

The Integration of CFD and Cutting-edge Multivariate Modeling in Future Forest Fire Research

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Abstract. Forest fires, as highly destructive natural disasters, are showing a trend of higher frequency and greater intensity against the backdrop of global climate change. This has put forward an unprecedented and urgent demand for the accuracy and timeliness of fire spread prediction models to support effective disaster prevention and mitigation decisions. To predict and research forest fires effectively, researchers have applied many methods and techniques to simulate forest fire models to find out some discipline that can swiftly turn into reality. The review aims to propose four main techniques used in forest fire simulation: computational fluid dynamics (CFD), cellular automata (CA), semi-empirical models with data assimilation and artificial intelligence-based techniques. Discuss and compare their advantages and disadvantages. Then gives out future prospective applications of hybrid modeling in fire simulation research and potential challenges that cannot be ignored.

Keywords: forest fires, CFD method, cellular automata (CA), semi-empirical models with data assimilation, multi-paradigm fusion

1. Introduction

Under the background of the global climate crisis, extreme weather occurs more frequently, leading to an increased risk of forest fires in many regions. Generally, forest fires contain three main types: surface fires, tree crown fires and underground fires. Over 90% of forest fire events occur on the surface or in the tree crown [1]. In recent years, whether it is the "Black Summer" fires in Australia or the super fires in California [2] and Canada in North America, they have all issued a serious warning to human society with their unprecedented scale, astonishing spread speed and huge ecological, economic and social damage. Forest fires are no longer a regional issue but have evolved into a complex environmental challenge with global implications. Wildfire behavior is a quintessential multi-scale, multi-physics-coupled nonlinear dynamical process, governed by intricate interactions among topography, vegetation (fuel) type/state, and dynamically varying meteorological conditions (particularly wind fields). This inherent complexity renders accurate wildfire spread

prediction a formidable scientific challenge due to the strongly coupled, non-equilibrium, and stochastic nature of the system.

Against this backdrop, the development of scientific, precise and efficient fire spread prediction models holds significant strategic importance. A reliable prediction system can not only provide key decision support for fire emergency response, for instance, optimizing the allocation of fire-fighting resources, planning evacuation routes, and determining the best time and location for fire suppression; it can also play a more significant role in the "forward" stage of disaster prevention and mitigation, such as in fire risk assessment, formulating preventive combustion plans, and conducting forest area management and urban planning. Therefore, systematically sorting out, evaluating and looking forward to the modeling methods of forest fires is not only a cutting-edge topic in academic research, but also an inevitable requirement to meet the urgent needs of real society.

2. Categorization of fire modeling methods

Through decades of development, fire models formed as a diverse structure with multiphases. To symmetrically understand and evaluate the fire models in a precise way, there are mainly three categories of modeling methods: physical-based model, semi-empirical model and data-driven model.

2.1. Physical-based model

CFD is the cue of the physical modeling area, playing an important role by solving a series of partial differential equation (PDEs) to describe the consistency of mass, momentum and energy during fire processes. In detail, fluid dynamics, heat transfer, and combustion are being simulated numerically.

Karafyllidis and Thanailakis studied in their earlier research, attempting to describe all influencing factors with PDEs, which "would likely lead to a very difficult system of equations to handle" and "would require astonishing computer memory and computing time" [3]. The CFD model is the ultimate embodiment of this idea. It precisely depicts the dynamic coupling between flames, combustibility, and the surrounding atmosphere, especially the changes in the wind field driven by fire (i.e., "fire generating wind") and turbulence effect. However, such high fidelity comes at the cost of huge consumption of computing resources. For instance, Zhou et al. (2020) cited literature to point out that typical CFD models such as FIRETEC and WFDS have much slower calculation speeds than real-time ones. For example, "FIRETEC takes 1-2 minutes to simulate one second", while the simulation of WFDS "is not suitable for applications that are faster than real-time" [4]. This makes pure physical models mainly applied in scientific research, aiming to reveal the intrinsic mechanisms of fire behavior rather than being directly used for large-scale operational emergency forecasting.

2.2. Semi-empirical/empirical models

Unlike physical models that pursue the depth of mechanism, semi-empirical and empirical models focus more on practicality and computational efficiency. These models establish algebraic relationships between the rate of spread (ROS) of fire and key influencing factors (such as fuel type, wind speed, and slope) through statistical regression analysis of a large amount of field fire experiment data or historical fire cases. The famous Rothermel model is the cornerstone of this paradigm, and the widely used FARSITE simulator is built based on the Rothermel model [5]. Similarly, in China, the Wang Zhengfei model is also a semi-empirical model with significant

influence, which is established based on a large amount of local experimental data [6]. These models excel in sheer speed, delivering rapid simulations across thousands to tens of thousands of hectares and forming the backbone of operational fire-prediction systems worldwide. Yet their virtues come at a cost: the physics is heavily simplified, their ability to capture complex fire-atmosphere interactions is limited, and their validity is tightly bound to the experimental range on which they were trained.

2.3. Discrete model

With the development of computational science, the third type of paradigm has gradually emerged. It does not directly solve continuous physical equations but adopts discretization methods directly from the data. The typical methods are Cellular Automata and Artificial Intelligent.

The CA model discretizes forest areas into grid cells (cells), each of which has a finite state (such as unburned, burning, and already burned). The spread of fire is simulated as an "emergent" phenomenon, which is driven by simple local state transition rules defined on each cell and its neighborhood [3]. The CA model ingeniously strikes a balance between computational simplicity and the ability to simulate complex behaviors and is easy to integrate with GIS data. Therefore, it is highly favored in academic research and visualization applications.

AI models, especially machine learning and deep learning models, represent the latest development direction. This type of model attempts to bypass traditional physical or empirical formulas and directly construct an end-to-end mapping from inputs (such as meteorological, terrain, and fuel data) to outputs (such as future frontline positions or combustion probabilities). For instance, Wu et al. utilized artificial neural networks (ANN) to directly learn the spatiotemporal patterns of fire spread from multi-dimensional variables [7]. The potential of data-driven models lies in their powerful nonlinear fitting capabilities, but their performance is highly dependent on the quality and quantity of training data, and the physical interpretability of the models is usually weak.

3. The Application of Computational Fluid Dynamics (CFD) in fire simulation

Computational Fluid Dynamics (CFD) is the method with the highest fidelity in physical modeling of forest fires. It reduces the fire phenomenon to a series of fundamental physical and chemical processes and solves the control equations of these processes through powerful computing capabilities, thereby reducing the dynamic behavior of the fire in three-dimensional space and time.

3.1. Physical and control equations

From a physics perspective, forest fires are an extremely complex phenomenon involving strong coupling of multiple physical fields. The essence of CFD simulation is to numerically solve a set of partial differential equations (PDEs) that describe these physical processes. This set of equations is usually referred to as the extended form of the Navier-Stokes equations and mainly includes:

- Mass conservation equation (continuity equation): It describes the conservation of fluid mass in any micro-element body, ensuring the continuity of the flow field. Such as the air and combustion products [8].
- Momentum conservation equation (Navier-Stokes equation): This is the core of fluid dynamics, describing the motion laws of fluid micro-bodies under the action of external forces (such as gravity and pressure gradients) and internal forces (viscous forces) (Newton's second law). In fire

simulation, it determines the evolution of the wind field, including the strong updraft (fire plume) driven by the buoyancy of the flame and the entrainment of the surrounding air [9].

- The energy conservation equation: It describes the transfer and transformation of thermal energy in a system. It encompasses convective heat transfer (heat carried by fluid motion), heat conduction (molecular thermal motion), and crucially, thermal radiation (electromagnetic wave heat transfer). Meanwhile, the huge chemical energy released by combustion is added as the source term to this equation and serves as the fundamental driving force for the entire fire process [10].

- Component transport equation: It describes the time-space distribution of the concentrations of different chemical components (such as oxygen, fuel vapor, carbon dioxide, water vapor, etc.) in a mixed gas. These equations consider the generation, and consumption of components caused by convection, diffusion and chemical reactions, and serve as a bridge connecting fluid dynamics and combustion chemistry [11].

- Radiative transfer equation (RTE): In a high-temperature fire environment, thermal radiation is the main mechanism for long-distance heat transmission and plays a decisive role in the spread of fire disasters. RTE is a complex integral-differential equation that describes the variations of radiation intensity in space and direction, considering the absorption, emission and scattering effects of media such as smoke, dust and gas [12].

3.2. Key sub-model

Due to the reasons that it is impossible to solve all those systems of equations completely, a series of “sub-models” must be involved during the real CFD practices in order to implement an approximation approach. For instance, the turbulence model, combustion model and radiation model. The selection of different sub-models directly determines the ultimate results and the calculation expenditure. Commonly, three main sub-models must be selected to construct the boundaries and conditions.

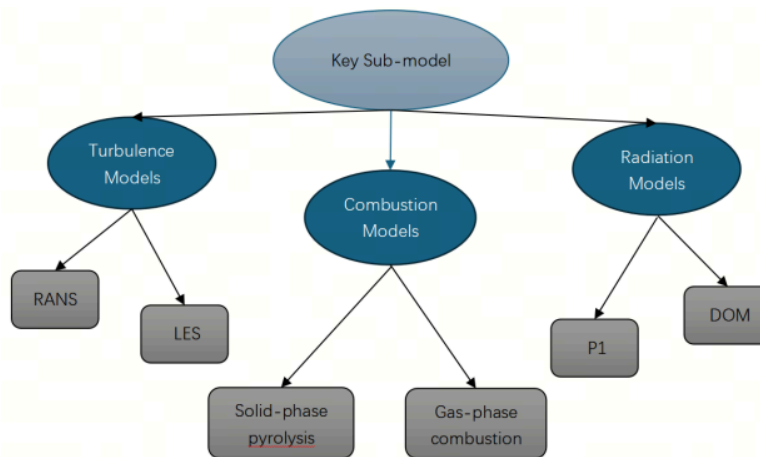


Figure 1. Key sub-model

3.3. Representation method of vegetation fuel

The combustion media is also a very essential topic that should be worked on. How to represent complex forest vegetation in the computational grid of CFD is a core challenge. There are two mainstream kinds of methods that are prevailing: the porous media approach and the discrete vegetation approach.

The porous media approach is to regard the entire vegetation area (such as the canopy layer and shrub layer) as a continuous porous medium, and the influence of vegetation on airflow in a fire is simulated by simulating the porous medium. P. Zinke, in his paper Application of a porous media approach for vegetation flow resistance, published in ResearchGate, has explored whether the porous medium method based on macroscopic flow parameters and Forchheimer-type equations can be applied to the flow in protrusion vegetation. The published data on permeability and flow resistance of two-dimensional arrays of rigid cylinders were analyzed. How to calculate the pore Reynolds number and pore friction coefficient for the calculation of source terms in the momentum equation was introduced. The derivation method of vegetation parameters was also discussed [13].

The discrete vegetation approach aims at explicitly modeling the geometry of a single tree or vegetation mass and places it in the CFD computational domain. This method can study the interaction between flames and individual vegetation elements more precisely, but it has a huge computational cost and is suitable for small-scale, research-oriented simulations. Although there is not much research directly related to this method, much other research has applied similar principal methods.

3.4. Numerical methods and typical software

To solve the above-mentioned complex systems of equations and sub-models, CFD relies on advanced numerical methods. The Finite Volume Method (FVM) is currently the most mainstream discrete method in the field of CFD. It divides the computational domain into a series of non-overlapping control volumes (grid cells) and integrates the control equation on each control volume, thereby ensuring the strict conservation of physical quantities, such as mass, momentum, and energy at the discrete level. In terms of software realization, there are many advanced software programs or codes specifically designed for fire simulation in the international market. For example, FIRETEC, developed by Los Alamos National Laboratory in the United States, is a physical model for wildfire simulation. It uses LES to simulate turbulence and couples it with atmospheric models capable of capturing large-scale fire-atmosphere interactions. It is a benchmark tool. WFDS was developed by NIST of the United States based on FDS, focusing on the simulation of wildfires, forest fires and urban fringe fires. FireFOAM is based on the open-source CFD platform OpenFOAM, featuring strong flexibility and scalability, and is widely used in the academic field.

4. The challenges of CFD methods and the rise of alternative paradigms

CFD has a certain superiority at deeply physical description, but in practical applications, the CFD method is facing two fundamental challenges. The models developed until now are either inaccurate or they demand staggering amounts of computer memory and computation time [3]. Accordingly, to analyze the complex turbulent structures and fine flame propagation in fires, CFD simulations typically need to be iteratively solved over millions or even billions of grids with extremely small time steps. This has led to a huge demand for computing time and resources, creating an insurmountable gap between it and the timeliness requirements of real-time emergency response. In pursuit of real-time performance, researchers have to seek computationally more "lightweight" methods. As Meng et al. clearly pointed out in their model designed for real-time visualization and interaction, to achieve real-time performance, it is necessary to "minimize complex computational processes" [1]. Therefore, they chose a lightweight model based on cellular automata instead of a physical model with high computational costs.

Another deep-seated challenge of CFD models lies in their reliance on a large number of input parameters and the inherent uncertainty of these parameters themselves. Zhou et al. early pointed out this problem, bias and uncertainties inevitably exist on both wildland fire model states and parameters [4]. This issue of parameter uncertainty makes it impossible for even the most physically complete CFD model to guarantee the accuracy of predictions. This predicament naturally leads to an important solution: data assimilation [14]. The core idea of data assimilation is that since both the model itself and its input parameters have uncertainties, real-time fire scene observation data (such as satellite fire points, unmanned aerial vehicle infrared images, etc.) should be utilized to continuously correct the model's running trajectory (state estimation) or optimize its key parameters (parameter estimation), thereby "pulling back" the simulation to a more realistic orbit. This provides a bridge connecting high-fidelity models with real-world observations.

5. N-depth analysis of alternative modeling

Facing the inherent challenges of the CFD method, researchers have developed a variety of alternative modeling paradigms. These paradigms offer diverse solutions for forest fire simulation by making different trade-offs among physical accuracy, computational efficiency and data dependency. This section will conduct a deep integration and analysis of the three major schools of thought: cellular automata (CA), semi-empirical models and data assimilation, and pure artificial intelligence (AI).

5.1. Cellular Automata (CA) - rule-driven discrete simulation

The method of CA first appears in 1997; Karafyllidis and Thanailakis have studied it by using cellular automata to predict forest fire spread [3]. In their paper, this model clearly demonstrates the basic constituent elements of the CA framework:

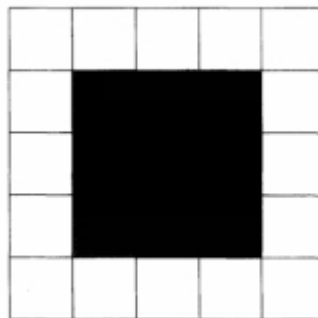


Figure 2. The mole neighborhood in cellular automata [3]

As Figure 2 exhibits the forest is divided into a two-dimensional regular square grid, and each grid is a "cell". The dividing process is called spatial discretization and cells. Each cell has a definite state at any moment T . In this model, the state is defined as the ratio of the combustion area to the total area of the cell with a value range of $[0, 1]$. 0 represents unburned, and 1 represents completely burned. The state of each cell follows the principle of neighborhood rule, that is the states' evolution of a cell is only influenced by its own state and that of its neighboring cells. This model adopts the Moore neighborhood, the eight adjacent (up, down, left and right) and diagonal cells around one cell. State transition function: This is the core of the CA model, defining how the state of a cell at the

next moment $T+1$ is determined by the neighborhood state at the current moment T . Karafyllidis' model constructs a concise and ingenious linear accumulation rule.

The innovation of this model lies in that it elegantly integrates complex physical effects (such as wind and terrain) into simple local rules by introducing a series of weight coefficients. The physical state changes of wind and terrain on flame diffusion are simulated by assigning values of different weights to adjacent cells. This method greatly simplifies the problem, avoids solving complex fluid mechanics and thermodynamic equations, and at the same time can qualitatively reproduce the basic physical behavior of fire spread. The CA model is far more efficient in computation than CFD, capable of easily handling large-scale and long-term simulations. Moreover, its discrete grid structure is naturally easy to integrate with GIS raster data such as terrain and vegetation maps. The trade-off, however, is a fragile physical basis: intricate fire-spread mechanisms—turbulence, radiative heat transfer, and more—are collapsed into simplified neighborhood-state rules, leaving the model ill-equipped to expose fire's underlying physics.

5.2. Semi-empirical models and digitalization are synchronized

If CFD represents the ultimate pursuit of physical authenticity and CA models represent the ingenious balance of computational efficiency, then "semi-empirical model + data assimilation" represents a third completely different but extremely important technical path: that is, to admit the imperfection of the model itself and "tame" and improve a fast but biased simplified model by constantly integrating real-time observation data.

The starting point of this study is that although existing operational fire prediction models (such as FARSITE) are fast in calculation, due to their reliance on simplified semi-empirical formulas (Rothermel model) and uncertain input parameters, their prediction results often deviate from the actual fire situation.

This study proposes an innovative "dual state and parameter estimation" framework, aiming to address both the bias of the model state and the uncertainty of the model parameters simultaneously. This framework consists of two modules that work in coordination:

- State Estimation module: The objective of this module is to correct the simulated live wire position (i.e., the state of the model) in real time. It adopts an advanced data assimilation algorithm - Ensemble Transform Kalman Filter (ETKF). The working principle of ETKF is that in each assimilation cycle, it fuses the forecast predicted by the model with the observed real observation to generate an "analysis" forecast that is closer to the real situation. This corrected fireline position will serve as the starting point for the next prediction. In this way, the state of the model is periodically "pulled" towards reality, preventing the accumulation and divergence of errors.

- Parameter Estimation module: Merely correcting the position of the live wire is not sufficient, because if the inherent parameters of the model (such as the calculation parameters of the spread rate) are incorrect, then even if starting from a correct position, the next prediction will still go off track. Therefore, this study introduces a parameter estimation module, whose goal is to dynamically optimize a key parameter in the FARSITE model - Fuel Adjustment Factors (FAFs). FAFs is a multiplier factor used to calibrate the spread rate of different fuel types. This module adopts a method based on Radial Basis Function Neural Network (RBFNN) and Monte Carlo sampling. Its ingenuity lies in the fact that it utilizes two consecutive observed firelines, taking the former as the starting point of the simulation and the latter as the reference for the "true value". Then, through a few real runs of FARSITE and a large number of "virtual" runs simulated by RBFNN, it quickly finds a set of FAFs, making the simulation results from the starting point most consistent with the "true value" reference. This set of optimized FAFs will be used for the prediction in the next stage.

The work of Zhou et al. demonstrated the key technical path of data assimilation, whose core significance lies in transforming the "open-loop" process of traditional fire simulation into a "closed-loop" system and achieving precise prediction through the "prediction-correction" cycle [4]. Acknowledging the uncertainty of the model and fusing data can enhance the performance of the simplified model. Take RBFNN as an example to demonstrate a fusion paradigm where AI empowers rather than replaces physical models. This technology provides support for addressing the uncertainty of fire prediction and promoting its business application.

5.3. Pure artificial intelligence prediction model - end-to-end prediction paradigm

Pure artificial intelligence (AI) models, particularly deep learning, have created a new and revolutionary avenue for forest fire prediction as a result of the quick development of massive data and computational capacity. Pure AI model test diagrams, in contrast to all other paradigms, immediately learn the fundamental rules of fire propagated from vast amounts of historical data, eschewing any explicit formulas based on physics or experience. An example of this paradigm is the study "Simulation of forest fire spread based on artificial intelligence" by Wu et al. building a robust artificial neural network and training it to be an end-to-end fire spread prediction is the fundamental premise behind the AI approach [7].

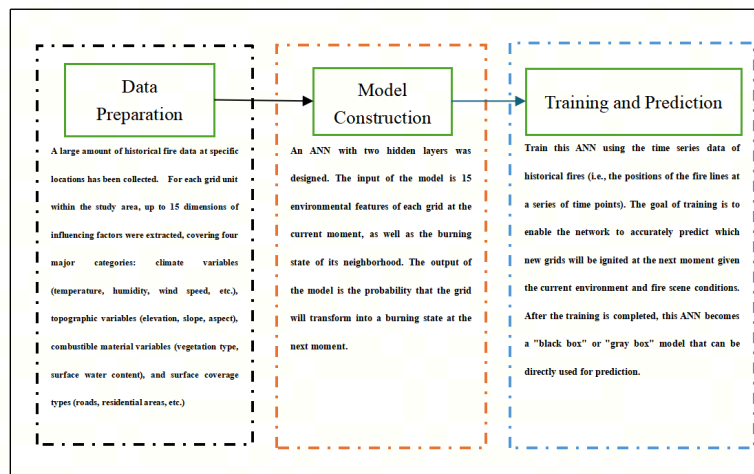


Figure 3. The core ideas and methods of artificial neural networks

To verify its performance, this study [7] also compared the ANN model with a traditional model built on the Wang Zhengfei model and CA. The results show that the prediction accuracy of the ANN model (with an F-measure of 0.90) is significantly better than that of the traditional Wang Zhengfei-CA model (with an F-measure of 0.80), proving its powerful prediction ability.

Pure AI models have significant advantages in fire prediction: they possess powerful nonlinear learning capabilities and can capture complex relationships. Data-driven approaches make it highly adaptable, enabling it to learn fire patterns for specific regions. There is no need to input difficult-to-measure physical and chemical parameters, and the relevant process influences are implicitly included. As Figure 3 depicts, it has to only input 15 current environment states characteristics and adjacent combustion states on each network cell, the output of this model will automatically give the possibility of next network cell turning into combustion state.

However, its limitations are prominent: Machine learning based has poor physical interpretability and a black box nature hinder mechanism analysis and decision-making interpretation [15]. Its

extrapolation ability is limited by the training data and may be unreliable in new situations [16]. Furthermore, the approach demands a large amount of high-quality historical data that is consistent in time and space, posing a substantial challenge for data-scarce regions [17]. Nevertheless, its potential still deserves attention and could play a pivotal role when integrated with other models [18].

6. Comparison and future outlook

Through an in-depth analysis of Computational fluid Dynamics (CFD) and its three alternative paradigms-cellular automata (CA), semi-empirical modeling and data assimilation, and pure artificial intelligence (AI) - we have presented a panoramic view of forest fire modeling that is diverse and highly complementary. No single paradigm can perfectly solve all problems. The breakthrough in the future must lie in the intelligent integration of multiple paradigms, learning from each other's strengths to offset weaknesses, and building a new generation of hybrid intelligent prediction systems.

6.1. Comparison of four methods

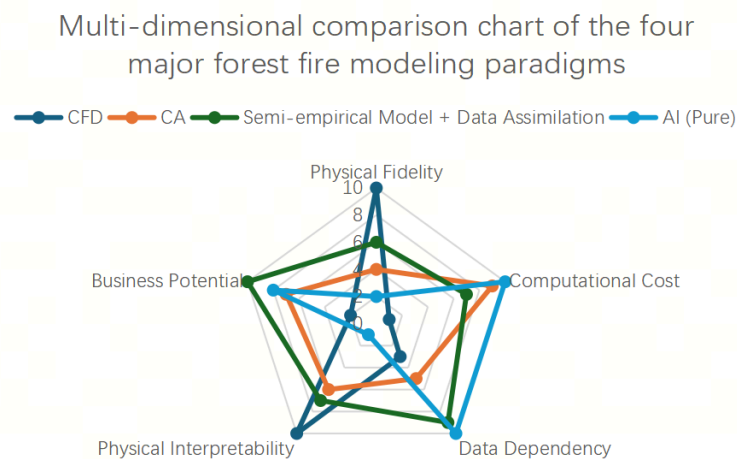


Figure 4. Multi-dimensional comparison chart of the four major forest fire modeling paradigms

To visually present the characteristics and trade-offs of various modeling paradigms, the following table conducts a systematic comparison from key dimensions such as physical fidelity, computational cost, data dependency, physical interpretability and business potential. The comparison chart (Figure 4) is a radar chart obtained by scoring different dimensions with a full score of 10.

Table 1. Analysis on advantages and disadvantages of four paradigms

Dimensions	CFD	CA	Semi-empirical Model + Data Assimilation	AI (Pure)
Core Advantages	Physics has strong interpretability and can reveal the internal mechanism.	The concept is simple, the calculation is efficient, and it is easy to combine with GIS.	By closely integrating the model with reality, it is highly practical and the prediction accuracy is dynamically improved.	It has a powerful nonlinear learning ability and can discover unknown patterns from data.
Core Disadvantages	The calculation cost is high, and the parameter uncertainty is large.	Weak in physics foundation and highly subjective in rule setting.	The prediction accuracy depends on the quality and frequency of the observed data.	Poor physical interpretability, questionable extrapolation ability, and reliance on big data.
Application Scenario	Scientific research, mechanism analysis, review of extreme fire behavior, and high-precision WUI simulation.	Large-scale trend simulation, teaching and popular science, real-time 3D visualization, interactive training.	Business-oriented fire prediction and real-time emergency response decision support.	Fire risk assessment, rapid prediction for specific areas, and as a sub-module of other models.

6.2. Future outlook: hybrid modeling

In the future development, hybrid modeling should be the core trend. The above clearly indicates that different paradigms each have their own strengths. Therefore, future research should not be a "zero-sum game" among paradigms, but rather a "coevolution" of complementary advantages. Hybrid Modeling will become the core driving force for the development of the field. Several directions of hybrid modeling research have promoting potential.

6.2.1. Direction 1: AI-accelerated CFD

The help with AI is one of the most promising ways to solve the computational bottleneck of CFD. Some computational modules in CFD simulation, such as turbulence closure, combustion chemistry or radiative transfer, occupy a significant amount of computational time. AI models (such as ANN, RBFNN, and ELM mentioned earlier) can be utilized to build Surrogate models for these high-cost modules. As Krzysztof Rojek et al. in their research literature proposes a method to accelerate CFD simulation by integrating traditional CFD solvers with AI modules, which can be used to support the research direction of AI-accelerated CFD [19].

6.2.2. Direction 2: data assimilation for CFD

Applying the data assimilation idea used in semi-empirical models in [1] to CFD models is the fundamental approach to addressing the uncertainty of CFD parameters and the initial field error. Although it is more technically challenging, its potential is huge. Real-time observational data (such as satellite hotspots, unmanned aerial vehicle infrared images, ground radar wind fields, etc.) can be utilized to dynamically adjust the initial conditions (such as wind fields), boundary conditions or key physical parameters (such as fuel moisture content, pyrolysis parameters) of CFD simulation through advanced assimilation algorithms like Kalman Filter (EnKF) [20]. This will enable expensive CFD simulations to be "anchored" in the real world, greatly enhancing the accuracy and

reliability of their predictions, and allowing them to play a true role in the refined forecasting of key areas.

6.2.3. Direction 3: multi-scale/multi-fidelity coupling

For vast forest areas, the significance and behavioral complexity of fires vary in different regions. Therefore, a multi-scale and multi-fidelity hybrid simulation system can be constructed. For instance, in a vast background area, use a fast-computing CA model or semi-empirical model (such as FARSITE) to conduct large-scale fire simulations. In some key areas, such as the main direction of the fire head, the intersection of forest fires and cities (WUI), or areas with complex terrain, a high-fidelity CFD model is "nested" for detailed simulation. Coupling is achieved between two or more models through boundary data exchange. A multi-scale method based on generative adversarial network (GAN) is proposed in the paper Multi - scale generative adversarial network for 2D subsurface reconstruction using multi - fidelity geological exploration data, which can be analogized to the research on multi-scale and multi-fidelity coupling of forest fires [21]. This method can make the best use of limited computing resources, achieving an optimized simulation of large-scale fire scenes that takes into account both global trends and local details.

7. Conclusion

Forest fire spread prediction is a challenging but crucial field. Computational Fluid Dynamics (CFD), as the gold standard for physical modeling, holds irreplaceable scientific value in revealing the physical mechanisms of fires and understanding complex fire behaviors. However, its high computational cost and inherent parameter uncertainty make it difficult to directly meet the urgent demand for operational real-time forecasting. This "gap" has given rise to a variety of efficient and practical alternative paradigms represented by cellular automata (CA), semi-empirical models and artificial intelligence (AI). This review, through systematic analysis and comparison, reveals the intrinsic trade-offs among different modeling paradigms. We believe that the fundamental breakthroughs in this field in the future will come from the deep integration of multiple paradigms. By organically integrating the physical insight of CFD, the computational efficiency of CA, the practical constraint ability of data assimilation, and the powerful data learning ability of AI, a new generation of hybrid intelligent forest fire prediction system is constructed, which is the inevitable path to achieving precise and efficient prediction of this complex natural disaster. This is not only a cutting-edge direction in scientific research, but also an urgent need to ensure ecological security and the safety of people's lives and property.

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