArthur wildfire danger metre is an empirical model that can be used to predict fire danger in a particular region (Zacharakis and Tsihrintzis 2023). The WFDS model is a sophisticated wildland-urban interface fire dynamics simulator that considers the effects of urbanisation on fire spread (Mohammadian Bishe et al. 2023). The Heathland model for wildfire is an evolutionary model based on the principles of genetic algorithms and uses fuel characteristics to predict the spread of fire. Lastly, the genetic algorithm approach for wildfire spread is a model that uses fuel characteristics and environmental conditions (Zhang et al. 2023).

When it comes to predicting and understanding the spread of wildfires, there are a range of models available to be used to simulate different scenarios and analyse the effects of different management strategies. Cellular automata (CA) models are powerful tools for simulating complex systems to capture emergent behaviour. The Rothermel Model is a widely used fire spread model that considers the physical properties of the fuel and the environment, while the FIRETEC model is an advanced fire spread model tailored to the user's needs. The coupled atmosphere-wildland fire environment (CAWFE) model is capable of simulating the interaction between fire, smoke, and the atmosphere, while the weather research and forecasting numerical weather prediction system (WRF-FIRE) is an advanced model for forecasting fire behaviour in complex terrain. The WRF-SFIRE model is capable of simulating the spread of wildfires over both short and long-term scales, and the McArthur wildfire Danger Metre is a useful tool for fire management and prevention. Finally, the Wildland–Urban Interface Fire Dynamics Simulator (WFDS) model is capable of simulating a variety of scenarios, and the Heathland Model for wildfire developed by (Anderson et al. 2015) is a mathematical model used to simulate fire spread in heathland ecosystems. Additionally, the genetic algorithm approach for wildfire spread is a powerful tool that can be used to estimate the spread of wildfires.

Each of these models has its advantages and disadvantages and should be chosen based on the needs of the user. For example, the Rothermel Model is a useful tool for predicting the spread of wildland fires but is limited in its ability to account for unpredictable variables, while the FIRETEC model is highly customisable but computationally intensive. The CAWFE model is a powerful tool for predicting the effects of wildland fire on the atmosphere but is expensive to purchase and maintain, and the WRF-FIRE model is capable of simulating both microscale and mesoscale atmospheric processes but is limited in its ability to represent fine-scale features. The WRF-SFIRE model is powerful but computationally expensive, while the McArthur wildfire Danger Metre is a simple system that indicates the likelihood of a fire occurring in a particular area but is not always accurate. Finally, the Wildland-Urban Interface Fire Dynamics Simulator (WFDS) model is capable of simulating a variety of scenarios but is limited in its ability to simulate complex terrain and other features, while the Heathland Model for wildfire is limited to heathland ecosystems and the genetic algorithm approach for wildfire spread requires a significant amount of computing time and resources to run.

In conclusion, there is a range of models available for predicting and understanding the spread of wildfires. Each model has its advantages and disadvantages and should be chosen based on the particular needs of the user. Understanding the strengths and weaknesses of each model can help to ensure that the chosen model is the right fit for the particular situation.

Real-time applications of wildfire spread prediction

Advancements in technology and the availability of large amounts of data have facilitated the development of real-time applications for predicting wildfire spread. These applications utilise various techniques, including ML algorithms, to analyse factors such as weather conditions, topography, vegetation type, and historical fire data. By leveraging real-time data streams and sophisticated modelling approaches, these applications offer invaluable insights and decision-support tools for wildfire management and response teams (Lourenço et al. 2021).

One prominent example of real-time wildfire spread prediction is the use of integrated systems that combine satellite imagery, weather forecasts, and computational models to generate dynamic fire behaviour predictions (Coen et al. 2020). These systems provide accurate and timely information on fire progression, helping authorities to allocate resources effectively and evacuate at-risk areas.

In addition, mobile applications are practical tools for both professionals and the general public to monitor and track wildfires in real time (Tan et al. 2017). These apps often feature interactive maps, alerts, and incident updates, empowering users to stay informed and take appropriate action during wildfire events.

In addition to aiding in fire suppression efforts, real-time wildfire spread prediction also plays a crucial role in proactive measures such as prescribed burning and land management planning. By simulating different scenarios and assessing potential outcomes, decision-makers can develop strategies to mitigate fire risk and enhance ecosystem resilience.

Overall, the integration of real-time wildfire spread prediction into operational workflows has the potential to significantly improve wildfire management practices, reduce the impact of wildfires on communities and ecosystems, and ultimately save lives. As technology continues to evolve and our understanding of fire behaviour strengthens, the future of wildfire prediction holds promise for even more sophisticated and effective tools to combat this growing threat.

Future directions in wildfire spread prediction modelling

Wildfire spread prediction modelling is poised for significant advancements. One promising avenue lies in the integration of ML techniques with existing physical models. By leveraging the large amounts of data available and harnessing the power of ML algorithms, researchers can enhance the accuracy and efficiency of wildfire spread predictions. Moreover, the development of hybrid models that combine the strengths of multiple modelling approaches is expected to gain support. These hybrid models have the potential to offer more robust predictions by incorporating both physical principles and statistical patterns.

Another important direction for future research involves the refinement of data assimilation methods coupled with dynamic forecasting models. By improving the assimilation of biophysical and climatic variables into predictive models, researchers can better capture the complex interactions driving wildfire behaviour. Furthermore, there is a growing recognition of the need for global-scale models that can accurately predict wildfire spread across diverse geographic regions. Such models must consider a wide range of factors, including soil characteristics, vegetation types, and weather patterns, to provide reliable predictions on a continental scale.

In addition to advancing modelling techniques, efforts to enhance the interpretability of ML-based models are crucial. As these models often operate as black boxes, increasing transparency in their decision-making processes is essential for building trust and confidence among stakeholders. In addition, addressing the computational challenges associated with ML-based models is paramount. Future research should focus on developing efficient algorithms and computing strategies to enable the widespread adoption of these advanced modelling techniques.

Overall, the future of prediction modelling for wildfire spread holds promise of significant advancements. By embracing interdisciplinary approaches, integrating advanced modelling techniques, and addressing key challenges, researchers can contribute to more accurate, reliable, and actionable predictions for wildfire management and prevention efforts worldwide.

Conclusion

This review of models for wildfire spread prediction underscores the multifaceted nature of wildfire dynamics and the diverse methods used to forecast fire behaviour. Through an extensive analysis spanning several decades of research, this review has identified key insights and critical areas for further study in wildfire prediction.

One of the most significant outcomes is the recognition of the evolving landscape of wildfire modelling. From empirical and semi-empirical models to advanced techniques, machine learning researchers have continuously innovated to develop more accurate and adaptable prediction methods. The diversity of approaches highlights the complex interplay of factors influencing fire spread, underscoring the need for flexible and robust modelling frameworks.

In addition, this review emphasises the pivotal role of data in wildfire prediction. Machine learning models, leveraging diverse datasets and advanced algorithms, offer unprecedented predictive capabilities, enabling more accurate forecasts of future fire behaviour. Remote sensing technology complements these efforts by providing crucial spatial data for updating models and enhancing prediction accuracy.

Moreover, the importance of considering regional variations in wildfire behaviour cannot be overstated. Different environmental conditions across geographic regions necessitate models capable of capturing local nuances and complexities. International collaboration and data sharing are essential for refining models and improving prediction accuracy at a global scale.

This review highlights the efficacy of combining machine learning algorithms with physics-based models as the best approach for creating and utilising fire spread models. By integrating these algorithms, such as neural networks with physics-based models, researchers can exploit the strengths of each technique to enhance predictive capabilities and improve simulation accuracy. Machine learning algorithms excel in discerning intricate patterns within data, while physics-based models enable the incorporation of critical environmental variables such as wind patterns, terrain features, and fuel characteristics, crucial for crafting realistic simulations of fire behaviour. By synergistically combining these approaches, a more reliable and accurate fire spread model can be developed, aiding in better prediction and management.

This review advances our understanding of wildfire prediction by synthesising findings from diverse methods and identifying opportunities for future research. By interpreting our findings at a higher level of abstraction and emphasising the importance of continuous innovation and collaboration, this review contributes to ongoing efforts to mitigate the impacts of wildfires and safeguard natural ecosystems and communities.

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