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Review

Modeling of Wildfire Digital Twin: Research Progress in Detection, Simulation, and Prediction Techniques

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Abstract: Wildfires occur frequently in various regions of the world, causing serious damage to natural and human resources. Traditional wildfire prevention and management methods are often hampered by monitoring challenges and low efficiency. Digital twin technology, as a highly integrated virtual simulation model, shows great potential in wildfire management and prevention. At the same time, the virtual–reality combination of digital twin technology can provide new solutions for wildfire management. This paper summarizes the key technologies required to establish a wildfire digital twin system, focusing on the technical requirements and research progress in fire detection, simulation, and prediction. This paper also proposes the wildfire digital twin (WFDT) model, which integrates real-time data and computational simulations to replicate and predict wildfire behavior. The synthesis of these techniques within the framework of a digital twin offers a comprehensive approach to wildfire management, providing critical insights for decision-makers to mitigate risks and improve emergency response strategies.

Keywords: digital twin; wildfires; fire spread model; fire detection; visualization

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1. Introduction

With global warming and the expansion of human activities, adverse conditions have led to the frequent occurrence of wildfires around the world [1]. Wildfires, as major global natural disasters, have become one of the serious challenges facing forest ecosystems and human societies globally. Wildfires not only cause devastating damage to human beings, biodiversity, and ecosystems but also often consume a large amount of human, material and financial resources [2,3]. The "Black Summer" wildfire that lasted for several months in Australia in 2019 [4], the California wildfires in the United States in 2020 [5], and the wildfire in Liangshan, Sichuan Province, China [6], have had a serious impact on the resources of various countries and even the world. The prevention and control of wildfires has become a global problem. Traditional wildfire management and response methods often face limitations. Therefore, there is a need to introduce new technological tools to improve the efficiency of fire response and suppression and to reduce the damage caused by fires.

Digital twin (DT) is a virtual digital copy with a physical entity. It refers to the technology behind the modeling, simulation, and analysis of physical entities, processes, or systems through digital technology to achieve the monitoring, simulation, prediction, and optimization of its real-time operating state [7]. With the development of computer technology, fire spread simulation has become an important tool for wildfire prevention and control [8]. Digital twin technology, as an emerging concept, integrates advanced technologies such as virtual reality, analog simulation, data analysis, and artificial intelligence [9]. It provides new ideas and methods for the approximate simulation of wildfire.

Recent studies have highlighted the inherent complexity and unpredictability of wildfire spread dynamics [10]. Traditional methods of wildfire prevention and control often struggle with limited data, slow response times, and difficulty accurately predicting fire behavior [11]. To address these challenges, we propose developing a wildfire digital twin model using digital twin technology. A digital twin offers a dynamic, real-time virtual representation of the physical environment [12], enabling more precise modeling and simulation of wildfire scenarios. This technology has been shown to enhance real-time situational awareness [13], improve the accuracy of wildfire predictions, and optimize resource allocation during firefighting efforts. The wildfire digital twin model can provide a basis for monitoring, early warning, prediction, approximate simulation, and decision-making in wildfire management [14,15]. It can also support virtual training for fire emergency responders, helping them improve their response speed and capabilities [16]. Consequently, the application of digital twin technology to wildfire management holds considerable theoretical and practical significance.

This paper first introduces the definition and fundamental principles of digital twin technology, followed by a systematic review of the relevant technologies required for a digital twin system tailored to the wildfire spread process. Focusing on the entire life cycle of wildfire spread, we discuss the latest advancements and practical applications in areas such as wildfire monitoring and early warning, fire spread simulation, and digital modeling, providing a detailed categorization of the associated technologies and methods. Through an analysis of various research outcomes, we propose, for the first time, a comprehensive wildfire digital twin model designed to assist related researchers in leveraging digital twin systems for wildfire management. The advantages and challenges of digital twin technology in wildfire management are also analyzed. This review aims to provide valuable insights and guidance for researchers and decision-makers, thereby promoting the broader application and development of digital twins in wildfire prevention and response.

2. Materials and Methods

2.1. Data Collection and Analysis

To establish the research background and assess the current status of studies related to the topic of our review, we conducted a comprehensive literature analysis in the Web of Science (https://www.webofscience.com/wos/, accessed on 12 July 2024) database. Common wildfires typically include forest fires, grass fires, crown fires, and bushfires [17]. Studies were selected based on the inclusion of specific keywords related to wildfire management and digital twin technology. So, we established the following search keywords in this database: "forest fire", "wildfire", "wildland fire", "grass fire", "crown fire", "bushfire", and "fire". Then, we combined these keywords with "digital twin" for advanced search. Since digital twin is a relatively new technological concept, the data collection for this study primarily focused on the past five years. Some early, sporadic foundational research may have been excluded, but after evaluation, this was found not to affect the comprehensiveness of our trend analysis. Only peer-reviewed journal articles, conference papers, and reviews were included to ensure the quality and reliability of the sources. Thus, the data in Figure 1 were obtained.

The results in Figure 1 show a growing trend in the number of research papers related to the application of digital twin technology in wildfire and fire studies over the past five years. Notably, the number of papers on "fire" combined with "digital twin" has steadily increased from 10 in 2020 to 36 in 2024. In contrast, studies specifically focused on "wildfire" have also risen, though at a slower rate, starting from 3 papers in 2020 and reaching 12 papers by 2023. This trend suggests an increasing interest in integrating digital twin technology into fire management research, highlighting its potential value. However, there are still fewer studies on "wildfire" compared to the broader category of "fire". This suggests a gap in research focused on applying digital twin technology to wildfires. The increasing trend emphasizes the importance of developing more refined digital twin models tailored specifically to the unique characteristics and challenges of wildfires, such as rapid spread and unpredictable behavior.

From this data, we can see that there are still obvious theoretical and technological gaps in the research of digital twin for wildfires. The purpose of writing this review is to fill this gap by gathering current research and providing new directions to relevant researchers.

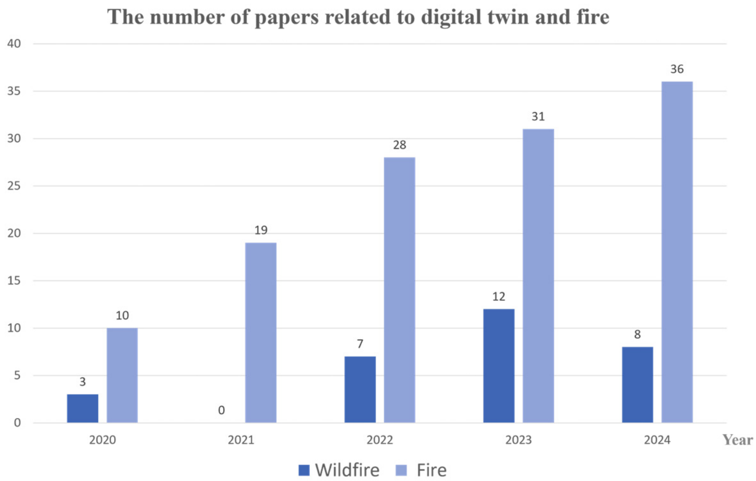


Figure 1. This is a figure of the number of papers related to the field of digital twin. We used advanced search to separately retrieve papers using keywords such as "wildfire" and "fire" with the topic of "digital twin". Data include studies published until August 2024.

2.2. Data Overview

As we have found, there is less research on the application of digital twin in wildfires. And the few existing applications of digital twin in conjunction with fires in the relevant literature often lack comprehensive integration [18–20]. In fact, through our research on the relevant literature [21], the digital twin has been found to have great potential and advantages in fire management (Figure 2). In the field of environmental monitoring, such as wildfire management, digital twin technology enables real-time monitoring of environmental conditions [22]. However, due to the complexity and variability of the forest environment and the high suddenness of fires, there is a relative lack of research results on the application of digital twin to the field of wildfires. Previously, this technology was mostly used in the field of fire for indoor building fires.

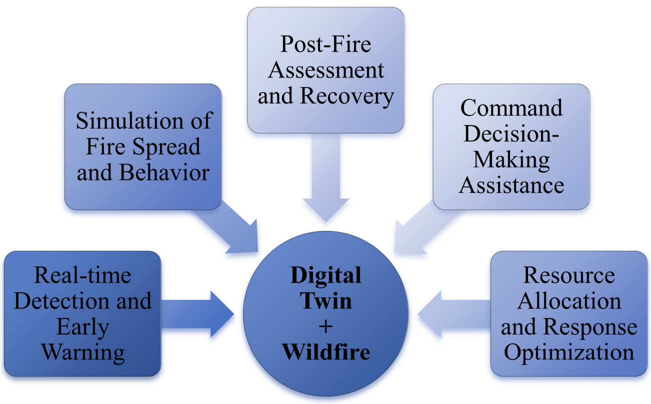


Figure 2. The potential of digital twin in fire management.

In terms of fire prevention, artificial intelligence is widely applied in fire safety and has become a key engine driving the development of digital twin intelligent fire protection. Ding et al. proposed an intelligent emergency digital twin system based on computer vision and deep learning. The evacuation data generated by the system helps evacuate fire scenes, achieving detection, tracking, and privacy protection of evacuees [23]. Zhang et al.

proposed a new Artificial Intelligence Digital Firefighting (AID-Fire) framework using AI engine-driven for real-time recognition of complex building fire information, including fire development, fire spread, and fire movement [24]. In terms of fire response, the digital twin can simulate fire scenarios in real time, including the spread of the fire, the types of combustibles, and the distribution of smoke, to provide decision support and command plans for firefighters [25]. In interactive fire suppression simulation, Meng et al. constructed different combustible models and successfully visualized the occurrence and extinguishing behavior of forest fires in 3D scenes [26]. Providing a foundation for the application of wildfire digital twin. Dourvas et al. combined cellular automata and digital twin for the first time and proposed a digital twin platform to monitor the humidity and temperature conditions inside a building that predicts and simulates the spread of fire within a building [27]. Similarly, Zhang et al. proposed a digital twin system for tunnel firefighting (Figure 3). They constructed a 3D digital twin through numerical simulation and full-size tunnel fire tests, demonstrating the feasibility of using 3D environments and digital twin in real-time fire safety management [28]. The “Wildfire Digital Twin” project, planned by NASA for 2024, is currently the most comprehensive application combining digital twin technology with wildfire management [29]. It represents a major step forward in this field. The digital twin system built in this project will use artificial intelligence and machine learning to predict potential burn spread paths in real time, merging data from multiple sensors to produce global models with high precision. It will provide a valuable advanced tool for firefighters and fire managers.

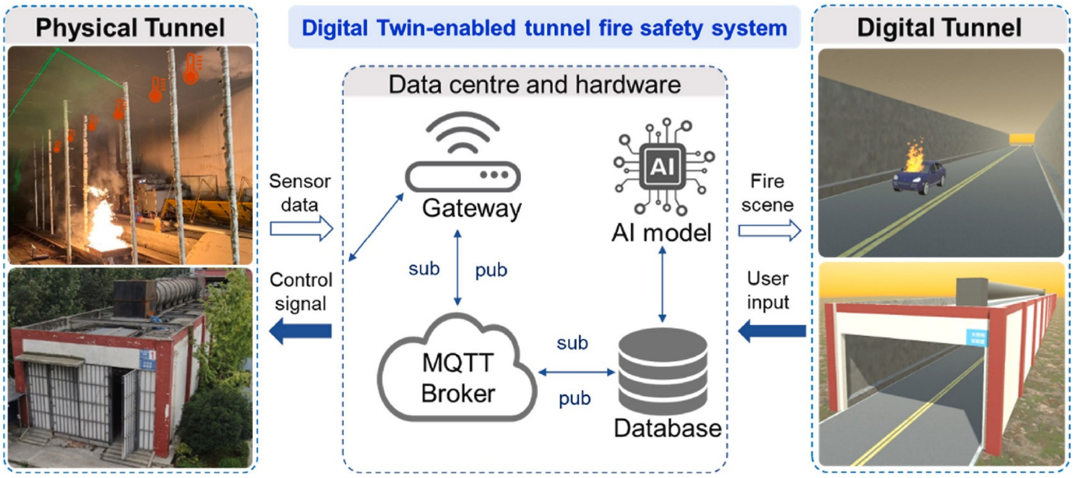


Figure 3. The overall digital twin framework for tunnel fire safety management [28].

3. Digital Twin Technology

3.1. Definition of Digital Twin

The term “Digital Twin” was not formally introduced until 2010 in a National Aeronautics and Space Administration (NASA) technical report [30]. NASA defined it as a simulation process that fully utilizes physical models, sensors, operational history, and other data to integrate multi-disciplinary, multi-physics, multi-scale, and multi-probability [31]. Since then, digital twins have begun to have an impact in both academia and industry. Related concepts such as cyber–physical worlds and the metaverse are also beginning to be widely disseminated and applied by scholars in a variety of research fields and industrial applications [32], such as industrial manufacturing, architecture and planning, and aerospace [33].

3.2. Technical Framework of Digital Twin

The core of digital twins lies in creating one or more highly detailed virtual models that reflect the state of physical entities, which are fully synchronized with their physical versions [34]. This synchronization is based on sensors and other data acquisition technologies, which theoretically continuously monitor real-time data about physical objects (position, temperature, humidity, pressure, etc.) and transmit these data back to the digital model. In addition, digital twins also include a data analysis framework for processing input data and simulating predicted future states, allowing for more effective decision-making and predictive maintenance [35]. Driven by data, frameworks, and models [36], digital twins can monitor, simulate, predict, and optimize their physical entities.

In this paper, the composition of the digital twin framework is divided into the following three parts: physical entity, digital twin core entity, and user entity, each with different functions (Figure 4). The physical entity is the cornerstone of the digital twin. The digital twin core entity is the key part of realizing the virtualization and simulation of physical entities. Additionally, the user entity is the final application link of the digital twin. Digital twin technology organically combines the above three parts, covering the complete process from data acquisition, processing, and analysis to user interaction, and realizing the dynamic mapping of physical entities and user entities.

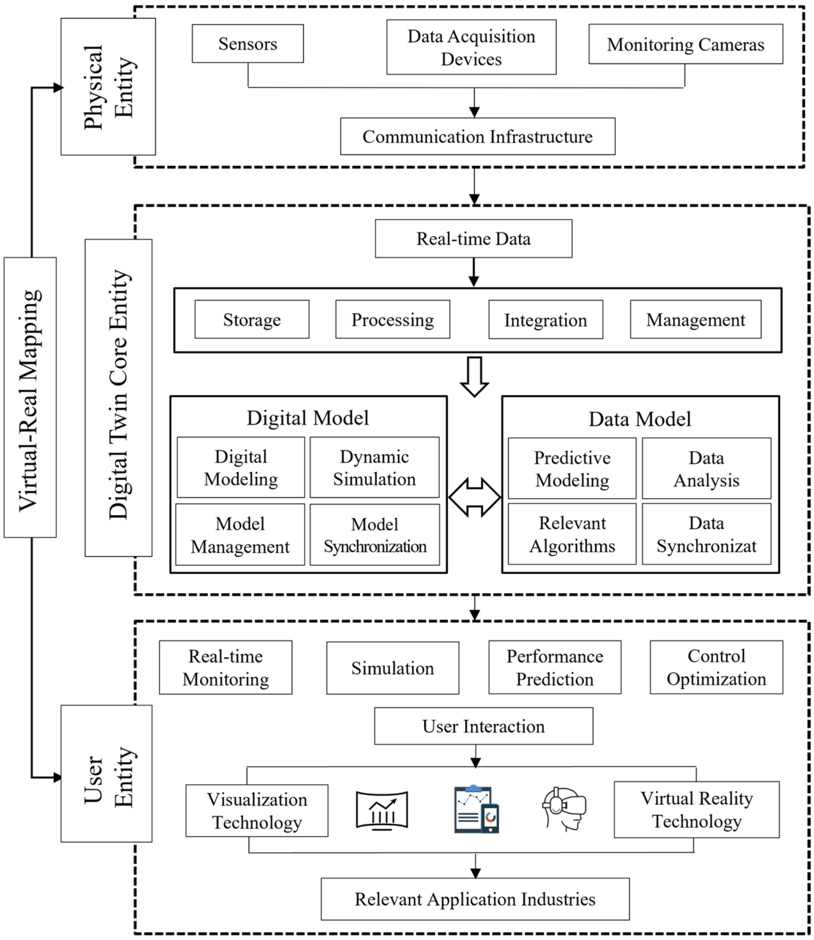


Figure 4. Technical framework of digital twin.

3.3. The Application of Digital Twin

In the process of continuous development and maturity of the technology, digital twin has become an advanced virtual simulation and prediction tool. It is now gradually expanding to a mixture of fields, including manufacturing, energy, healthcare, and so on (Figure 5).

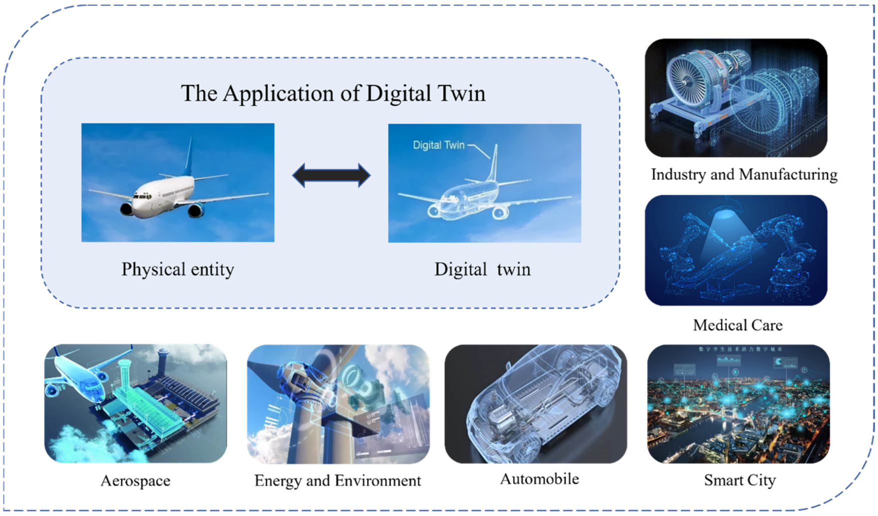


Figure 5. Application areas related to digital twin.

In Industry 4.0, digital twin is used to improve productivity and reduce costs through the real-time monitoring of production lines, predictive maintenance of equipment, and simulation of manufacturing processes [37]. In addition, the technology is widely used in product design, production, forecasting, and cycle management [38,39].

Digital twin is widely used to enhance urban infrastructure management [40], optimize traffic flow [41] and emergency response and management [42], and assist in smart city management and improve the sustainability of cities [43–46].

In medical care, digital twin combined with related technologies provide new solutions for patient care, predictive analysis, and clinical operation training [47–49].

In aerospace, digital twin helps predict and solve potential problems by simulating the life cycle of aircraft, from design to manufacturing, use to maintenance [50,51]. In addition, digital twin technology is widely used for satellite systems, spacecraft, and lunar exploration [52].

Digital twin enables the monitoring, prediction, and optimization of energy and environmental systems by creating digital copies of physical entities [53]. Digital twin effectively monitors air quality [54] and water resources [55], predicting environmental change trends through real-time data collection and virtual model simulation. In ecosystem management, digital twin helps to understand the dynamic changes of ecosystems and develop more effective conservation and restoration strategies [56,57].

4. Wildfire Detection and Real-Time Data Acquisition

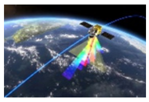
The development of a wildfire digital twin relies heavily on advanced methods and technologies for real-time monitoring and data collection. This section discusses key advances in wildfire detection and real-time data collection methods to highlight their role in the wildfire digital twin model.

4.1. Wildfire Detection

To reduce losses from wildfires, countries around the world attach great importance to wildfire detection, which is an essential part of wildfire management. The initial phase of fire management involves the timely and accurate detection of fires, and once detected, continuous monitoring is essential to assess their development and potential threat. The real-time data provided by wildfire detection is an important input source for the wildfire digital twin model. Accurate and effective detection data can ensure that the digital twin model truly reflects the real-time status of the fire scene.

The measures for wildfire detection can usually be categorized into four spatial levels, namely, ground patrol, near-ground observation, aerial patrol, and space satellite monitoring [58]. Various technologies, such as IoT sensors, remote sensing, and drones, are employed to gather high-quality data. Table 1 shows the detection measures and related technologies for the four spatial levels: ground patrol, near-ground observation, aerial patrol, and space satellite monitoring.

Table 1. Summary of wildfire detection measures and technologies.

Spatial Levels	Measures	Related Technology	Scope of Application	Sketch Map
Ground	1. Manual patrol 2. Ground monitoring station	Internet of Things (IoT)/Wireless sensor networks/Wireless communication	Small forest areas Easily accessible regions Fixed locations	
Near Ground	1. Watch towers 2. Surveillance camera 3. Unmanned aerial vehicles (UAV)	Automated Systems/Infrared and visible light imaging/ High resolution	Large forest areas Complex terrains	
Aerial	1. Helicopters 2. Aircraft patrol 3. High-altitude UAVs	Real-Time image transmission/Infrared and visible light imaging	Large forest areas Hard-to-reach regions Complex terrains	
Space	1. Satellite monitoring	Remote sensing/Geographic information system/Global positioning system/radar	Global coverage Large forest areas	

4.1.1. Unmanned Aerial Vehicle Detection

UAV detection is the deployment of UAVs to forest sites, using equipped infrared sensors, cameras, and other devices to capture real-time details of the fire scene. UAVs allow for high-altitude views or close views of the fire scene. The advantage is the ability to access high-altitude, remote, and hazardous areas, providing high-quality aerial fire imagery and hotspot maps. The current innovative approach to wildfire prevention is the use of UAVs equipped with advanced fire detection models. Saydirasulovich et al. proposed a target detection model customized for the UAV imagery environment, which enhances the effectiveness of fire detection [59]. Zhang developed a specialized UAV system for wildfire detection, based on which Zhao designed a saliency detection method to enhance the efficiency of locating and identifying wildfires in aerial images [60]. Li et al. designed an image acquisition platform consisting of a tripod head and a camera for unmanned aerial vehicles. It uses intelligent recognition technology to real-time identify and detect the occurrence of fire, which is suitable for the on-site monitoring of actual fire [61]. Chen et al. proposed a lightweight wildfire smoke detection model for UAV imagery [62] that contributes to the intelligence of UAV detection. However, there are some challenges and limitations in UAV detection, such as the effect of weather conditions on UAV flight, the endurance of UAVs, and the stability and security of data transmission [63]. Therefore, when utilizing UAVs for fire detection, various factors need to be fully considered to ensure the effectiveness and safety of UAV detection.

4.1.2. Satellite Monitoring

Remote sensing technology plays a crucial role in wildfire detection. The use of satellite remote sensing technology for fire detection is currently a relatively efficient method [64]. It detects fires by observing features such as hotspots and smoke on the ground through images [65]. Satellite monitoring can achieve the monitoring of large-scale fires and provide high-resolution fire monitoring data. In recent years, with the abundance of Earth observation data and the deployment of new remote sensing satellites, the spatiotemporal resolution of wildfire detection has been significantly improved [66]. In particular, geostationary (Meteosat, GOES, Himawari), medium-resolution satellites (such as Landsat-8 or Sentinel-2), and other high-resolution, high-speed repetitive satellites provide powerful tools for monitoring of wildfires [65]. Liu et al. proposed a new method for extracting fire spread rate in near real-time based on Himawari-8 satellite data [67]. Ban et al. used a deep learning-based framework to study Sentinel-1 SAR dense time series [68], used for the monitoring of wildfire progression through smoke, clouds, and nighttime. In addition, distributed satellite systems (DSS) have also demonstrated their potential applicability in wildfire monitoring, providing wide coverage and short revisit intervals [69]. However, the use of satellite monitoring for wildfires is limited by spatial and temporal resolution, as well as interference from other factors. It is difficult to realize early small fire point detection and rapid real-time detection. Therefore, it is less suitable for the high real-time demands of the digital twin wildfire detection module.

4.1.3. Ground Monitoring

In the field of wildfire detection, the most traditional methods usually rely on manual observation, such as ground monitoring stations and watchtowers [70]. Ground monitoring stations are established in forest areas, equipped with various commissioners, sensors, and monitoring equipment to conduct real-time monitoring of fire-related environmental parameters such as temperature, humidity, wind speed, and wind direction [71]. In early research on wildfire detection, the strategic layout and networking of watchtowers were crucial to the establishment of an effective fire detection system [72,73]. In the past decade, the technology and equipment for ground detection have been significantly improved. Automation and intelligent technologies are gradually being introduced into watchtowers. For example, improvements were made by combining technologies such as automated vision systems and sensor networks [74]. In addition, the ground monitoring station has also adopted advanced wireless communication and IoT technologies, contributing to the establishment of wildfire monitoring command network [75].

Although ground-based monitoring can achieve continuous monitoring and data collection of fires, this manual observation process is susceptible to a variety of external factors, including data transmission, communication problems, and weather conditions, which may lead to inefficient monitoring. In addition, existing monitoring facilities still have some limitations, such as limited coverage, inability to cover all detection areas, and high maintenance costs [76]. Therefore, wildfire research at this spatial level has been decreasing in recent years.

4.1.4. Wildfire Detection Technology

Fire detection based on computer vision technology is currently the most suitable method for integrating with digital twin models in wildfire management. This process begins with capturing images or video streams through surveillance cameras or UAVs. These visuals undergo preprocessing to enhance their quality, such as noise reduction and image enhancement. Subsequently, fundamental features like color, motion, texture, and shape are extracted from these processed images. These features are then fused to create a comprehensive dataset. Various algorithms, including machine learning and deep learning techniques, analyze these data to monitor fires and simulate or predict their propagation. Ultimately, this enables specific applications in early warning systems, intelligent fire management, and real-time updates (Figure 6).

Traditional fire detection mostly uses pattern recognition for feature extraction, which is categorized into flame detection and smoke detection according to the detection object [77]. Most of the previous studies mostly analyzed the static and dynamic features of flames and smoke to perform fire detection. The relevant features include shape, location, texture, color characteristics, and motion characteristics. For example, Toreyin et al. described a fire detection method based on color and motion characteristics to detect fires and flames in real time by processing video data generated by ordinary cameras monitoring the scene [78]. Toulouse et al. proposed a logistic regression-based fire pixel monitoring method using the size, color, space, and motion characteristics of fire [79]. Li et al. proposed a flame detection framework based on flame color, dynamics and flickering characteristics to develop an autonomous flame detection method [80]. Combining spectral, spatial, and temporal features and fuzzy reasoning, Ho et al. proposed a machine vision-based fire early detection algorithm [81].

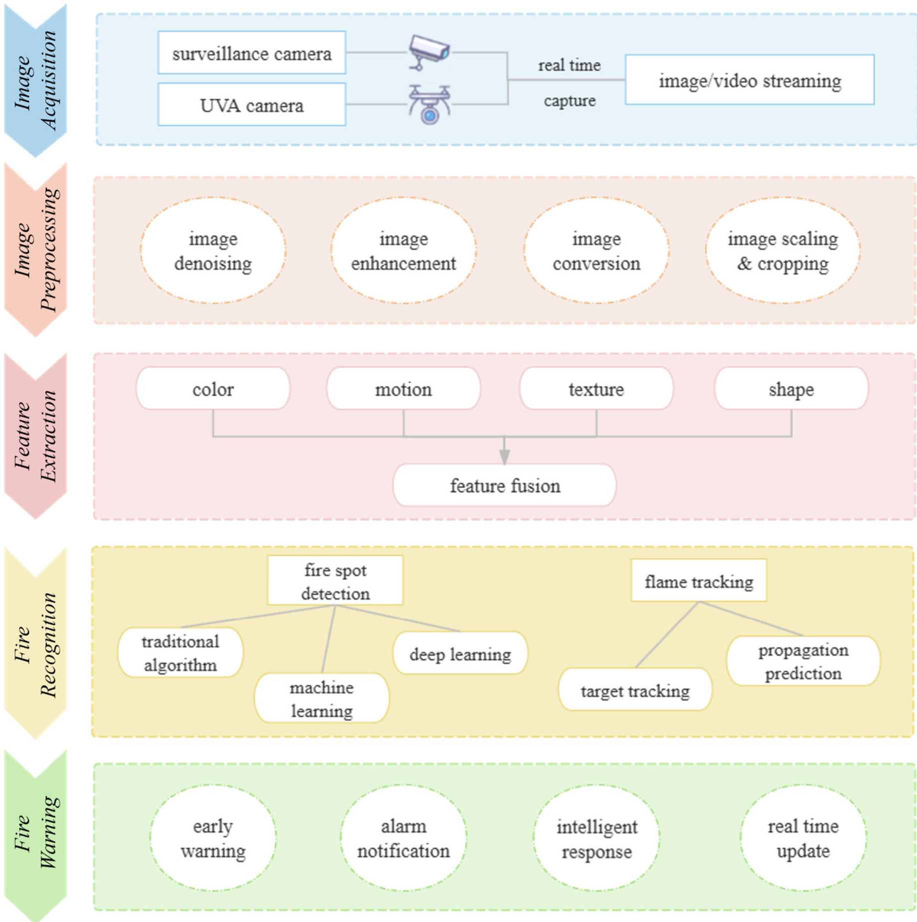


Figure 6. Flow chart of fire detection based on computer vision technology.

However, the examples cited above are traditional fire detection methods. In recent years, with the advancement of science and technology and the development of intelligence, fire detection methods have become more diversified and efficient. As computer arithmetic has grown, many researchers have begun to use deep learning models in conjunction with UAVs, surveillance cameras, or satellite imagery for fire spot monitoring tasks [82,83]. This class of methods can improve the real-time accuracy of fire detection techniques required for digital twin systems.

Since 2014, deep learning has been gradually introduced into fire detection [84]. Target detection models such as you only look once (YOLO), regions with convolutional neural network (R-CNN), faster-RCNN, and single-shot multibox detector (SSD) are used for fire detection tasks in fire monitoring to achieve the identification and localization of fire points in images. Li et al. develop fire detection algorithms based on advanced target detection convolutional neural network (CNN) models such as faster R-CNN, region-based fully convolutional networks (R-FCN), SSD, and YOLO v3 [85]. The results show that the CNN-based algorithm is significantly better than the traditional algorithm, and the YOLO-based algorithm has optimal accuracy and speed. Since YOLOv1 was proposed in 2016 [86], the YOLO series has become the leader in the field of real-time object detection, and its different versions have attracted much attention for their application effects in fire detection tasks [59,87].

After the YOLOv3 [88] and YOLOV5 [89–91] models, the YOLOv8 model has been dramatically optimized structurally and is designed to be fast, accurate, and easy to use.

Enhanced model detection of small targets is important for small target detection tasks such as flames. Leon et al. adopted and implemented the recent YOLO model to detect and locate smoke and wildfires using ground and aerial imagery [92]. Mohamed adapted and optimized the YOLOv8 and YOLOv7 models for smoke and flame detection, which improves fire detection accuracy [93].

In addition to the YOLO series, other deep learning algorithms have shown potential for fire detection [94]. The convolutional neural network is a network structure commonly used in deep learning, and image recognition algorithms based on this network can effectively learn and extract complex image features automatically [95]. Researchers have trained CNN models to enable fire detection (Figure 7). For example, in one study, Khan et al. proposed a deep learning-based method for wildfire detection. The method synergistically combines CNNs and recurrent neural networks (RNNs) for wildfire classification and detection in smart urban environments [96]. Huang et al. improved the accuracy of the visual fire detection method by combining CNN-based spatial features and wavelet transform-based spectral features [97]. Many studies have proposed lightweight CNN models for fire detection on resource-constrained devices. For example, Pan et al. proposed a novel fire–smoke cooperative region detection and classification framework for fire monitoring. The framework uses weakly supervised fine segmentation and the lightweight faster R-CNN technique [98].

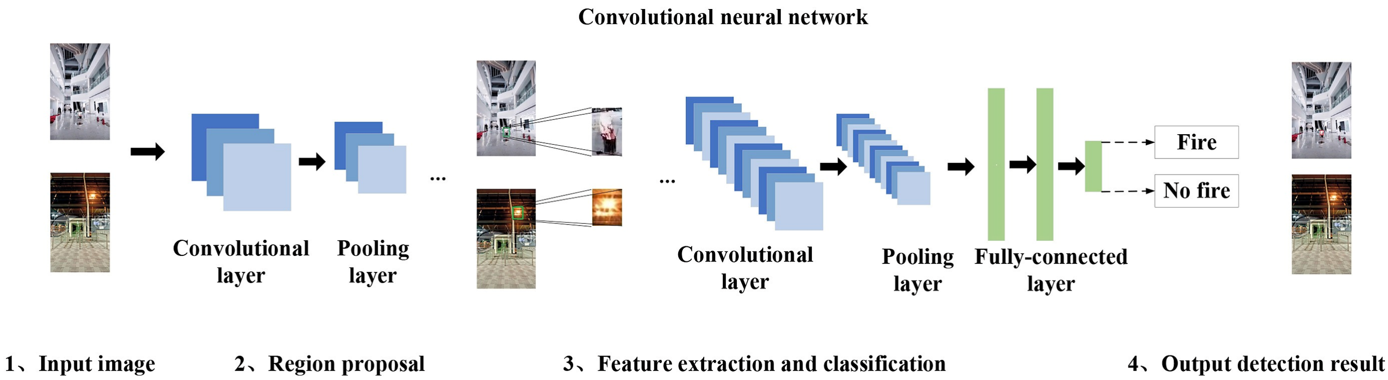


Figure 7. Flow chart of image fire detection algorithms based on detection CNNs [85].

Furthermore, there are image segmentation models such as U-Net and mask R-CNN for the task of flame region segmentation in fire monitoring. Using an image segmentation model, the flame region in an image can be separated from the background to achieve accurate identification and localization of the fire region. Ref. [99] optimizes local contextual and global index methods based on physical mechanisms, while a new U-Net model is developed for accurate fire detection. Ref. [100] proposes a new instance segmentation method based on the mask R-CNN model for early wildfire detection and segmentation.

In summary, various researchers and scholars have adopted various techniques and methods in wildfire monitoring to realize timely monitoring, early warning, and emergency response to wildfires. By integrating the above techniques and methods, the wildfire digital twin can realize real-time and efficient detection, improving the accuracy and reliability of the model.

4.2. WFDT Data Collection

To build a robust wildfire digital twin, comprehensive wildfire data collection is critical [101]. Various technologies, such as IoT sensors, remote sensing, and drones, are employed to gather high-quality data [102]. IoT sensors can be strategically placed throughout forested areas to continuously monitor environmental variables like temperature, humidity, soil moisture, and wind speed [103]. These sensors offer granular, localized data, helping to detect early signs of wildfire risks. Remote sensing technologies, including satellites and aerial platforms, provide a broader perspective, capturing large-scale data on vegetation, fuel loads, and fire spread [104]. Remote sensing tools can deliver valuable information on the characteristics of fires, surface, and smoke [105]. UAVs further enhance data collection capabilities by offering high-resolution, real-time imagery, and thermal data in areas that are difficult or dangerous for humans to access. Equipped with multispectral and thermal cameras, UVAs can monitor hotspots and fire fronts, providing up-to-date information to ground teams and decision-makers [103]. The digital twin uses these real-time data to model fire behavior, simulate various scenarios, and evaluate potential intervention strategies. Additionally, feedback from the physical environment—such as sudden changes in wind direction or unexpected fire spread—is incorporated into the digital twin through these continuous data streams. This feedback loop allows the digital twin to adjust its simulations and predictions promptly.

The integration of these technologies ensures a continuous and comprehensive flow of data into the wildfire digital twin, allowing it to maintain a high degree of accuracy in representing the physical environment.

5. Simulation and Prediction Model of Wildfire Spreading Process

The model of the wildfire spread process is the theoretical basis for designing and developing a digital twin system for wildfires. The digital twin system simulates the spread process of fires approximately by applying wildfire spread models and data-driven models. This section provides an overview of existing wildfire spread models and algorithms.

5.1. Model of Wildfire Spread Speed

Globally, many countries that are frequently troubled by wildfires have established several sets of wildfire spread models, among which the more widely used ones are the Rothermel model from the U.S., the McArthur model from Australia, the Wang Zhengfei wildfire spread model from China, the Canadian forest fire spread model [106], etc. When establishing the digital twin system, the appropriate wildfire spread rate model should be selected according to the specific application requirements and available data resources. This section summarizes the existing wildfire spread models into three categories (Table 2): physical model, empirical model, and semi-empirical model [107].

Table 2. Advantages and disadvantages of wildfire spread rate model in digital twin system.

Category	Classical Model	Performance and Benefits	Drawbacks	Applicable Scenarios
Physical Model	Models based on fluid dynamics, thermodynamics, etc.	Highly accurate, strong adaptability	High computational complexity and data requirements	High-precision simulation
Empirical Model	McArthur model, Canadian forest fire spread model, etc.	Computationally efficient, easy-to-use	Limited accuracy and strong limitations	Rapid initial assessment and real-time monitoring
Semi-Empirical Model	Wang Zhengfei model, Rothermel model, etc.	High computational efficiency, good accuracy, high flexibility	Strong dependency, may require frequent calibration and updates	Balance calculation efficiency and simulation accuracy

5.1.1. Physical Model

The physical model is based on the analysis and description of the physical and chemical processes involved in the spread of fire. The model not only uses physical and chemical principles to simulate the behavior of wildfires but also takes into account the interactions between the fire and its environment. Examples include heat transfer, pyrolysis processes, and the effects of wind and topography. The physical model is suitable for high-precision simulations and can accurately describe the fire spread process for a wide range of fuel types and conditions.

A typical model of wildfire spread based on physical processes was proposed in a paper by Fons in 1946, and the principles of this model involved the basic thermodynamic and aerodynamic mechanisms of flame propagation [108]. In recent years, researchers have progressively developed physical models based on more complex mechanisms. For example, Pirk et al. proposed a tree combustion model that combines heat transfer with fluid dynamics [109]. Similarly, Hadrich et al. proposed a new mathematical formulation for the plant combustion process by integrating the effects of heat transfer, char insulation, and mass loss [110], which realistically simulates the pyrolysis of wood and thus the propagation process of forest fires (Figure 8).

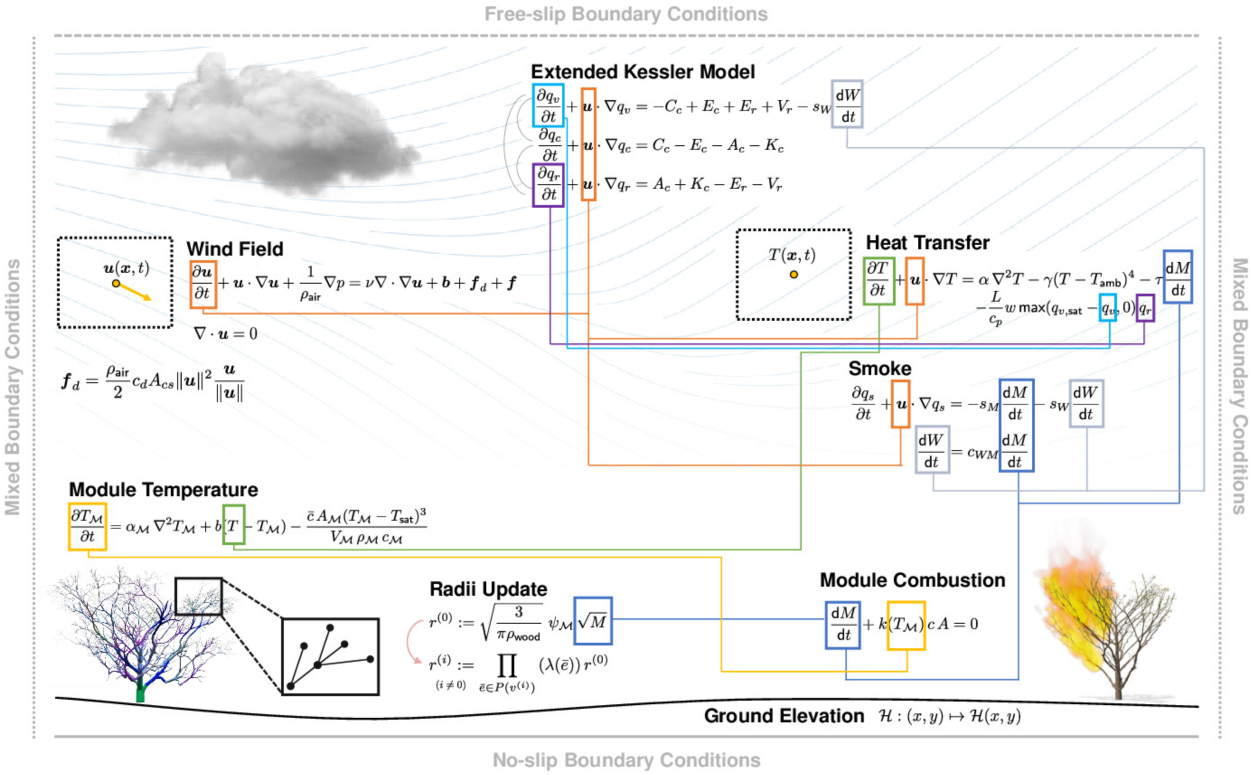


Figure 8. Model of the entire process of plant combustion [110].

5.1.2. Empirical Model

The empirical model relies on historical fire data and established empirical formulae to predict fire spread and is usually simple and efficient. It is suitable for large-area fire simulations. Typical empirical models include the McArthur model from Australia and the Canadian forest fire spread model. The McArthur model is based on many point-burning experiments to investigate quantitative relationships between wildfire spread rates and key parameters. On this basis, fire spread rate, flame height, and fire intensity are calculated to predict fire behavior [111]. This model is one of the most widely used empirical models for predicting the risk and behavior of forest and grassland fires in Australia [112]. Similarly, the Canadian forest fire spread model was developed based on many field experiments and historical fire data and is widely used in Canada's fire management and prediction systems. The main ones include the Canadian forest fire behavior prediction system (FBP) and the fire weather index system (FWI) [113]. Although empirical models are usually based on historical data and may not be as accurate as physical models, their predictions are still highly informative in most cases.

5.1.3. Semi-Empirical Model

The semi-empirical model combines the advantages of physical and empirical models, using existing observation methods and data to make feedback corrections to parameterized physical models. By studying the relationship between observed and predicted values, systematic errors can be eliminated to improve the accuracy and practicality of predictions. Examples include the Wang Zhengfei model in China and the Rothermel model in the United States.

Wang Zhengfei wildfire spread model is a semi-empirical model from China that combines physical models and empirical formulae by taking fuel characteristics, meteorological conditions, and topographical factors into account [114]. This model is able to predict the rate and direction of fire spread more accurately. The Rothermel model, developed in the United States as a semi-empirical model based on the law of conservation of energy, provides an estimate of the rate of fire spread by analyzing fuel, weather, and terrain data. It is one of the most commonly used fire spread models [115]. The Van Wagner model is a semi-empirical model for Canadian forests that considers factors such as canopy fuels, wind speed, and flame height. It is used to predict the rate of spread and fire behavior of predicted crown fires [116].

In fact, existing fire spread models mainly rely on numerical experiments and simulations of small-scale fire experiments, lacking validation of full-scale and large-scale real fire scenarios. In this situation, assessing the spread accuracy of wildfire digital twin remains a critical but unresolved issue. Although laboratory environments and small-scale simulations provide important theoretical foundations, the applicability and reliability of their results in actual large-scale fires still need to be validated. Therefore, how to test and verify the performance of wildfire digital twin systems in real environments to ensure their effectiveness in practical applications remains an important research direction.

5.2. Methods for Spatial Propagation of Wildfire Spread

To simulate the dynamic spread of wildfires effectively, researchers must select suitable spatial propagation methods [117]. These methods should be based on the chosen fire spread rate model to ensure that the simulation results tend to be accurate. Spatial propagation methods for wildfire spread can be categorized into grid-based simulation and vector-based simulation.

Grid-based simulation is represented by cellular automata. The cellular automata model is a discrete model that divides geographic space into regular grids, with each grid cell updated based on the state of surrounding cells [26]. They are commonly used to simulate physical systems [118]. Figure 9 shows the principle of cellular automata applied in 3D simulation of wildfire spread. In order to simulate the spread of real-time interactive tree crown fires, Liu et al. introduced a new cellular automaton model based on reaction and radiation physics equations and verified the functionality of the model [119]. Rui et al. artificially improved the spatiotemporal consistency of the wildfire spread model by combining the cellular automata model with the Wang Zhengfei wildfire model. A temporal correction factor was also added to improve the accuracy of wildfire spread prediction [120].

In addition, vector-based simulations often employ the Huygens principle to model the spread of wildfires. The fire spread model based on Huygens' principle operates by considering the fire front as a continuous curve, which expands over time. Each point on this curve acts as a source of secondary wavelets that propagate outward, influenced by factors such as fuel type, slope, meteorological conditions, and time step [121]. The cumulative effect of these wavelets determines the overall shape and progression of the fire front. This approach allows for an approximate yet effective simulation of the dynamic behavior of a spreading fire, accommodating the complex interactions within the environment. For example, the FARSITE fire growth simulator based on the U.S. Forest Service's Fire Behavior Prediction System is a vector-based Huygens-type model, which simulates the expansion of fire by continuously propagating a wavelet of the flame front. Using this vector-based computational approach, FARSITE can accurately simulate changes in the shape and location of the flame front [122]. Some scholars have carried out new theoretical research based on Huygens' principle. For example, Dehkordi et al. combined the Randers metric and Huygens' principle to propose several models for the propagation of flatland wildfires in the presence of wind [123].

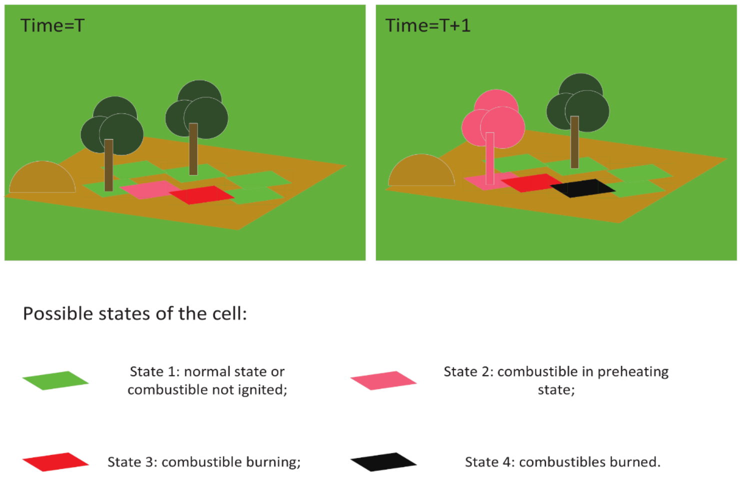


Figure 9. Principle of cellular automata in 3D scene [26].

After refining the corresponding spatial propagation spread model, the researchers combined the spread model with visualization techniques to develop the digital interactive system. Meng et al. proposed a lightweight cellular automata-based forest fire spreading method to be applied to the virtual 3D world. They captured the burning process of individual plants realistically by using cells to represent a library of plant models of different plants and by constructing 3D geometric models of plants [26]. The occurrence, spread, and extinguishing behavior of wildfires were successfully visualized in a virtual 3D scene. Cai et al. used a flame spread model based on cellular automata to construct a typical forest scene in the southwestern mountainous area of China in Unity3D, thus achieving a digital twin of forest fire spread [124]. Meng et al. used the improved Huygens principle as the theoretical basis for the spread of wildfires and simulated the spread of wildfires in three-dimensional scenes [125].

6. Visualization Technology and Tools

Visualization of physical entities is one of the core tasks in digital twin [7]. The technology is to visualize physical entities through an intuitive graphical interface or simulation, including from simple data visualization to complex 3D models and virtual reality [126]. In order to simulate the spread of fire and recreate real wildfire scenes in real time, the wildfire digital twin requires detailed digital simulations of physical entities such as forest environment, vegetation distribution, and flames. Using 3D modeling technology, high-precision forest digital twin visualization models can be constructed. The main components include static modeling and dynamic display.

6.1. Visual Modeling

The nonrigid, multi-scale, and complex physicochemical mechanisms of wildfires increase the difficulty of modeling [112]. The wildfire digital twin uses geometric modeling techniques and related tools to achieve accurate simulation and display of forest terrain, vegetation, and flames.

In terrain modeling, the development of high-resolution remote sensing technologies (including stereo vision [127], synthetic aperture radar [128], UAV photogrammetry [129], Lidar [130], and oblique photography [131]) has significantly boosted the accuracy and efficiency of digital elevation model (DEM) data acquisition and terrain modeling [132]. Through the fusion of remotely sensed data and GIS technologies, terrain features, including slope, slope direction, and elevation, are accurately constructed. Furthermore, in order to achieve large-scale and detailed terrain, a rule-based system and noise function-based programmatic terrain generation methods have been widely applied in game development and virtual reality environments [133].

In vegetation modeling, detailed 3D combustible models are created based on the growth characteristics and distribution of different vegetation types (e.g., trees, shrubs, and grasses). Researchers used parametric modeling [134] and the Lindenmayer System [135] to generate diverse vegetation models by defining parameters of vegetation growth (e.g., height, density, branching angle). In addition, hyperspectral imaging and point cloud modeling are also commonly used methods [130]. These techniques allow for the creation of detailed 3D models of vegetation, which can be applied in fields such as ecological monitoring and forest management.

Flame modeling is the most challenging part of the wildfire digital twin system. In flame modeling, advanced graphic processing techniques are used to generate high-quality fire visualization images. Thus, the dynamic change and spreading process of the flame is simulated. In recent years, significant progress has been made in flame visualization technology based on ray tracing [136], particle systems [137,138], and volume rendering [139] techniques. With the continuous improvement of computer hardware performance and the continuous optimization of algorithms, achieving 3D visualization of flame propagation through numerical simulation and artificial intelligence is also a current research hotspot [140].

6.2. 3D Dynamic Simulation

The 3D visualization simulation in the field of digital twin requires the support of powerful visualization techniques and real-time 3D technologies [141]. The process begins with the creation of high-fidelity 3D models using software such as 3ds Max, Maya, AutoCAD (https://www.autodesk.com/, accessed on 28 July 2024), and Blender (https://www.blender.org/, accessed on 28 July 2024) [142]. These tools enable the detailed modeling of the forest environment, including terrain, vegetation, and other physical entities (Figure 10).

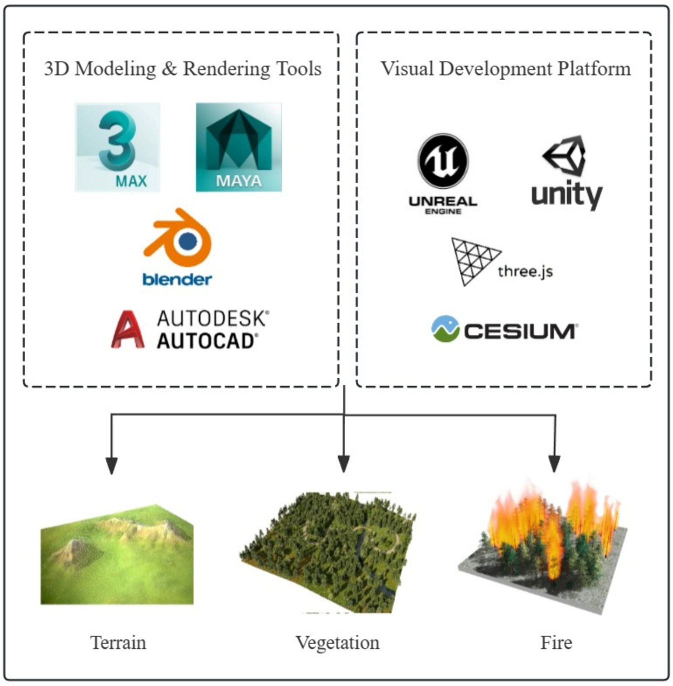


Figure 10. Flow chart of WFDT 3D simulation tool.

Once the models are created, they are integrated into visualization development platforms such as Unreal Engine (https://www.unrealengine.com/, accessed on 28 July

2024), Unity3D (https://unity.com/, accessed on 28 July 2024), and Cesium (https://cesium.com/, accessed on 28 July 2024). Unity 3D and Unreal Engine are both advanced 3D game engines that provide high-quality 3D rendering effects [143]. They are widely used in various real-time 3D visualization applications [144]. Li et al. used Unity3D to construct a digital twin-oriented poplar plantation system based on a virtual forest modeling and data analysis framework [20]. Cirulis et al. used Unity3D combined with Oculus headsets to create digital twins suitable for any swamp ecosystem for experimenting with various interactions in replicated virtual environments [56]. In addition, Cesium is an open-source 3D geographic information platform. It is built on WebGL technology and can process and display large-scale geographic spatial data [145], suitable for three-dimensional geographic display of fire spread.

7. The Overall Framework of Wildfire Digital Twin (WFDT)

The wildfire digital twin (WFDT) framework provides a comprehensive architecture. It is designed to achieve real-time detection, prediction, and decision-making management of fire spread by creating digital copies of wildfires. The model combines generic support technologies such as the Internet of Things, sensors, and artificial intelligence algorithms, aiming to improve the efficiency and science of fire management. (Figure 11)

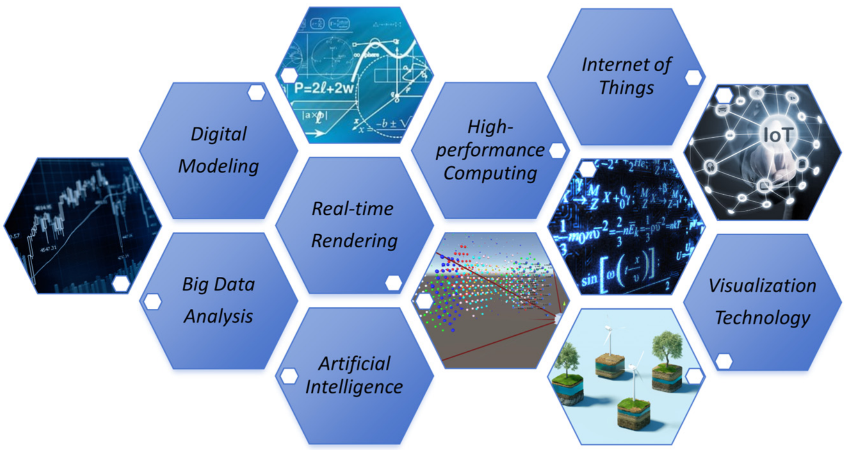


Figure 11. The schematic diagram of generic support technology.

This section will discuss the design of the wildfire digital twin framework. Figure 12 shows the overall framework structure of the WFDT, which consists of a physical entity layer, a virtual entity layer, a data layer, and an application layer. Below, we provide a detailed description of each component and its role within the WFDT framework.

- Physical entity layer
  The physical entity layer is the foundation of the digital twin system, which includes the actual physical environment and devices [146]. The physical world component is responsible for the collection of real-time data related to wildfire dynamics and the surrounding environment.
  First, sensor networks are deployed in the forest to monitor environmental parameters such as temperature, humidity, wind speed, and rainfall. These parameters are crucial for understanding fire behavior as they influence fire ignition, spread, and intensity. In addition, surveillance cameras are installed at key locations to provide real-time video data of fire occurrence and spread. Sensors and surveillance cameras provide localized data, while remote sensing offers a broader view, allowing for comprehensive coverage of the wildfire area. Remote sensing imaging technology is used to obtain high-resolution images to ensure comprehensive monitoring of large forest areas. These devices and technologies together form a multi-level, real-time monitoring system that provides reliable data support for the digital twin model.

- Virtual entity layer
  The virtual world component forms the core of the wildfire digital twin, where collected data are used to create a dynamic and interactive digital replica of the physical wildfire environment [147]. Live data feeds from IoT sensors, drones, and remote sensing platforms continually update the virtual entity of the WFDT, ensuring it reflects the current situation of the fire scene.
  The virtual entity layer transforms data from the physical entity layer into virtual models for simulation and detection, mainly including wildfire simulation models and fire monitoring models. The wildfire simulation model combines a spread rate model and a spatial propagation model to simulate the behavior of fire approximately under different environmental conditions. On the other hand, the fire monitoring model integrates functions for fire prediction, detection, and tracking. The fire prediction module uses real-time data to forecast potential fire outbreaks and their likely paths, while the detection module identifies the location of existing fires. The tracking module continuously monitors the fire's progression, updating the virtual environment as new data becomes available. In addition, the virtual entity layer includes a virtual visualization module. By visualizing fire behavior, terrain, and vegetation, decision-makers can more intuitively observe the development trend of fires and make effective decisions.
- Data layer
  The data layer acts as a bridge between the physical world and the virtual world, ensuring that data is effectively collected, processed, and utilized [148]. It is responsible for several key functions, including data collection, storage, processing, and integration [149]. The real-time database stores live data from sensors and monitoring devices at the fire scene, while the field database maintains historical data and geographic information. In the data module, data are continuously gathered from various sources in the physical world and undergoes data fusion and integration processes. Then, the data analysis module performs in-depth analysis to extract effective information and provide feedback to the physical and application layers. Finally, processed data are securely stored to ensure easy access and retrieval by the various components of the WFDT.
  The digital twin system integrates feedback from the physical environment through these data streams, allowing it to model fire behavior, simulate various scenarios, and evaluate potential intervention strategies.
- Application layer
  The application layer leverages the outputs from the virtual world and the insights gained from data analysis to support various wildfire management. As the final display and application part of the WFDT, this layer is crucial for practical applications, including real-time fire monitoring, early warning, approximate simulation, decision-making, and ecological restoration. Specifically, it enables early detection and alerts of potential wildfires, supports decision-makers in developing effective response strategies, and assists in training emergency responders through immersive simulation scenarios. By integrating these capabilities, the application layer ensures that the WFDT is effectively employed in diverse wildfire management tasks, enhancing both preparedness and response.

In summary, the WFDT framework can build an all-round wildfire management and emergency response system. WFDT is constructed through real-time monitoring at the physical entity layer, simulation and prediction at the virtual entity layer, data processing and analysis at the data layer, and practical application and decision support at the application layer.

The WFDT framework incorporates a synchronous interaction mechanism between the physical and virtual worlds. Data collected from the physical world is continuously fed into the virtual world to update fire simulations and visualizations. In turn, the virtual world generates feedback based on these simulations, which can be used to adjust monitoring strategies, enhance data collection, or optimize resource deployment in the real world fire scene. This iterative feedback loop ensures that the digital twin remains accurate, relevant, and responsive to changing conditions at the fire scene.

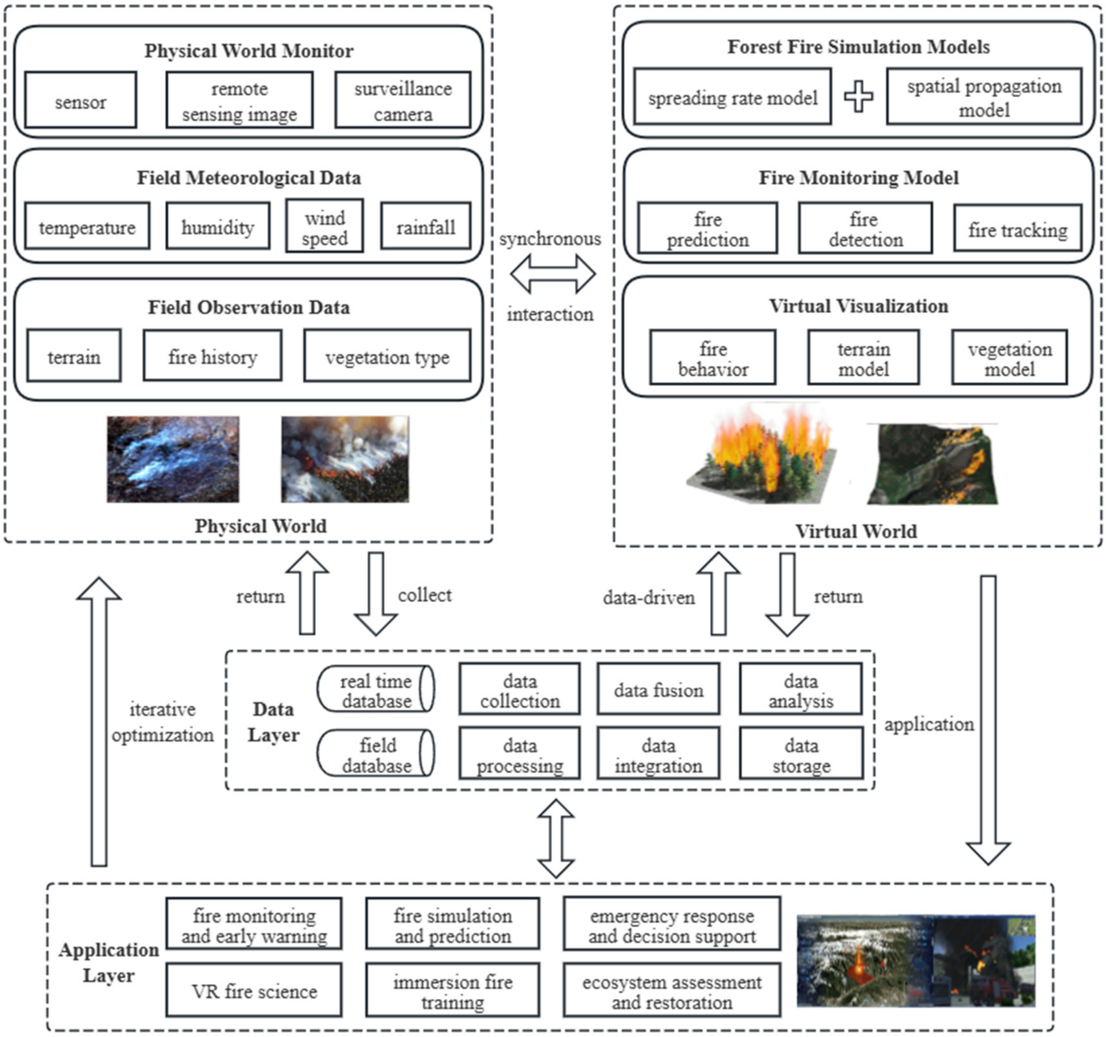


Figure 12. Wildfire digital twin framework.

By incorporating continuous, real-time data streams and simulations, the WFDT model provides a more accurate and responsive wildfire management system. This integration of real-time monitoring and predictive modeling represents a significant advancement over existing techniques. The existing traditional wildfire risk platforms typically rely on satellite data and are limited by the frequency of data collection and image resolution [150,151]. This limits their practicality in implementing decisions. Unlike traditional platforms that rely on periodic data updates, digital twins integrate data from sensors, drones, and other monitoring tools in real time. Most fire behavior models use predetermined, static simulations. These models cannot adapt to rapidly changing conditions. In contrast, digital twins enable predictive simulations that are continuously refined with new data inputs [152].

However, the following challenges remain in the design and development of WFDT:

First, data collection and processing is the major challenge. The system relies on high-cost IoT devices for real-time data collection. It also needs to effectively integrate heterogeneous data from multiple sources such as surveillance, meteorology, and ground observation. Therefore, it is a great challenge to acquire and process these heterogeneous data economically and efficiently.

Second, the accuracy and real-time performance of the model is another key challenge. Due to the complexity and uncertainty of the fire-spreading process, existing models are often deficient in accuracy and real-time performance. Therefore, how to improve the computational efficiency and real-time performance of the models while ensuring their accuracy is an urgent problem.

Third, the scalability and adaptability of the system are also important challenges in WFDT. With increasing demand for fire monitoring and emergency response, the system should ideally have scalability and adaptability. This would allow it to be deployed flexibly across different scenarios, with adjustments and optimizations suited to various fire types and environmental conditions.

Therefore, how to assess the accuracy, scalability, and economic benefits of wildfire digital twin remains an important scientific question that needs to be addressed in this field. These challenges emphasize the need for further research to improve the scientific rigor and effectiveness of smart wildfire digital twin in fire management.

8. Conclusions

It is well established that traditional wildfire management methods face limitations in efficiency and accuracy. Digital twin, by integrating advanced technologies like real-time monitoring, AI-driven prediction, and dynamic simulations, has shown promise in overcoming these challenges. In recent years, influenced by the latest scientific and technological revolution and industrial changes, digital twin has emerged as a powerful tool for fire management. In this context, we review the progress of the application of digital twin technology in wildfire detection, simulation, and prediction. It is shown that digital twin can have significant advantages in practical applications of wildfire management. It can combine external monitoring, prediction, and feedback mechanisms to provide timely guidance for firefighting.

The wildfire digital twin (WFDT) model proposed here establishes a foundational framework for a more comprehensive and responsive wildfire management system. One of the primary advantages of the WFDT model is its ability to offer near real-time simulation and predictive capabilities. Furthermore, the WFDT model's integration of monitoring, prediction, and feedback mechanisms creates a closed-loop system, providing continuous updates that enable firefighting teams to make timely adjustments based on evolving conditions. Notably, this approach focuses on large-scale approximate simulations rather than precise modeling of physical or chemical processes, providing a practical, scalable solution for analyzing wildfire dynamics. While this may slightly reduce accuracy, it allows us to study and simulate wildfires on a larger scale without very precise information on forest stand.

Despite its promising potential, digital twin technology in wildfire management remains in the early stages. Future research should focus on enhancing model precision and exploring the integration of multiple models to create more adaptable and flexible systems. In particular, coupling digital twins with other data-driven or physics-based models could improve compatibility and expand application scenarios. Furthermore, coupling digital twin models with advances in remote sensing, machine learning, and IoT technologies could further refine simulations. Given the limited real-world validation so far, it is crucial to expand field studies and implement pilot projects that utilize digital twin systems. These practical applications will provide essential data to evaluate and validate the accuracy of the proposed models. Moving forward, it is important to conduct more experiments or field tests to verify the validity of these models in real-world conditions.

In summary, while the application of digital twin in wildfire management shows great promise, further research is needed to refine these models and validate their effectiveness with real-world scenarios. By continuously deepening theoretical research and technological innovation, the digital twin could become a powerful tool in modernizing wildfire prevention and control, aiding in the modernization of forest protection and disaster management.

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