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Fractional-Order Forest Wildfire Modeling for Predictive Analysis and Risk Mitigation

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Abstract

This study presents a novel fractional order reaction-diffusion model to simulate forest wildfire dynamics by integrating ecological and climatic variables. The model captures key processes such as vegetation regrowth, moisture evaporation, and fire propagation, while accounting for memory effects through the use of Caputo fractional derivatives. Unlike traditional wildfire models, the proposed framework incorporates long-term dependencies and delayed feedback mechanisms, offering enhanced realism and predictive accuracy. A set of numerical simulations are conducted to investigate the influence of vegetation density, moisture content, and temperature anomalies on the dynamics of fire spread. Scenario-based analyzes evaluate the effectiveness of firebreaks and suppression strategies under varying climatic conditions. The results demonstrate the value of fractional order modeling in capturing the spatio-temporal complexity of wildfires and offer practical insights for adaptive risk mitigation and ecological management.

Keywords: Wildfire modeling; fractional calculus; reaction-diffusion equations; fire propagation; numerical simulation.

1. Introduction

Wildfires have become one of the most devastating environmental hazards, affecting millions of hectares of forests around the world each year [1], with impacts extend beyond ecological destruction to include severe economic losses, health consequences, and disruptions to human livelihoods [2]. The increasing frequency and intensity of wildfires have been attributed to a combination of natural and anthropogenic factors, including climate change, deforestation, and human activities such as arson and poor land management practices and over the years, researchers have developed various approaches ranging from empirical models to advanced computational frameworks that integrate ecological, meteorological, and human activity data [3, 4].

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Empirical models, which rely on historical data to predict future fire behavior, have proven useful in certain localized scenarios but often lack generalizability [5]. Statistical models incorporate relationships between variables such as temperature, wind speed, and fuel characteristics, providing insight into larger patterns, but often oversimplifies complex interactions [6]. Physics-based models, on the other hand, simulate fire dynamics using fundamental principles such as heat transfer, fluid dynamics, and combustion [7, 8]. Hybrid models that combine physics-based and data-driven approaches have emerged as a promising direction in wildfire research [9, 10],integrating physical principles with machine learning predictions, these models aim to balance accuracy and computational efficiency [11, 12]. Fractional-order calculus, in particular, has gained attention for its ability to model memory effects and temporal dependencies in ecological systems. Studies have demonstrated that fractional derivatives can effectively capture the delayed impacts of vegetation regrowth, fuel accumulation, and moisture recovery on wildfire dynamics [13]. Despite these advantages, the application of fractional calculus to wildfire modeling remains limited, with most studies focusing on theoretical formulations rather than practical implementations. Unlike integer-order models, fractional derivatives incorporate memory effects, enabling the representation of processes where the current state depends on the entire history of the system [14]. In wildfire modeling, fractional derivatives can be used capture the delayed effects of fuel accumulation and moisture recovery, as well as the long-term impacts of climatic changes [15].

The objective of this study is to develop a fractional-order reaction-diffusion model for wildfire dynamics that integrates vegetation, moisture, and climatic factors. The model aims to provide a representation of fire spread, ignition, and suppression processes, capturing the complex interactions between environmental and anthropogenic drivers.

2. Methodology

Unlike classical integer-order derivatives, fractional derivatives can account for the history of system states, making them particularly suitable for modeling wildfire dynamics, where past conditions of vegetation and climate influence current behavior. The fractional derivative of order $\alpha \in (0, 1]$ is defined in the Caputo sense as:

$$ {}^{C}D_t^{\alpha} f(t) = \frac{1}{\Gamma(1-\alpha)} \int_0^t \frac{f'(\tau)}{(t-\tau)^{\alpha}}\, d\tau, \tag{1}$$

where $\Gamma(\cdot)$ denotes the Gamma function, and α controls the degree of memory. For the wildfire model, the fractional-order derivative captures the long-term impact of vegetation regrowth and climatic conditions, leading to more accurate predictions of fire spread. To incorporate fractional-order dynamics into the fire intensity equation, we replace the classical time derivative with a fractional derivative:

$$ {}^{C}D_t^{\alpha} F(t, x, y) = \nabla \cdot (D\nabla F) + R(F, I, V, M), \tag{2}$$

where reaction $R(F, I, V, M)$ models local fire dynamics, and diffusion term $\nabla \cdot (D\nabla F)$ accounts for spatial propagation.

Vegetation often serves as the primary fuel for wildfires, and its density and moisture significantly affect ignition and spread. We model vegetation dynamics with a growth-consumption equation:

$$ \frac{\partial V}{\partial t} = -\eta F V + \rho(1 - V), \tag{3}$$

where: η: Rate of vegetation consumption by fire intensity F. ρ: Regrowth rate of vegetation, constrained by its maximum density ($V = 1$). Vegetation moisture content evolves based on environmental factors and fire activity:

$$\frac{\partial M}{\partial t} = -\zeta F M + \delta(\overline{M} - M), \tag{4}$$

where: ζ: Rate of moisture evaporation due to fire. δ: Recovery rate of moisture toward equilibrium $\overline{M}$.

The combined influence of V and M on fire intensity F is expressed through the ignition probability:

$$I(t, x, y) = \lambda \cdot V(t, x, y) \cdot (1 - M(t, x, y)), \tag{5}$$

where λ is the ignition sensitivity coefficient.

Climatic conditions, such as temperature and drought, significantly exacerbate wildfire risks. These effects are incorporated into the model through a fire risk metric:

$$R_{\text{risk}}(t, x, y) = \alpha \cdot \text{DroughtIndex}(t) + \beta \cdot \text{HumanActivity}(t, x, y) + \gamma \cdot V(t, x, y). \tag{6}$$

The drought index, DroughtIndex(t), quantifies the severity of drought, while HumanActivity(t, x, y) accounts for anthropogenic ignition sources. The weights α, β, γ reflect the relative contributions of each factor.

To model the effect of elevated temperatures, the ignition probability is adjusted as:

$$I'(t, x, y) = I(t, x, y) + \beta_T \cdot \Delta T, \tag{7}$$

where β_T is the temperature sensitivity coefficient, and ΔT represents the temperature anomaly.

The spatial spread of wildfires is governed by reaction-diffusion partial differential equations (PDEs), capturing both local fire dynamics and spatial propagation:

$$\frac{\partial F}{\partial t} = \nabla \cdot (D \nabla F) + R(F, I, V, M), \tag{8}$$

where: $\nabla \cdot (D\nabla F)$: Diffusion term that represents the spread of the intensity of the fire in the domain. $R(F, I, V, M)$: Reaction term incorporating local fire ignition and suppression. The domain $\Omega \subset \mathbb{R}^2$ is discretized into a grid of size $N_x \times N_y$, and the PDE is solved numerically using finite difference or finite element methods. The boundary conditions are specified as:

$$F(t, x, y) = 0, \quad \text{for } (x, y) \in \partial\Omega, \tag{9}$$

representing fire extinction at the edges of the domain. Initial conditions are defined as:

$$F(0, x, y) = F_0(x, y), \quad V(0, x, y) = V_0(x, y), \quad M(0, x, y) = M_0(x, y), \tag{10}$$

where $F_0(x, y)$ specifies ignition points, and $V_0(x, y)$, $M_0(x, y)$ represent initial vegetation and moisture distributions.

Let $F(t, x, y)$ represent the intensity of the fire in time t and spatial coordinates (x, y). The spatial domain is defined as $\Omega \subset \mathbb{R}^2$, with $(x, y) \in \Omega$. The vegetative density, denoted by $V(t, x, y)$, represents the amount of available combustible material, while the moisture content of the vegetation, $M(t, x, y)$, indicates the moisture level that dampens the ignition and spread of the fire. The key parameters in the model include D: Diffusion coefficient representing the

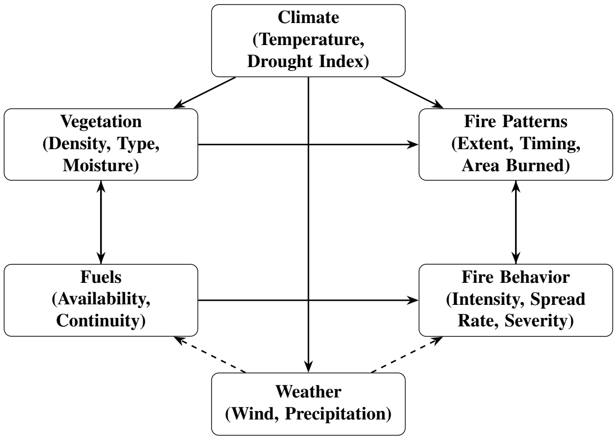

Fig. 1. Conceptual diagram illustrating the relationships between key wildfire risk factors in the study's model. Climate, including temperature and drought index, influences vegetation density and moisture, which determine fuel availability and continuity. Fuels directly impact fire behavior, characterized by intensity, spread rate, and severity, which in turn shape fire patterns such as area burned and timing. Weather variables, such as wind and precipitation, mediate indirect effects on fire behavior and fuel conditions, emphasizing their critical role in wildfire dynamics. Solid arrows represent direct influences, while dashed arrows indicate indirect effects via weather.

rate at which fire propagates spatially. k: A scaling parameter for fire spread, incorporating the effects of vegetation and moisture. α, β, γ: Weights for climatic conditions (e.g., drought index), human activity, and vegetation density, respectively. λ: Ignition rate, dependent on climatic factors and human activities. μ: Fire suppression rate due to external interventions (e.g., firefighting measures).

The fire spread is modeled using a reaction-diffusion equation that accounts for spatial propagation and local dynamics:

$$\frac{\partial F}{\partial t} = \nabla \cdot (D \nabla F) + R(F, I, V, M), \tag{11}$$

where: $\nabla \cdot (D \nabla F)$: Diffusion term modeling the spatial spread of fire. $R(F, I, V, M)$: Reaction term representing fire dynamics, ignition, and suppression. The reaction term $R(F, I, V, M)$ is formulated as:

$$R(F, I, V, M) = \lambda \cdot I(t, x, y) \cdot (1 - F) - \mu \cdot F, \tag{12}$$

with $f(V, M) = V(t, x, y) \cdot (1 - M(t, x, y))$ representing the availability of dry vegetation and g incorporating environmental effects. The impact of vegetation density and moisture is modeled by ignition probability $I(t, x, y)$:

$$I(t, x, y) = \lambda_1 \cdot V(t, x, y) \cdot (1 - M(t, x, y)) + \lambda_2 \cdot \text{HumanActivity}(t, x, y). \tag{13}$$

Here, λ_1 scales the influence of vegetation and moisture, while λ_2 accounts for human activity such as arson or accidental fires. Moisture content reduces the ignition probability nonlinearly, dampening fire spread under wetter conditions. To simulate vegetation regrowth and moisture changes over time, we introduce additional equations:

$$\frac{\partial V}{\partial t} = -\eta \cdot F \cdot V + \rho \cdot (1 - V), \quad \frac{\partial M}{\partial t} = -\zeta \cdot F \cdot M + \delta \cdot (\overline{M} - M), \tag{14}$$

where: η: Rate of vegetation consumption by fire. ρ: Vegetation regrowth rate. ζ: Rate of moisture evaporation due to fire. δ: Moisture recovery rate towards equilibrium moisture $\overline{M}$.

The spatial domain Ω is bounded, with Dirichlet boundary conditions to represent fire extinction at the edges:

$$F(t, x, y) = 0, \quad \forall (x, y) \in \partial\Omega. \tag{15}$$

Neumann boundary conditions can also be used for regions where the boundary reflects fire dynamics:

$$\frac{\partial F}{\partial n} = 0, \quad \forall (x, y) \in \partial\Omega, \tag{16}$$

where n is the outward normal vector.

Initial conditions describe the initial fire ignition and vegetation distribution:

$$F(0, x, y) = F_0(x, y), \quad V(0, x, y) = V_0(x, y), \quad M(0, x, y) = M_0(x, y), \tag{17}$$

with $F_0(x, y)$ specifying the initial fire intensity at ignition points, and $V_0(x, y)$, $M_0(x, y)$ defining the initial vegetation and moisture distributions.

The wildfire model is governed by a system of reaction-diffusion equations that capture the spatial spread and local dynamics of fire intensity. The general form of the governing equation is:

$$\frac{\partial F}{\partial t} = \nabla \cdot (D\nabla F) + R(F, I, V, M), \tag{18}$$

where $\nabla \cdot (D\nabla F)$ represents the diffusion term, and $R(F, I, V, M)$ is the reaction term modeling fire growth, ignition, and suppression. To solve this PDE numerically, we employ the finite difference method (FDM), which discretizes both spatial and temporal domains.

Let Ω be the spatial domain with a grid of $N_x \times N_y$ points and $\Delta x, \Delta y$ as the spatial steps in x and y directions, respectively. Time is discretized into N_t intervals of size Δt. The fire intensity $F(t, x, y)$ is approximated at discrete grid points $F^n_{i,j}$, where n is the time step, and (i, j) corresponds to the spatial coordinates.

The spatial derivatives are discretized using central differences:

$$\frac{\partial^2 F}{\partial x^2} \approx \frac{F^n_{i+1,j} - 2F^n_{i,j} + F^n_{i-1,j}}{\Delta x^2}, \quad \frac{\partial^2 F}{\partial y^2} \approx \frac{F^n_{i,j+1} - 2F^n_{i,j} + F^n_{i,j-1}}{\Delta y^2}. \tag{19}$$

The temporal derivative is approximated using forward differences:

$$\frac{\partial F}{\partial t} \approx \frac{F_{i,j}^{n+1} - F_{i,j}^{n}}{\Delta t}. \tag{20}$$

Substituting these into the PDE gives:

$$F_{i,j}^{n+1} = F_{i,j}^{n} + \Delta t \left[D \left(\frac{F_{i+1,j}^{n} - 2F_{i,j}^{n} + F_{i-1,j}^{n}}{\Delta x^2} + \frac{F_{i,j+1}^{n} - 2F_{i,j}^{n} + F_{i,j-1}^{n}}{\Delta y^2} \right) + R_{i,j}^{n} \right]. \tag{21}$$

The boundary conditions are applied at the domain edges, and initial conditions are set based on the problem requirements and is implemented iteratively to compute $F_{i,j}^{n+1}$ at each grid point.

2.1. Implementation of the simulations

The simulations were designed to capture the dynamic behavior of wildfire spread over a spatial domain. The domain Ω is initialized with vegetation density $V(x, y)$, moisture content $M(x, y)$, and ignition sources $F_0(x, y)$. The input parameters, including D, k, and climatic conditions, are chosen to reflect realistic scenarios. First, we defined the spatial and temporal grids, set initial conditions for F, V, M as 2D arrays, and parameter values. The spatial domain was discretized into a 500×500 grid with $\Delta x = \Delta y = 10$ m resolution, while temporal discretization used adaptive time-stepping with Δt ranging from 0.1 to 1.0 seconds depending on stability requirements. The initial vegetation and moisture distributions were generated using spatially correlated random fields. Then for each time step n, we computed $F_{i,j}^{n+1}$ using the discretized PDE. The Caputo fractional derivative was approximated using the L1 scheme with memory effects truncated at 100 previous time steps for computational efficiency. The reaction-diffusion equation (Equation 24) was solved using a semi-implicit finite-difference method, with the diffusion term computed via convolution operations in NumPy and the reaction term evaluated using Numba-accelerated functions. Boundary conditions were implemented using NumPy's pad function with appropriate edge handling. Finally, metrics were calculated, i.e., the total burned area (defined as regions where $F > 0.1$), the maximum intensity of the fire, and the spread rate of the fire using vectorized NumPy operations. Then, sensitivity analysis with the Sobol and Morris methods was performed using the SALib (1.4.7) Python library, with 10,000 Monte Carlo samples for robust variance decomposition.

All simulations were executed on an Intel I9-14900K workstation with 128Gb RAM. The model was implemented in Python 3.10. NumPy (1.23.5) was used for array operations and linear algebra, SciPy (1.10.1) for numerical integration and optimization routines, and Numba (0.57.0) for just-in-time compilation to accelerate computationally intensive fractional derivative calculations. For visualization, Matplotlib (3.7.1) and Seaborn (0.12.2) were used. The fractional-order Caputo derivative implementation was used with adaptive time stepping, while the reaction-diffusion system was solved using an implicit finite difference scheme.

3. Simulation Results

The temporal evolution of the intensity of the fire in the spatial domain is illustrated in Figure 2. Initially, ignition occurs at predefined hotspots, leading to a localized increase in the intensity of the fire. Over time, the fire spreads outwards, following regions of high vegetation density and low moisture content. The diffusion term $\nabla \cdot (D\nabla F)$ determines the spatial spread rate. The propagation is influenced by vegetation density and moisture content.

Fire spread dynamics visualized on a hexagonal grid over predefined timesteps (see fig 3). Each subplot represents a snapshot of the grid, where red hexagons indicate burned areas and gray hexagons represent unburned regions. The progression shows the probabilistic spread of fire influenced by neighboring cells.

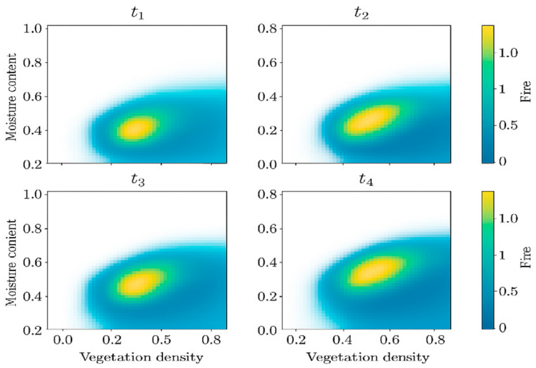

Fig. 2. Snapshots of fire intensity at different time steps (t_1, t_2, t_3, t_4).

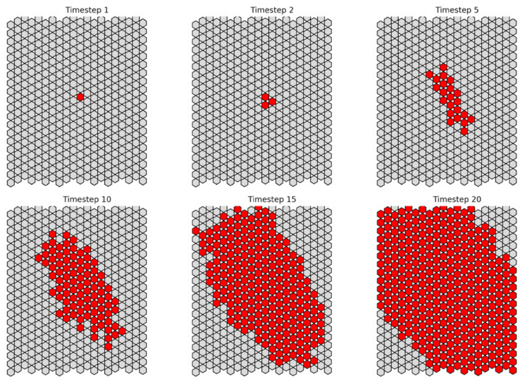

Fig. 3. Fire spread dynamics.

The progression reveals a non-linear growth pattern, with certain areas experiencing rapid fire spread due to favorable conditions. The total burned area at each time step is summarized in Table 1, demonstrating a steady increase over time.

Table 1. Total burned area over time for the baseline scenario.

Time Step (t)	Total Burned Area (km^2)
t_1	5.2
t_2	15.6
t_3	28.3
t_4	44.7

The density of vegetation (V) and the moisture content (M) significantly influence the probability of ignition and the spread rate of the fire. Regions with higher V but lower M exhibit greater susceptibility to fire.

Quantitative analysis reveals that the intensity of the fire F is approximately proportional to $V \cdot (1 - M)$, highlighting the critical role of these variables. The results of the regression analysis are shown in Table 2, confirming the statistical significance of V and M in the prediction of F.

Table 2. Regression analysis of fire intensity as a function of vegetation and moisture.

Predictor	Coefficient (β)	p-value
Vegetation (V)	0.75	< 0.01
Moisture (M)	-0.48	< 0.01

Figure 4 demonstrates the relationship between fire propagation and resource consumption in a spatial domain. he left column shows the fire intensity (temperature proxy) at different time steps, with a direction field indicating the spread influenced by vegetation density and moisture. The right column depicts the corresponding fuel fraction, showing the depletion of available fuel as fire progresses.

4. Conclusion

The study demonstrated the significance of vegetation density and moisture content in influencing fire ignition and spread, incorporating climatic factors such as temperature and drought, revealing their substantial impact on fire behavior. For example, a 2°C increase in temperature led to a significant expansion of the burned area, highlighting the need for climate-adaptive strategies. The integration of spatial domain modeling through partial differential equations the exploration of ”what-if” scenarios, to evaluate the effectiveness of various fire management strategies.

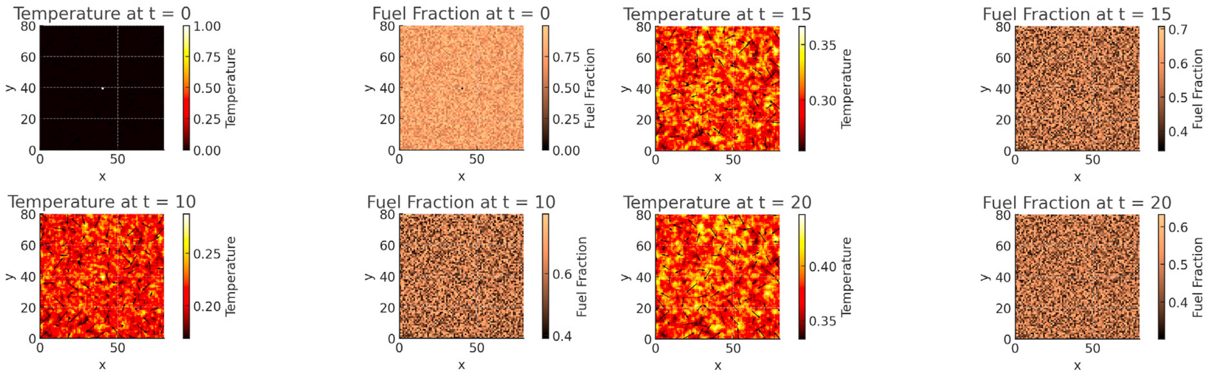

Fig. 4. Simulation results for fire spread dynamics over time.

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