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Review

Research Progress on Satellite Remote Sensing Monitoring and Early Warning of Forest Fires in China

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Abstract

Wildfires pose significant hazards to ecosystems and socioeconomic systems. The rapid growth of forest resources in China has led to an increase in fuel load, while the combined effects of climate change, human activities, and the impacts of cross-border wildfires have further heightened wildfire risks. Therefore, establishing efficient monitoring and early warning systems is of paramount importance. This study comprehensively reviews the research progress of satellite remote sensing-based wildfire monitoring and early warning in China, focusing on four core directions: fuel parameter estimation, smoke area identification and fire spot localization, dynamic tracking and monitoring of fire spots, and post-fire assessment. It emphasizes the analysis of the application of multi-source satellite data and multi-technology integration methods. The results indicate that the accuracy of active fire detection in China's satellite-based wildfire monitoring system has been continuously improved. The application of GF-series satellites has effectively enhanced the precision of smoke area identification and fire spot detection, while multi-scale early warning models, dynamic monitoring technologies, and post-fire assessment technologies have demonstrated remarkable effectiveness in their application. However, current challenges include systematic deficiencies in key technologies, low efficiency in achievement transformation, and outdated operational systems. In the future, China needs to enhance the precise prevention and control capabilities for wildfires and safeguard forest ecological security by means of establishing space-air-ground integrated systems, strengthening technology R&D and transformation, and upgrading operational systems.

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1. Introduction

Forests, as a core component of terrestrial ecosystems, perform key functions such as carbon sink regulation, biodiversity conservation, and ecological barrier construction. However, forest fires, as typical ecological disturbances, exhibit distinct characteristics of being multi-dimensional and cross-domain in their harms[1,2].

From the perspective of ecosystems, fires not only directly burn down vegetation communities such as arbors, shrubs, and herbs, resulting in a sharp decline in the primary productivity of forest ecosystems, but also further disrupt the habitats and food chain structures of animals and plants in forests. This leads to a drastic reduction in the population of rare species and significantly reduces regional biodiversity[3,4]. In the long term, fires also alter the physical and chemical properties of soil: they burn the litter layer on the surface, causing the loss of soil organic matter, damage the soil aggregate structure, and further trigger soil erosion and land degradation, exerting long-term negative impacts on regional ecological balance[1,5,6].

From the socio-economic perspective, forest fires pose a direct threat to the lives and property safety of residents in forested areas. High-temperature flames, thick smoke, and flying embers caused by fires easily result in casualties among residents, and at the same time burn down houses, transportation facilities, and agricultural land, leading to severe economic losses. In addition, large-scale forest fires also have indirect impacts on regional socio-economic development. For example, they disrupt the industrial chain of the forestry industry, causing a shortage of timber supply and the shutdown of related processing enterprises; they affect the development of the forest tourism industry, reducing the economic value of ecotourism resources; if fires occur in key water conservation areas, they may also pollute the water environment and threaten the safety of residents' drinking water[7–9].

Since the 1990s, China has successively launched a series of key forestry ecological projects, including the Natural Forest Protection Project, the Grain for Green Project, and the Fast-Growing and High-Yield Forest Base Construction Project. By 2025, China’s forest coverage rate has increased from 16.55% at the initial stage of the projects to 25.09%, and the forest stock volume has exceeded 20.988 billion cubic meters[1,10–12]. However, the rapid growth of forest resources has also led to a significant increase in the fuel load within forests. Additionally, some forest areas face issues such as excessive fuel accumulation density and single fuel structure, which have significantly raised the occurrence probability and spread speed of forest fires[13,14].

Furthermore, the combined effects of human activities and climate change have further exacerbated the risk of forest fires[15,16]. On one hand, human activities in forest areas—such as crop cultivation and forest tourism development—have caused a surge in human-caused fire sources. Illegal fire use, including fire for sacrificial rituals and production purposes, has become one of the main causes of forest fires. On the other hand, global climate anomalies have led to frequent extreme weather events in some of China’s forest areas. For instance, extreme high temperatures and increased drought days in summer, coupled with reduced precipitation in winter, have lowered the moisture content of vegetation in forest areas and increased the dryness of fuels, significantly reducing the critical temperature for fire occurrence[17–20].

Moreover, China’s border forest areas adjacent to countries such as Russia and Mongolia are significantly affected by cross-border fire incursions. In recent years, cross-border forest fire incidents in border areas have accounted for 8% to 12% of the total number of fires nationwide, posing enormous challenges to fire prevention work in border forest areas[4,18,21,22]. The combined effect of the aforementioned factors has resulted in a frequent occurrence of major and extraordinarily serious forest fire incidents in China in recent years, accompanied by frequent casualties and property loss accidents. Given the severe hazards and high incidence of forest fires, constructing an efficient forest fire early warning and monitoring system to achieve the fire prevention goal of “detecting fires early, suppressing them when small, and extinguishing them completely” has become a top priority for safeguarding forest ecological security and ensuring the stable development of regional social economy[23,24].

After decades of development, China has gradually established a nationwide forest fire monitoring network, forming a 4-level three-dimensional monitoring system consisting of "ground patrol, near-ground monitoring, aerial patrol, and satellite monitoring". Among these, ground patrol serves as the basic monitoring method, which primarily relies on manual patrol inspections, ground video surveillance systems, and infrared detection equipment to achieve real-time monitoring of key forest areas[25–27]. Near-ground monitoring, on the other hand, acquires data on microclimates and fuel conditions in forest areas through deployed devices such as meteorological stations and fuel moisture content monitoring stations. Aerial patrol uses aircraft including helicopters, fixed-wing planes, and drones to conduct rapid inspections and fire location in medium-to-large forest areas, and is particularly suitable for regions with complex terrain that are difficult to cover by ground patrol[27–29].

Meanwhile, satellite monitoring has become the core technical means for macro forest fire monitoring and long-term tracking, thanks to its unique advantages of wide coverage, high spatiotemporal resolution, and strong monitoring continuity. From a technical principle perspective, satellite monitoring mainly uses on-board equipment such as visible light sensors, infrared sensors, and thermal imagers to capture areas with abnormal surface temperatures in forest regions. By integrating auxiliary information such as vegetation indices and topographic data, it realizes the identification and localization of forest fires[30,31]. Its application scenarios include not only the macro monitoring of daily forest resource distribution, vegetation growth status, and potential fire risk factors in forest areas, but also the real-time tracking of fire conditions (e.g., burning range, fire spread direction, and fire site temperature) after a forest fire occurs. Additionally, through the comparison of multiple post-fire satellite images, it can assess the vegetation loss area and carbon stock loss caused by fires, as well as monitor the dynamics of post-fire vegetation recovery[25,32–34].

These monitoring data provide scientific decision support for forestry authorities to formulate fire prevention strategies, deploy fire-fighting forces, and carry out post-fire recovery and reconstruction work. To enhance the coverage and response speed of satellite monitoring, China has currently established 4 national-level satellite forest fire monitoring stations in Beijing, Kunming, Urumqi, and Harbin, forming a monitoring network covering key forest areas in Northeast, Southwest, Northwest, and North China. At present, this network can simultaneously receive remote sensing data from China's Fengyun meteorological satellites, the U.S. NOAA satellite series, and the EOS satellite series. Through multi-source satellite data fusion technology, the accuracy and timeliness of forest fire identification have been significantly improved[12,35].

Currently, the accuracy rate of open fire identification by China's satellite forest fire monitoring system has reached over 90%, and the positioning error of fire points can be controlled within 1 kilometer. For forest fires covering an area larger than 1 hectare, the average detection time by satellite monitoring is no more than 30 minutes, which is much faster than the response speed of traditional ground and aerial patrols. In addition, satellite monitoring data can be shared in real time with local forestry departments and emergency rescue teams through the National Forest Fire Monitoring and Early Warning Platform, providing technical support for cross-regional and cross-departmental joint prevention and control of forest fires[2,12,23,36].

In summary, satellite monitoring technology has become an indispensable technical means in China's current national daily fire monitoring operations, and plays an irreplaceable role in the "early detection and early disposal" of forest fires.

2. Research Progress

2.1. Background

Against the backdrop of global innovation in ecological monitoring technology, remote sensing technology has become a core supporting technology for forest resource surveys and dynamic monitoring of the ecological environment, thanks to its advantages of non-contact measurement, wide-range coverage, and multi-spatiotemporal scale observation. Research on forestry remote sensing technology in China began in the 1970s. After more than 50 years of development through three stages—"introduction and absorption, independent R&D, and operational application"—it has formed a technical system covering multiple fields such as forest resource inventory, pest and disease monitoring, and fire early warning[1,5,11,37].

Currently, the application coverage rate of China's forestry remote sensing technology has reached 92%, among which satellite remote sensing contributes over 75% to forest fire monitoring. It has thus become a key technical means supporting the monitoring and evaluation of forest resources and the ecological environment[5,8,34,38]. At present, research on satellite remote sensing early warning for forest fires in China mainly focuses on four core directions: firstly, remote sensing estimation of fuel parameters, which provides basic data for fire risk level assessment; secondly, smoke area identification and fire point localization, which enables rapid detection and accurate positioning of fire situations; thirdly, dynamic monitoring of large forest fire burning, which tracks

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the fire spread path and changes in fire area scope; fourthly, post-fire loss assessment and vegetation recovery monitoring, which provides a decision-making basis for post-disaster reconstruction.

This section will systematically sort out and analyze the research progress of satellite remote sensing monitoring and early warning technology for forest fires, combining three decades of research results in the aforementioned directions.

2.2. Combustible Material Parameter Estimation Technology and Practice of Forest Fire Prediction Model

2.2.1. Theoretical Basis and Technological Evolution of Forest Fire Forecasting

Forest fire danger prediction is a technical method that quantifies key factors such as meteorology, fuel, fire sources, and terrain to assess the occurrence probability and spread risk of forest fires in specific regions. Among these, meteorological factors (temperature, humidity, wind speed, and precipitation) determine the external environmental conditions for fire danger occurrence; fuel factors (type, moisture content, load, and distribution) affect the fire occurrence probability and burning intensity; and fire source factors (human-caused and natural fire sources) are the direct triggers of fires. These three factors together constitute the core elements of forest fire prediction[2,5].

Research on forest fire prediction in China began in 1955. Limited by technical conditions in the early stage, it mainly relied on ground meteorological observation data. Combining the climatic characteristics and forest stand structures of key forest areas (e.g., Northeast and Southwest China), and referring to the technical frameworks of the former Soviet Union's Fire Weather Index, the Canadian Forest Fire Weather Index (FWI) System, and the U.S. National Fire Danger Rating System (NFDRS), researchers developed empirical fire danger rating prediction models based on meteorological factors[5,19,36]. Although these models realized the qualitative classification of fire danger levels, they had limitations such as low spatial resolution and delayed parameter acquisition, making it difficult to meet the needs of large-scale and real-time fire danger early warning[39,40].

Since the 1990s, with the rapid development of remote sensing, geographic information systems, the Internet, and database technologies, forest fire prediction technology has entered the "multi-technical integration" phase[10,31,41]. Remote Sensing technology enables large-scale and high-frequency inversion of fuel parameters and meteorological elements; Geographic Information System (GIS) technology supports spatial overlay analysis and model visualization of multi-source data; and Internet and database technologies ensure real-time data transmission and efficient storage. The integrated application of these technologies provides a feasible path for obtaining high-precision fire danger prediction parameters and conducting daily national forest fire danger rating predictions[8,42].

Domestic scholars have carried out extensive exploration around the integrated application of technologies, yielding a number of fire danger prediction technology achievements with independent intellectual property rights. This has promoted the transformation of forest fire prediction from "qualitative assessment" to "quantitative early warning".

2.2.2. Domestic practice in estimating Combustible material Parameters and developing fire risk models

In terms of national-scale fire danger prediction model development, Yi et al. took the lead in conducting research based on NOAA/AVHRR satellite data. Taking advantage of the 1 km spatial resolution of NOAA/AVHRR data, this study retrieved national vegetation growth and greenness information every 10–15 days, updated national vegetation coverage and snow coverage data at the same interval, and integrated concurrent temperature, humidity, and precipitation data observed by ground meteorological stations. It further developed a national forest fire occurrence prediction model with county-level units as the prediction unit, along with a supporting application system[43,44].

This system was put into operational use during the national spring and autumn fire prevention periods from 1999 to 2000. It issued a total of 127 fire danger early warning messages and accurately predicted the occurrence risk of 32 medium-sized forest fires, achieving an early warning accuracy rate of 83%. This laid the foundation for the operational application of national-scale forest fire early warning.

In terms of regional-scale fire danger early warning technology research, different scholars have carried out targeted explorations based on the ecological characteristics of key forest areas. Researchers focused on the Greater Khingan Range forest area as the study region and conducted fuel parameter inversion using MODIS satellite data: it estimated forest fuel moisture content via MODIS Band 6 (1.6 μm) data, characterized vegetation coverage using the MODIS NDVI index, and retrieved land surface temperature with MODIS Band 31 (11 μm). A fire danger index model incorporating three factors—"moisture content, vegetation coverage, and temperature"—was thus constructed[12,20,45].

This model was validated during the 2003 fire prevention period in the Greater Khingan Range forest area, achieving identification accuracy rates of 88%, 85%, and 91% for low-, medium-, and high-risk fire areas, respectively. It effectively supported regional forest fire prevention and control decisions. In contrast, Wang et al. focused on fire danger early warning in the grassland-forest transition zone of the Greater Khingan Range in Northeast China. Given the region's characteristics of herb-dominated fuels and fast burning speed, a grassland fire danger rating prediction model was developed based on MODIS data[46]. The study retrieved herbaceous vegetation coverage using the MODIS NDVI index, characterized vegetation growth status with the MODIS EVI index, and integrated wind speed and precipitation factors from ground meteorological data. A 5-level grassland fire danger rating standard was established, and a supporting fire danger prediction system was developed. This system was applied during the 2004–2005 grassland fire prevention period, successfully warning of 15 grassland fires with an average advance warning time of 4–6 hours, providing strong support for the rapid response to grassland fires[23,31].

Additionally, Qin et al. conducted cross-regional and multi-scale research on fuel parameter estimation and fire danger model development. The research team carried out field observation experiments in Northeast China forest areas, Southwest China forest areas, Guangdong Province, Guangxi Zhuang Autonomous Region, and Jiangxi Province. By collecting fuel samples from different forest stand types, they established a quantitative relationship model between MODIS data and fuel type, greenness, and moisture content[47].

On this basis, integrating GIS technology and database technology, a national forest fire early warning quantitative estimation model with a spatial resolution of 1 km^2 was constructed. A forest fire early warning system integrating data collection, parameter inversion, model calculation, and early warning issuance was also developed. This system was applied for cross-border fire danger prediction in China and Southeast Asia from 2009 to 2012, processing over 2,300 satellite images and issuing 48 cross-border fire danger early warning messages, effectively facilitating regional joint prevention and control[10,47,48].

2.3. Remote Sensing Identification Technology and Satellite Application in Forest Fire Smoke Areas

2.3.1. The correlation between the formation mechanism of smoke zones and forest fire monitoring

During the combustion process of vegetation such as forests and grasslands, the formation of smoke regions is the result of the combined action of multiple physical and chemical processes. On one hand, free water and bound water in vegetation evaporate when heated, generating a large amount of water vapor. On the other hand, under incomplete combustion conditions, organic components such as lignin, cellulose, and hemicellulose decompose to produce substances including carbon-containing particles, volatile organic compounds, and nitrogen oxides. These components mix with water vapor and diffuse under the influence of atmospheric dynamic forces, forming smoke regions with continuous spatial distribution characteristics—including linearly extending smoke plumes and clump-distributed smoke puffs[34,49,50].

From the perspective of optical properties, particulate matter in smoke regions exerts a strong scattering effect in the visible light band (400–760 nm), while primarily exhibiting an absorption effect in the near-infrared band (760–2500 nm). This unique spectral response characteristic serves as the core basis for satellite remote sensing to identify smoke regions.

Smoke regions exhibit a dual effect in forest fire monitoring. On one hand, dense smoke regions block thermal radiation information from the underlying fire site, leading to missed detections or misjudgments in satellite fire point detection algorithms that rely on thermal infrared bands. This poses significant challenges to the real-time monitoring of forest fires[50,51]. On the other hand, the spatial distribution characteristics of smoke regions can serve as an important basis for indirectly determining fire site information. For instance, the extension direction of smoke plumes is highly correlated with wind speed and wind direction, and the center position of the fire site can be inferred by tracking the trajectory of smoke plumes. Additionally, the diffusion range of smoke puffs is positively correlated with fire intensity: generally, the area of smoke regions formed by medium-intensity fires can reach 5 to 8 times the area of the fire site, while that of high-intensity fires can expand to 10 to 15 times the area of the fire site[52].

Based on this, if smoke region distribution information can be captured in a timely manner via optical satellite images, it can not only compensate for blind spots in fire point detection but also predict the spread trend of fire intensity in advance. This provides key support for forest fire prevention departments to deploy early warning measures and allocate fire-fighting forces, thereby reducing the occurrence probability and loss degree of major and extraordinarily serious forest and grassland fires[53,54].

2.3.2. The Technical Advantages and Application Potential of China's High-Resolution Satellites in Smoke Zone Identification

Since launching the High-Resolution Earth Observation System in 2010, China has successfully launched multiple optical satellites, including Gaofen-1 (GF-1), Gaofen-2 (GF-2), Gaofen-4 (GF-4), and Gaofen-6 (GF-6). This has established a satellite observation system covering "high spatial resolution, high temporal resolution, and high spectral resolution," providing unique technical support for smoke region identification[25,46,55].

In terms of sensor design, the aforementioned Gaofen satellites are all equipped with dedicated visible light and near-infrared band channels. Their spectral response design in the blue band (400–500 nm) is particularly tailored to meet the needs of smoke region identification[56].

From a technical principle perspective, the blue band of Gaofen satellites is suitable for smoke region identification mainly based on two points: firstly, the scattering coefficient of carbon-containing particles (0.1–1 μm in diameter) in smoke regions for blue light (approximately 5–10 km^{-1}) is significantly higher than that for green light (2–5 km^{-1}) and red light (1–3 km^{-1}). As a result, smoke regions appear as distinct dark tones in blue band images, creating a strong contrast with surrounding vegetation (bright green) and bare land (bright yellow); secondly, the blue band is less affected by atmospheric scattering—compared with the near-infrared band, the radiation error of blue light in atmospheric transmission paths is only 1/3 that of the near-infrared band, enabling more accurate reflection of the actual distribution range of smoke regions.

It is important to note that although the visible/near-infrared channels of Gaofen satellites are less sensitive to forest fire thermal anomaly information (e.g., high-temperature fire areas) than the thermal infrared channels of MODIS, the distinction between smoke regions and clouds can be further enhanced through the ratio calculation of the blue band (400–500 nm) and red band (630–690 nm) (blue/red band ratio). Typically, the blue/red ratio of smoke regions is greater than 1.2, while that of clouds is mostly less than 0.8. This characteristic can effectively reduce misjudgments caused by smoke-cloud confusion[50,51].

In practical applications, Gaofen satellites have demonstrated great potential in smoke region identification for multiple forest fires in China. During the 2021 forest fire in Liangshan Yi Autonomous Prefecture, Sichuan Province, the GF-2 satellite captured a smoke region of approximately 23 km^2 with 1 m resolution blue band images. The extracted smoke plume direction was completely consistent with the wind direction observed on the ground, providing accurate data for fire site positioning and fire spread prediction. During the 2023 grassland fire in the Greater Khingan Range of Inner Mongolia, the GF-6 satellite successfully identified 3 small fire points obscured by smoke regions using 2 m resolution images, compensating for the missed detection issue of MODIS fire point detection[55,57].

In recent years, with the successive deployment of Gaofen-7 and Gaofen-12, combining the advantages of optical remote sensing and microwave remote sensing (microwaves can penetrate smoke regions to obtain fire site information), it is expected to build an integrated forest fire monitoring system covering "smoke region identification, fire point positioning, and fire spread tracking," further improving the accuracy and timeliness of China's forest fire early warning.

2.4. Satellite Remote Sensing Detection technology and Application of Forest Fire Ignition Points

2.4.1. The Technical Principle and Core Advantages of Ignition Point Detection

The large amount of thermal energy released during the combustion of vegetation such as forests and grasslands forms thermal anomaly signals that are significantly different from the surrounding environment. This serves as the core physical basis for satellite remote sensing detection of fire points. According to Planck's Law of Blackbody Radiation, the higher the temperature of an object, the more prominent its thermal radiation intensity response in the mid-wave infrared (3–5 μm) and far-infrared (10–12 μm) bands. Specifically, the thermal radiation flux density in fire point areas can reach 10 to 100 times that of normal vegetation areas. This strong spectral difference provides a physical basis for satellite sensors to capture fire point information[1,10,37].

Thermal infrared remote sensing technology has two core advantages in fire point detection: Firstly, super-resolution detection capability—relying on the high sensitivity of thermal infrared sensors to high-temperature signals, it can identify fire points smaller than the sensor's spatial resolution. For example, the NOAA/AVHRR sensor, with a nadir spatial resolution of 1.1 km × 1.1 km, can detect small forest fires as small as 0.1 hm^2 (approximately the size of 1.4 standard football fields) through mixed pixel decomposition algorithms[58]. Secondly, large-scale dynamic monitoring capability—thermal infrared sensors can penetrate partial thin clouds and smoke, enabling all-weather, large-scale fire monitoring. This effectively compensates for the spatial coverage limitations of ground patrols and aerial patrols. Internationally, NASA (National Aeronautics and Space Administration) began fire point detection research based on AVHRR data as early as the 1970s. The fire point detection algorithm it developed—the MODIS Fire and Thermal Anomaly Algorithm—achieves automated global fire point extraction by setting brightness temperature thresholds for thermal infrared channels[46,59,60]. This has provided important reference for the development of fire point detection technology in China.

2.4.2. The Development History of Forest Fire Ignition Point Detection Technology in China

Research on satellite remote sensing-based fire point detection for forest fires in China began in the 1980s. It has undergone three stages of evolution—initial exploration, technological development, and innovative application—and gradually formed a technical system adapted to domestic needs.

During the initial exploration stage (1980s–1990s), Chinese scholars focused on the localized application of foreign satellite data and conducted basic research on fire point detection methods. For example, regarding the thermal infrared channel (Band 6, 10.4–12.5 μm) of Landsat TM satellites, researchers established a fixed-threshold-based fire point identification method by comparing brightness temperature differences between fire pixels and non-fire pixels. For NOAA/AVHRR data, they explored the brightness temperature difference threshold method ($\Delta T = CH3 - CH4 > 5$ K) using the mid-wave infrared (CH3, 3.55–3.93 μm) and far-infrared (CH4, 10.3–11.3 μm) channels [58]. During the "May 6" Greater Khingan Range Extraordinary Forest Fire in 1987, the research team used Landsat TM and NOAA/AVHRR data to generate daily fire site range and fire point distribution maps. This provided key data support for the command center to formulate fire-fighting strategies and deploy rescue forces, marking the transition of China's remote sensing-based fire point detection technology from theoretical research to practical application.

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In the technological development stage (1990s–2010s), with the popularization of remote sensing technology, domestic scholars began to optimize fire point detection algorithms to improve identification accuracy and anti-interference capability. Yi et al. innovatively introduced an expert system into AVHRR data-based fire point detection and constructed a multi-dimensional identification model incorporating spectral rules (brightness temperature thresholds), spatial rules (fire point clustering), and temporal rules (fire point persistence). By excluding interfering pixels such as clouds, water bodies, and high-temperature bare land, this model increased fire point identification accuracy from 72% (with traditional threshold methods) to 88%, and reduced the misjudgment rate to below 5%[61]. Additionally, to address the mixed pixel issue in NOAA/AVHRR data, Qin et al. (2004) proposed a linear decomposition algorithm. By inverting the proportion of fire pixels in mixed pixels, this algorithm enabled quantitative identification of sub-pixel-level fire points, further expanding the technical application scope[61,62].

In the innovative application stage (2010s–present), with the launch of new domestic and foreign satellites, scholars have carried out method innovations based on high-resolution and hyperspectral data. Li et al. utilized the short-wave infrared channel of Sentinel-2 satellites, leveraging the reflectance differences between fire points and vegetation in this band. Combined with machine learning algorithms, they constructed a fire point detection model suitable for small-scale forest areas, achieving an identification accuracy of 92%[63]. Chen et al. designed a multi-channel collaborative identification algorithm for the Medium Resolution Spectral Imager data of FY-3 satellites. Through combined thresholds of mid-wave infrared, far-infrared, and visible light channels, this algorithm effectively eliminated the interference of nighttime cloud cover on fire point detection, increasing the nighttime fire point identification accuracy to 89%[64].

2.4.3. The Classification of the Core Method System for Ignition Point Detection

Based on the satellite spectral characteristics relied on by detection algorithms, fire point detection methods can be divided into two main categories: reflection characteristic-based detection methods and brightness temperature characteristic-based detection methods. These two methods differ significantly in technical logic, applicable data, and application scenarios.

2.4.3.1. Detection Method Based on Reflection Characteristics

First, the core principle of the reflection characteristic-based detection method is as follows: Charred materials and ash produced by vegetation combustion have extremely low reflectance in the short-wave infrared band (1.5–2.5 μm), while normal vegetation has relatively high reflectance in this band due to weak water absorption by cell walls. This significant difference serves as the key basis for fire point identification[65]. To further improve identification accuracy, the algorithm usually integrates features of the visible light band (0.4–0.7 μm) and near-infrared band (0.7–1.1 μm) to exclude interfering pixels such as clouds and bare land—for example, clouds have high reflectance in the visible light band but low reflectance in the short-wave infrared band, which is opposite to the reflectance characteristics of fire points; bare land has high reflectance in the near-infrared band, which can be effectively distinguished from the low reflectance of fire points. This method is mainly applicable to multispectral satellite data equipped with short-wave infrared channels. Typical application cases include: Yu et al. conducted fire point detection in the Huzhong Forest Area of Heilongjiang Province using Landsat-8 OLI satellite data. By setting a combined threshold of "short-wave infrared reflectance < 0.08 and near-infrared reflectance < 0.2", the fire point identification accuracy reached 90%, successfully capturing 12 micro-fire points with an area of < 0.05 hm^2[66]; He et al. utilized the short-wave infrared channels (Band 11 and Band 12) of the Sentinel-2A satellite to construct a short-wave infrared reflectance ratio index (R11/R12). By leveraging the difference of this index between fire point areas (R11/R12 > 1.2) and non-fire point areas (R11/R12 < 1.0), they realized the automatic extraction of fire points in the Shangri-La Forest Area of Yunnan Province, with processing efficiency three times higher than that of traditional methods[67].

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2.4.3.2. Detection Method Based on Bright Temperature Characteristics

In contrast, the brightness temperature characteristic-based detection method relies on brightness temperature data captured by thermal infrared channels and constructs identification criteria by comparing the brightness temperature difference between fire pixels and non-fire pixels. It is currently the mainstream method for fire point detection using medium-low resolution satellites. According to differences in the wavelength of thermal infrared channels, it can be further subdivided into mid-wave infrared-far-infrared synergy method and multi-channel threshold method: The mid-wave infrared-far-infrared synergy method takes advantage of two traits—mid-wave infrared channels are more sensitive to high-temperature fire points, while far-infrared channels are less affected by atmospheric water vapor absorption, making brightness temperature data more stable. The algorithm calculates the brightness temperature difference between the two channels and sets a threshold to achieve fire point identification[39]. For example, Qin et al. set a threshold of $\Delta T > 12$ K for the Southwest Forest Area using MODIS data, achieving a fire point identification accuracy of 87% and controlling the misjudgment rate within 6%. For the multi-channel threshold method, during daytime observations, solar radiation causes high reflectance in pixels such as clouds and bare land in the visible/near-infrared bands, which may interfere with fire point identification[68]. To address this, the algorithm adds constraint conditions for visible/near-infrared channels on the basis of thermal infrared channel thresholds—for example, it uses the Normalized Difference Vegetation Index (NDVI) to exclude clouds and bare land, and uses red band reflectance to exclude high-reflectance interfering pixels[69].

2.4.4. The Operational Application Achievements of Forest Fire Ignition Point Detection in China

Over the past more than 20 years of technological research and development as well as system construction, China has formed an integrated "method-system-application" operational system for fire point detection, providing stable support for national forest fire prevention work.

In terms of technical system construction, domestic research teams have developed a series of fire monitoring application systems based on the characteristics of different satellite data. For example, the multi-source satellite forest fire monitoring system developed by Wu et al. integrates fire point detection algorithms for data such as NOAA/AVHRR, MODIS, and FY-3/MERSI. It realizes full-process automation of data automatic reception, preprocessing, fire point extraction, and result output, capable of processing over 150 satellite images per day and generating 2–3 versions of national fire point distribution maps. This provides real-time data support for forestry departments at all levels[70]. Additionally, the Gaofen Satellite Forest Fire Emergency Monitoring System developed by the Institute of Information Technology, Chinese Academy of Forestry is designed for high-resolution satellite data such as GF-1/2/6. It achieves rapid response in fire point detection and fire site range extraction, and played a key role in emergency response to forest fires in Sichuan Ganzi Tibetan Autonomous Prefecture (2022) and Inner Mongolia Hulunbuir City (2023)[12,29,57,71].

In terms of national-level operational application, the Satellite Forest Fire Monitoring System of the National Forest Fire Prevention and Control Headquarters of China has achieved leapfrog development in data sources and monitoring capabilities since its establishment and operation in 1995: During 1995–2005, the system only relied on NOAA/AVHRR data, generating one national fire point report per day with a fire point identification accuracy of approximately 75%; From 2005 to 2015, it incorporated FY-2/FY-3 satellites and MODIS data, forming a multi-source data fusion monitoring model. The monitoring frequency was increased to twice a day, and the accuracy reached over 85%; Since 2015, it has further integrated Gaofen series satellite data, realizing a collaborative model of "medium-low resolution large-scale monitoring + high-resolution detailed monitoring". The fire point identification accuracy has remained stably above 90%, and its coverage capability for hard-to-monitor areas such as border fires and alpine fires has been significantly improved. According to statistical data released by the National Forestry and Grassland Administration of China, from 2018 to 2023, the national system has provided a total of more than 2,100 fire point monitoring reports, accurately identifying over 18,000 forest fire points nationwide. It has gained an average of 2–3 hours

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of early warning time for fire command and suppression, reducing the national incidence of major and extraordinarily serious forest fires from 0.8 times per 10,000 km² in 2018 to 0.3 times per 10,000 km² in 2023. This fully demonstrates the core supporting value of remote sensing-based fire point detection technology in forest fire prevention[72,73].

2.5. Satellite Remote Sensing Monitoring Technology for the Burning Dynamics of Forest Fires

2.5.1. The Situation of Forest Fire Prevention and Control in China and the Necessity of Dynamic Monitoring

Against the backdrop of global climate change, extreme weather events such as extreme high temperatures and droughts occur frequently, significantly increasing the occurrence risk and hazard degree of forest fires. The IPCC Sixth Assessment Report points out that the global frequency of forest fires increased by 18% from 1980 to 2020, with the most significant increase in fire intensity observed in mid-to-high latitude regions[74]. As a major forestry country, China has significantly increased investment in forest fire prevention at all government levels since the "May 6" Extraordinary Forest Fire in the Greater Khingan Range in 1987. According to data from the 2024 China Forest Fire Bulletin, from 1988 to 2023, national forest fire prevention funds increased from 120 million yuan to 12.8 billion yuan, and the scale of professional firefighting teams expanded from 8,000 to 156,000 personnel. These efforts have reduced the annual number of forest fires from 15,000 to 6,000, and the annually affected forest area from 1.5 million hm² to 120,000 hm², achieving remarkable overall prevention and control results[9,36].

However, China still faces severe challenges in the current forest fire prevention situation: First, the occasional occurrence of major and extraordinarily serious forest fires has not been fundamentally changed. A total of 28 major and extraordinarily serious forest fires occurred nationwide from 2019 to 2023, with an average burned area of over 1,000 km² per fire—far exceeding the hazard degree of general fires. Second, casualties still occur. In addition to the 2019 forest fire in Muli County, Liangshan Yi Autonomous Prefecture, Sichuan Province, which killed 31 firefighting personnel, the 2020 forest fire in Shangri-La, Yunnan Province, and the 2022 forest fire in Longyan, Fujian Province, both caused injuries to multiple firefighters. This reflects the constraint of delayed fire site information acquisition on firefighting decision-making. Third, the pressure of cross-border fire prevention has increased. An average of 15–20 cross-border fires occur annually between China's northeastern border and Russia's Far East forest areas, and between China's southwestern border and northern Myanmar forest areas. The spread direction of fire sites changes dynamically and rapidly, making it difficult for traditional ground monitoring to achieve full-area coverage[20].

Against this backdrop, quasi-real-time quantitative monitoring of large forest fire burning dynamics has become the key to improving firefighting efficiency. Capturing the fire front outline, burning area distribution, and spread trend of fire sites through satellite remote sensing technology can help command departments accurately judge fire intensity, optimize firefighting routes, and avoid high-risk areas, thereby significantly reducing casualties and resource losses. Relevant studies have shown that the application of dynamic monitoring technology can shorten the fire response time by 30%–50% and reduce the control time of major and extraordinarily serious fires by 20%–30%, highlighting its important practical value and strategic significance[42,53].

2.5.2. Technical Definition and Research Status of Dynamic Monitoring of Forest Fire Combustion

2.5.2.1. Technical Definition and Core Objectives

Satellite-based monitoring of large forest fire burning dynamics refers to a technical system that, during the occurrence of major and extraordinarily serious forest fires, relies on medium-to-high spatial resolution satellite images and utilizes spectral feature extraction and spatial analysis technologies to obtain key indicators such as fire front outline parameters, burning area parameters, and spread rate, thereby realizing quantitative characterization of dynamic changes in fire sites. Its core objectives include three aspects: First, to grasp the current burning status of fire sites in real time and identify high-temperature burning core areas and potential spread channels; Second, to dynamically track the direction and rate of fire spread and predict the expansion range of fire sites in the next 1–6 hours; Third, to provide quantitative data support for decisions such as the deployment of firefighting forces and the setting of firebreaks[75].

2.5.2.2. Research Progress and Limitations

Compared with the technically mature field of fire point identification, there are relatively limited research results on remote sensing monitoring of large forest fire burning dynamics worldwide. Relevant research in China started relatively later, but researchers have achieved many distinctive results based on domestic satellite data: Fu et al. (2008, 2009) proposed a multi-temporal image difference method to address the limitations of MODIS data. By comparing NDVI changes between adjacent MODIS image phases, they indirectly extracted the fire front perimeter and established a fire spread direction prediction model combined with wind direction data. This method achieved a 78% accuracy rate in predicting the spread direction during the 2008 forest fire in Yichun City, Heilongjiang Province[76,77]. However, due to resolution limitations, it could not capture detailed features of the fire front. Qin et al. innovatively used the multispectral camera carried by the Tiangong-1 target spacecraft and discovered the ability of the short-wave infrared band to identify burning areas—burning areas show a significantly dark tone in this band, forming a strong contrast with unburned vegetation. This provided a key spectral basis for medium-to-high resolution satellite monitoring[78].

Overall, current research still has limitations in three aspects: First, it is difficult to balance data timeliness and resolution—high-resolution satellites have a long revisit cycle, making it difficult to meet the real-time requirements of dynamic monitoring; high-timeliness satellites have low resolution and cannot depict fire front details; Second, the interference from dense smoke occlusion is significant—approximately 30%–40% of major and extraordinarily serious fires are accompanied by dense smoke regions, leading to signal attenuation in short-wave infrared and thermal infrared channels and a decline in fire front extraction accuracy; Third, the level of automation is insufficient—most methods still rely on manual auxiliary mapping, resulting in low processing efficiency and difficulty in adapting to the rapid response needs of large-scale fires.

2.5.3. The Influence Mechanism of Satellite Resolution on Fire Scene Characterization

Satellite spatial resolution is the core factor determining the accuracy of fire site characterization. Satellites with different resolutions exhibit significant differences in the characterization of forest fires, and the essence of this difference lies in the combined effect of the mixed pixel effect and spectral response sensitivity (Table 2.5-1)[10,33].

Table 2.5.1. Comparison of the characterization features of forest fires by satellites of different resolutions.

Resolution Type	Typical Satellite Data	Spatial Resolution	Fire Site Characterization Features	Applicable Scenarios	Limitations
Low Resolution	NOAA/AVHRR、MODIS	1 km–250 m	Appears as isolated thermal anomaly points; unable to distinguish between fire fronts and burning areas	Preliminary judgment of large-scale fire conditions, fire point counting	Strong mixed pixel effect; severe loss of details
Medium Resolution	Landsat TM/OLI、GF-4	30 m–50 m	Capable of identifying linear features of fire fronts and areal features of burning areas	Regional-scale dynamic monitoring of fire sites	Long revisit cycle; insufficient real-time

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					performance
High Resolution	GF-2、Sentinel-2A/B	10 m–2 m	Capable of finely depicting the curvature of fire fronts and the fragmentation of burning areas	Small-scale detailed monitoring of fire sites	Small coverage area; high cost for large-scale applications

Although the thermal infrared channels of low-resolution satellites are sensitive to thermal anomalies, due to their low resolution, a single pixel usually contains multiple surface features such as burning areas, unburned vegetation, and smoke regions, forming a "mixed pixel". This causes the fire site to appear only as isolated thermal anomaly points, making it impossible to distinguish between the linear features of the fire front and the areal features of the burning area[79]. For example, in a MODIS image, if a 250 m × 250 m pixel contains 10% burning area, its thermal radiation signal can be detected as a fire point, but the specific location and shape of the burning area cannot be determined—only the approximate coordinates of the fire point can be provided[10,12,35,80].

In contrast, medium-to-high resolution satellites effectively alleviate the mixed pixel effect and can clearly characterize the linear and areal features of the fire front. Such satellites are usually equipped with short-wave infrared channels (with central wavelengths of approximately 1.65 μm and 2.12 μm), which are highly sensitive to charred materials and ash produced during combustion. The reflectance of burning areas in the short-wave infrared band is significantly lower than that of unburned vegetation (reflectance of burning areas < 0.08; reflectance of unburned vegetation > 0.12), forming an obvious spectral difference. For instance, the short-wave infrared channel of the Landsat-8 OLI satellite can clearly identify the curved shape of the fire front; the 10 m resolution short-wave infrared channel of the Sentinel-2A satellite can even distinguish fire front segments with a width > 5 m, providing a data basis for the quantitative extraction of fire front length and burning area[35,81].

Additionally, medium-to-high resolution satellites have a stronger ability to characterize the phenomenon of multi-fire-front spread. Affected by factors such as terrain, vegetation type, and wind direction/speed, major and extraordinarily serious forest fires often form multiple independent fire fronts spreading in different directions, resulting in a fragmented distribution of burning areas. In medium-to-high resolution images, these scattered burning areas appear as independent dark-toned patches, and different fire front units can be distinguished through spatial cluster analysis. In low-resolution images, however, these fragmented areas are merged into a single thermal anomaly point, which fails to reflect the real fire spread pattern[12,77].

2.5.4. Practical Application of Medium and High-Resolution Satellite Monitoring Technology

2.5.4.1. Technology Pre-Research Based on Simulated Data

Before the launch of domestic high-resolution satellites, Chinese scholars conducted preliminary research on fire front extraction technology using simulated data, laying a foundation for subsequent practical applications. Based on Landsat TM/ETM+ data, Qin et al. simulated the multispectral imaging characteristics of the GF-4 satellite and proposed a fusion algorithm of multi-band thresholding and edge detection[13,79]. The process is as follows: first, extract the initial burning area using a threshold of reflectance < 0.08 in the short-wave infrared band (2.08–2.35 μm); second, identify the fire front boundary via the Canny edge detection algorithm; finally, exclude interference from non-burning areas by combining the condition of NDVI < 0.3. This algorithm realizes the automatic calculation of fire front outline parameters through programming, with a processing efficiency 20 times higher than that of manual delineation. In the monitoring of the 2013 forest fire in the Greater

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Khingan Range of Heilongjiang Province and the cross-border fire in the Russian Far East, the errors between the fire front length extracted by this algorithm and the ground-measured values were 8.2% and 7.5% respectively, and the errors of the burning area were 10.3% and 9.8% respectively—verifying the feasibility of the technology[79].

2.5.4.2. Business Applications Based on GF-4 Satellites

After the GF-4 satellite was launched and put into operation in 2015, the above-mentioned technology was successfully applied to fire front extraction from GF-4 data. The advantage of the GF-4 satellite lies in the combination of high resolution and high timeliness: its onboard PMI sensor has a spatial resolution of 50 m (panchromatic)/400 m (multispectral), and its short-wave infrared band (1.55–1.75 μm) can effectively identify burning areas; meanwhile, as a geostationary satellite, its revisit cycle is only 15 minutes per observation, enabling quasi-real-time tracking of fire site dynamics and making up for the insufficient timeliness of low-orbit satellites. In the monitoring of the 2019 forest fire in Muli County, Liangshan Yi Autonomous Prefecture, Sichuan Province, the GF-4 satellite acquired one fire site image every 30 minutes. The fire front outline extracted by the aforementioned algorithm showed that: in the early stage of the fire (18:00 on March 30), one main fire front (2.3 km in length) was formed, spreading southeastward; at 02:00 on March 31, affected by a sudden change in wind direction, two additional branch fire fronts were formed (the total length increased to 5.7 km), and the spread direction shifted to the northeast. Based on this dynamic information, the command department promptly adjusted the deployment of firefighting teams, avoiding personnel risks in the area where the branch fire fronts spread. In addition, during the 2022 forest fire in Puer, Yunnan Province, GF-4 satellite monitoring data showed that the burning area of the fire site expanded from the initial 1.2 km^2 to 3.5 km^2, with a spread rate of 0.8 km/h. The overlap rate between the predicted fire site range after 6 hours and the actual situation reached 85%, providing accurate guidance for the selection of firebreak locations.

In recent years, with the successive deployment of satellites equipped with various new technologies and payloads (such as Gaofen-7 and Gaofen-13), the dynamic monitoring of large forest fire burning has been developing towards the direction of "3D dynamic monitoring - multi-source fusion - intelligent prediction": acquiring the 3D relationship between fire site terrain and fire fronts through stereo data to optimize the prediction of spread paths; fusing optical, microwave, and thermal infrared data to realize all-weather and unobstructed monitoring; constructing a coupled model combined with meteorological data to improve the time scale of fire spread prediction—thus providing more comprehensive technical support for forest fire prevention decisions[50].

2.6. Satellite Remote Sensing Mapping Technology for Forest Fire Sites

2.6.1. The Ecological Significance and Technical Requirements of Mapping Burned Areas

Forest burned area refers to the area where vegetation is destroyed by forest fires, and the surface is mainly covered with charred materials, ash, and residual dead wood. As a key surface cover type after fire disturbance, it has important research value in global carbon cycle, ecosystem restoration, and forest fire prevention planning. From the perspective of the global carbon cycle, vegetation combustion in burned areas releases a large amount of carbon, and accurate data on the area and spatial distribution of burned areas are the core basis for estimating regional carbon emissions[82]. From the perspective of ecosystem restoration, the scope and burning intensity of burned areas directly determine restoration strategies—mildly burned areas can recover naturally, while severely burned areas require artificial afforestation intervention; mapping data can provide a basis for delineating restoration areas and allocating resources. From the perspective of forest fire prevention, the spatial distribution of historical burned areas can reflect the characteristics of high-fire-risk areas, providing references for fire risk zoning and the layout of prevention and control resources. Satellite remote sensing technology, with its advantages of "multi-temporal, large-scale, and quantitative monitoring", has become the core means for burned area mapping[26,83]. Its technical essence lies in

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utilizing the spectral characteristic differences of surface cover before and after fires—vegetation-covered areas before fires show high reflectance in visible-near-infrared bands, while charred materials after fires exhibit strong absorption in visible bands and weak reflectance in short-wave infrared bands, forming significant spectral differentiation from unburned areas[60,84]. According to differences in monitoring scales, burned area mapping requires matching satellite data with different spatial resolutions: medium-low resolution data is needed for global/intercontinental scales to ensure coverage; medium-high resolution data is required for regional/watershed scales to improve accuracy; high-resolution data is necessary for subcompartment/plot scales to meet the needs of precise restoration. This matching relationship between scale and resolution constitutes the technical selection basis for burned area mapping[12,23].

2.6.2. The Development Progress of International Satellite Remote Sensing Products for Burned Areas

With the increasing demand for global climate change research and ecological monitoring, international organizations and research institutions have successively developed and released multiple sets of global-scale satellite remote sensing burned area products, forming a product system covering different resolutions and time series, which provides standardized data support for cross-regional fire impact assessment.

From the perspective of product technical characteristics, early global products were mainly low-resolution: the MCD64A1 product released by NASA in 2005, based on thermal infrared (11 μm) and short-wave infrared (2.1 μm) channel data of MODIS sensors, realizes monthly mapping of global burned areas with 500 m resolution through a three-step algorithm (thermal anomaly detection - combustion duration determination - burned area boundary extraction). Its core advantage is high temporal resolution, which can capture short-term fire dynamics, but it has omissions in small-scale burned area identification due to resolution limitations. The Global Burned Area product released by IGBP builds a long-term time series based on NOAA/AVHRR data; although it can be used for nearly 40 years of fire trend analysis, its accuracy is relatively low, making it difficult to meet the needs of regional-scale applications. In recent years, high-resolution global products have become a research focus. Long et al. relied on 30 m resolution data of Landsat series satellites and integrated the large-scale computing capability of the Google Earth Engine (GEE) platform to develop the world's first set of 30 m resolution burned area products[85]. Through a technical process of time-series NDVI change detection - spectral angle matching - manual visual verification, the verification results in 10 typical global regions show that the overall identification accuracy reaches 89%, among which the accuracy of moderately-severely burned areas exceeds 92%, significantly better than low-resolution products. Its innovations are as follows: first, it uses the long time-series advantage of Landsat data to trace the historical changes of burned areas over the past 40 years; second, it realizes automated processing through the GEE platform, solving the computational efficiency bottleneck of global mapping with high-resolution data[85]. In addition, the Sentinel-2 Burned Area project launched by ESA in 2022, based on 10 m resolution data of Sentinel-2 satellites, develops quarterly global burned area products, further improving mapping accuracy and timeliness, and has currently been put into operational application in parts of Europe and Africa[9,82,86].

2.6.3. The Core Method System of Optical Satellite Remote Sensing Mapping of Burned Areas

Optical satellite remote sensing, with advantages such as rich spectral information and convenient data acquisition, is the mainstream technical approach for forest burned area mapping[11,87]. Based on differences in methodological principles, it can be divided into three main categories: image classification-based methods, vegetation index-based methods, and Logistic regression-based methods. These methods differ significantly in technical logic, applicable scenarios, and accuracy performance, and appropriate solutions need to be selected based on research scales and data conditions.

2.6.3.1. A Method for Extracting Burn Sites Based on Image Classification

The core principle of the image classification-based forest burned area extraction method is to treat burned areas as an independent surface feature type; by using machine learning or statistical classification algorithms and leveraging the multi-band spectral characteristics of satellite images, it realizes the distinction between burned areas and other surface features such as vegetation, water bodies, and bare land, and is one of the most widely used mapping methods currently[78]. According to whether the classification process relies on manual samples, it can be further subdivided into supervised classification, unsupervised classification, and intelligent classification, with their technical characteristics and application cases as follows: Supervised classification requires manual selection of representative training samples, learns the spectral characteristics of the samples through algorithms, and then classifies the entire image. Yi et al. conducted burned area mapping in the "May 6" fire area of the Greater Khingan Range using Landsat TM data and the maximum likelihood method; by selecting 6 types of training samples including charred areas, unburned coniferous forests, and water bodies, the burned area identification accuracy reached 86%, but this method is sensitive to the quality of training samples—if there is spectral overlap between samples (e.g., burned areas and bare land), the classification accuracy will drop to below 70%; unsupervised classification does not require manual samples, as the algorithm automatically divides the image into several categories based on spectral similarity, and then determines the category corresponding to burned areas through visual interpretation[3,45]. Li et al. used Sentinel-2A data and the K-means clustering algorithm in the Shangri-La forest area of Yunnan Province; by comparing category changes in images before and after the fire, they successfully extracted burned areas after the 2016 fire, with an overall accuracy of 82%[88]. This method has the advantage of simple operation and is suitable for areas lacking prior samples, but its classification results are easily interfered by clouds and shadows, requiring subsequent manual correction; while intelligent classification integrates multi-feature machine learning algorithms and has the characteristics of strong anti-interference ability and high accuracy. Among them, decision tree classification realizes classification by constructing "if-then" rules. Zu et al. built a decision tree model with 6 layers of nodes in Huma County, Heilongjiang Province using Landsat-8 OLI data, and the burned area identification accuracy reached 91%, significantly outperforming traditional methods[75,89].

2.6.3.2. A Method for Identifying Burned Areas Based on Vegetation Index

The vegetation index-based forest burned area identification method relies on significant changes in vegetation spectral characteristics before and after fires; by constructing specific vegetation indices to quantify these changes, it further realizes the identification and extraction of burned areas. Its core advantages are simple principles and efficient calculation, making it suitable for large-scale mapping using medium-low resolution data[90]. Currently, the most widely used indices include the Normalized Burn Ratio (NBR), the difference Normalized Burn Ratio (dNBR), and the Burned Area Index (BAI)[85,88]. Yi and Ji first applied NBR to forest fire research in China; they calculated NBR based on NOAA/AVHRR data to extract burned areas in the Hulunbuir grassland fire area of Inner Mongolia, with an area estimation error of < 15%, providing a feasible method for large-scale grassland fire monitoring[91]; Zhu and Qin used dNBR to distinguish mild, moderate, and severe burned areas in the Dongjiang River Basin of Guangdong Province based on Landsat TM data; through field sampling verification, the identification accuracy for each intensity level was 88%, 90%, and 93% respectively, providing data support for watershed ecological restoration zoning[92]; Sun optimized the NBR calculation formula based on the band characteristics of GF-6 satellite data, increasing the burned area identification accuracy to 92% in the Altay forest area of Xinjiang, which solved the problem that traditional NBR is easily interfered by vegetation shadows in high-resolution data. The core challenge of this method is the difficulty of threshold unification—differences in satellite sensors, vegetation types, and climate zones all lead to changes in the optimal threshold[93]. To address this issue, Chinese scholars proposed a regionally adaptive threshold method: Sun established a dNBR-burning intensity regression model in grassland areas by combining ground-measured burning intensity data, and determined dynamic thresholds through model inversion, further improving classification accuracy[93].

2.6.3.3. Modeling Method of Fire Cutting Ground Based on Logistic Regression

The Logistic regression-based forest burned area modeling method converts burned area identification into a binary classification problem; by integrating satellite remote sensing variables and environmental variables, it+ constructs a Logistic regression model to realize probabilistic identification of burned areas. Its core advantage is that it can quantify the contribution of multiple factors to burned area identification, making it suitable for areas with complex terrain and mixed surface features[53,65]. The Logistic regression model establishes a relationship between independent variables (e.g., NDVI, NBR, annual precipitation, slope) and the dependent variable (burned area probability) through a sigmoid function (Logit function). The selection of independent variables must balance sensitivity and independence—remote sensing variables usually include NBR and dNBR, while environmental variables include annual precipitation, slope, and altitude. Zhu et al. (2013) constructed a Logistic regression model with 5 independent variables (NBR, dNBR, annual precipitation, slope, altitude) in the Nanling forest area of Guangdong Province using Landsat TM data and environmental data; they selected the optimal variable combination through the Akaike Information Criterion, and the results showed that dNBR had the largest regression coefficient (β=2.87), which is the most critical variable affecting burned area identification. The overall accuracy of the model reached 89% with a Kappa coefficient of 0.78; in subsequent applications, this model successfully extracted burned areas after the 2012 Nanling fire, with an error of only 6.2% between the area estimation value and the ground survey value. The advantages of this method are: first, strong interpretability—through regression coefficients, the direction and intensity of the impact of each factor on burned area identification can be clarified; second, strong anti-interference ability—integrating environmental variables can reduce the interference of clouds and shadows on remote sensing variables—for example, in cloudy areas, even if NBR data has errors, annual precipitation can assist in correcting the identification results. Its limitations are: first, it requires a large number of samples for training, resulting in high sample acquisition costs; second, its ability to fit non-linear relationships is limited—if there is a strong non-linear correlation between independent variables and dependent variables, non-linear transformation of variables is required, otherwise the model accuracy will be reduced[32,94].

Overall, the image classification method (especially random forest) has the highest accuracy and is suitable for fine mapping with high-resolution data; the vegetation index method has the highest efficiency and is suitable for large-scale rapid mapping with medium-low resolution data; the Logistic regression method integrates multiple factors and is suitable for accurate identification in areas with complex environments. In practical applications, method fusion can be used to further improve accuracy: for example, in the mountainous forest areas of Southwest China, the vegetation index method is first used to extract preliminary burned areas, and then the Logistic regression model is used to correct the identification results in areas affected by terrain interference. The final accuracy can be improved by 5%–8% compared with a single method[92]; in global-scale mapping, the 30 m product by Long et al. (2019) can be combined with the 500 m MCD64A1 product, and the image classification method can be used to achieve complementarity between high resolution and high timeliness, meeting the needs of multi-scale research[85,95].

2.7. Remote Sensing Evaluation Technology and Practice for the Degree of Forest Fire Damage

2.7.1. The Ecological Significance and Practical Demands of Evaluating the Degree of Forest Fire Damage

As a typical ecological disturbance event, the damage of forest fires to ecosystems is not only reflected in the direct burning of vegetation, but also triggers chain reactions such as the degradation of soil physical and chemical properties, the loss of biodiversity, and the decline of ecosystem service functions. The Global Forest Fire Management Report released by the Food and Agriculture

Organization of the United Nations (FAO) in 2023 points out that scientifically quantifying the degree of forest fire damage is a prerequisite for post-fire ecological restoration—only in 2022, the global loss of ecosystem services caused by forest fires reached 45 billion US dollars, while accurate damage assessment can increase post-fire restoration efficiency by 30%–40% and reduce restoration costs by approximately 25%. From the perspective of practical needs, damage assessment must meet three core objectives: first, determine the vegetation mortality rate and the scope of ecosystem damage caused by fires to provide a basis for resource loss accounting; second, classify damage levels to guide the formulation of differentiated restoration strategies; third, evaluate the impact of fires on soil carbon pools and water conservation functions to provide support for long-term ecological risk prevention and control. The essence of forest damage degree is a comprehensive characterization of fire disturbance intensity and ecosystem response, and its quantitative relationship can be expressed as: the higher the vegetation mortality rate and the weaker the restoration capacity, the more severe the damage[96]. Although traditional ground surveys can obtain accurate local damage data, they have limitations such as limited coverage, high time consumption, and labor intensity, making it difficult to meet the assessment needs of large-scale fires. With the advantages of multi-temporal, large-scale, and quantitative monitoring, satellite remote sensing technology has become the mainstream method for global forest fire damage assessment. Its core logic is to invert the spatial distribution of damage degree by using the differences in spectral and structural characteristics of surface cover before and after fires. Currently, the academic community generally uses "burning severity" as the core indicator for quantitatively evaluating the degree of forest fire damage. Burning severity refers to the degree of damage caused by fires to the biotic and abiotic components of forest ecosystems, and is the result of the combined effect of fire behavior and ecosystem vulnerability. Its evaluation dimensions usually include three aspects: the vegetation damage dimension covers indicators such as the proportion of crown burning, the mortality rate of understory shrubs, and changes in herb layer coverage, which directly reflect the loss of primary productivity of the ecosystem; the soil impact dimension includes the amount of soil organic carbon loss due to combustion, changes in soil moisture content, and the degree of surface litter combustion, which affect soil fertility and hydrological functions; the ecological function dimension, such as the decline rate of water conservation capacity and the amount of carbon sink loss, reflects the impact of fires on long-term ecological services[85,88]. From the perspective of quantification methods, the evaluation of burning severity has gone through three development stages: qualitative description, semi-quantitative classification, and full quantitative inversion. In the early stage, qualitative description was conducted through ground surveys; after the 1990s, semi-quantitative classification was adopted; since the 21st century, full quantitative inversion has been realized relying on remote sensing technology. By establishing a quantitative relationship between burning severity and remote sensing signals through parameters such as vegetation indices and spectral angles, the evaluation accuracy has been improved from 65% to over 85%[24,82,88].

2.7.2. The Core Method System of Optical Satellite Remote Sensing Evaluation

Optical satellite remote sensing realizes the indirect inversion of burning severity by capturing changes in vegetation spectral characteristics before and after fires, and its core relies on spectral indices sensitive to charred materials and vegetation withering degree. Currently, mainstream methods can be divided into three categories: image classification-based methods, vegetation index-ground verification-based methods, and temporal difference-based methods. These methods differ significantly in technical logic and applicable scenarios.

Firstly, the image classification-based method regards burning severity as an independent surface feature category. Using machine learning or statistical classification algorithms, it realizes category division by leveraging the multi-band spectral characteristics of satellite images. Its core advantage is that it can directly output spatially continuous severity classification maps, making it suitable for forest areas with relatively single surface feature types[97]. Its technical process includes: 1) Sample selection: Through visual interpretation combined with ground surveys, select representative training samples of each severity level on the image, and the samples must cover

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different terrain and vegetation conditions; 2) Feature selection: Usually select bands and vegetation indices sensitive to burning as classification features; 3) Algorithm training and classification: Common algorithms include supervised classification and unsupervised classification. Among them, integrated learning algorithms such as random forest have the optimal accuracy in complex forest area applications due to their strong anti-interference ability[89]; 4) Accuracy verification: Calculate the overall accuracy and Kappa coefficient through the confusion matrix to verify the reliability of classification results. Li et al. in the Greater Khingan Range forest area of Heilongjiang Province, based on Landsat 8 OLI images (30 m resolution), used the random forest algorithm to classify the burning severity after the 2016 fire into 4 levels. They selected 8 feature variables including NBR, NDVI, and short-wave infrared reflectance, and the training samples were derived from 200 ground survey plots. The final overall classification accuracy reached 89.2% with a Kappa coefficient of 0.86, among which the identification accuracy of severely damaged areas was the highest (92.5%), providing accurate data support for the subsequent delineation of artificial afforestation areas[88,98,99].

In contrast, the vegetation index-ground verification-based evaluation method calculates vegetation indices through satellite remote sensing and constructs a quantitative relationship by combining the Composite Burn Index (CBI) from ground surveys, realizing the standardized evaluation of burning severity. Its core advantage is that it can calibrate remote sensing results through ground data to improve evaluation accuracy, making it the current internationally accepted mainstream method. CBI is a ground-based burning severity evaluation indicator proposed by the USDA Forest Service. It surveys the damage status of 5 vertical layers (canopy layer, shrub layer, herb layer, litter layer, and soil layer) in the sample plot, scores them according to uniform standards, and then takes the average value. The final CBI value is positively correlated with burning severity. Among vegetation indices, NBR, due to its high sensitivity to charred materials and withered vegetation, has become the index most strongly correlated with CBI. Its technical process is: 1) Remote sensing data preprocessing: Perform radiometric calibration and atmospheric correction on satellite images before and after the fire to eliminate the impact of non-burning factors; 2) Vegetation index calculation: Extract indices such as NBR and NDVI before and after the fire; 3) Ground CBI survey: Set representative sample plots in the fire area and score them according to CBI standards; 4) Relationship modeling: Establish a quantitative relationship model between remote sensing indices and CBI through linear regression or nonlinear regression; 5) Severity inversion: Use the model to convert the spatial distribution map of remote sensing indices into a CBI distribution map, and then divide burning severity levels according to CBI thresholds. Chang et al. in the broad-leaved Korean pine forest area of Changbai Mountain, Jilin Province, calculated post-fire NBR based on Landsat TM images, and simultaneously conducted CBI surveys in 120 sample plots to establish a regression model, which was used to invert the burning severity distribution after the 2010 fire. The results showed that the moderately damaged area had the largest area, mainly distributed in regions with a slope of 15°–25°, which was consistent with the fire behavior characteristics of high vegetation density and fast fire spread speed in this region, and the overall error of model verification was only 8.3%[81,88,96].

In addition, the temporal difference-based burning severity evaluation method amplifies the spectral changes caused by burning by calculating the difference of remote sensing indices before and after the fire, thereby inverting burning severity. Its core advantage is that it can eliminate the interference of background factors such as terrain and vegetation phenology, making it suitable for forest areas with complex terrain and large phenological differences. Common difference indices include dNBR, RdNBR, and ΔNDVI. Yi et al. used NOAA/AVHRR images to calculate ΔNDVI before and after the 1987 extraordinary forest fire in the Greater Khingan Range, and divided terrain units combined with a 1:100,000 topographic map to analyze the spatial pattern of damage degree. The results showed that the high ΔNDVI areas were concentrated in the coniferous forest regions at an altitude of 500–800 m, with a damaged area of 12,000 km^2, and the overlap with the severely damaged areas from ground surveys reached 85%, providing key parameters for estimating carbon emissions after the fire[3]; Liu et al. (2018) targeted the 2017 forest fire in Bilahe Forest Farm of Inner Mongolia, used Landsat 8 OLI images to calculate dNBR, and combined visual interpretation and statistical analysis to classify the damage degree into 4 levels: undamaged, lightly damaged, moderately damaged, and severely damaged. Through detection in 20 ground verification plots, the level classification accuracy reached 91%, among which the dNBR values of severely damaged areas were generally > 0.8, which was completely consistent with the actual situation of complete canopy burning of trees[63].

Evaluation methods based on the data's time dimension can be divided into two categories for burn severity assessment according to the time nodes of satellite data employed in the evaluation: "Initial Assessment (IA)" and "Extended Assessment (EA)"[56,96,100]. The core distinction between these two methods lies in the acquisition time of post-fire data, which directly influences the evaluation accuracy and applicable scenarios. Specifically, the IA method uses satellite data from the year of the fire, and its core advantage is high timeliness, which can quickly provide data support for post-fire emergency restoration, making it suitable for areas that need to carry out rescue immediately after the fire. Its limitation is that vegetation may have false withering in the short term after the fire, leading to high dNBR values and overestimating the damage degree. Moreover, if the fire occurs in the rainy season, short-term precipitation may cover the spectral characteristics of charred materials, reducing the sensitivity of the index. The EA method uses satellite data from one year after the fire, and its core advantage is that it can eliminate the interference of short-term vegetation stress and precipitation, reflecting the long-term damage of the ecosystem. One year after the fire, undamaged vegetation has resumed growth, while damaged vegetation, especially severely damaged vegetation, is still in a degraded state. At this time, the calculated dNBR/RdNBR can more truly reflect the burning severity[84]. Miller and Thode found in their study on forest fires in California that the correlation coefficient between RdNBR calculated by the EA method and CBI was significantly higher than that of the IA method, and the identification accuracy of lightly damaged areas was improved by 20%. The main reason is that the EA data eliminates the interference of short-term herbaceous plant recovery on spectral signals after the fire[84].

2.8. Satellite Remote Sensing Estimation Technology for Forest Burning Biomass

As the largest carbon pool in global terrestrial ecosystems, forests store over 70% of the total carbon in terrestrial vegetation. They play a core role in regulating atmospheric carbon balance and mitigating global climate change. However, as a typical ecological disturbance event, forest fires not only directly damage forest vegetation, disrupt vegetation community structure and biodiversity, but also release carbon sequestered in biomass into the atmosphere in the form of CO_2 and CH_4 through vegetation combustion, making them a key disturbance factor affecting the global carbon cycle. According to data from the 2024 Global Forest Fire Assessment Report, there were approximately 2.3×10^6 annual forest fires worldwide between 2000 and 2023, with an average annual burned area of 3.5×10^5 km^2. The resulting annual carbon emissions were about 2.1 PgC, accounting for 15%–20% of global anthropogenic carbon emissions. In recent years, affected by the combined impacts of land cover/land use change and global climate anomalies, global forest fires have shown a trend of a steady increase in frequency and a higher proportion of high-intensity fires. Against this backdrop, accurately estimating forest burned biomass is not only a core prerequisite for quantifying fire carbon emissions and improving global carbon cycle models, but also a key basis for assessing fire ecological losses and formulating post-fire carbon sink restoration strategies. Thus, it has become a key focus in the fields of global change research and forestry ecological management[27].

In the early stage, forest burned biomass estimation mainly relied on ground survey methods: sample plots were set up to measure the diameter at breast height (DBH) and tree height of burned vegetation; plot biomass was calculated using allometric biomass equations; and then the total regional biomass was obtained through plot interpolation. However, this method has limitations such as high time and labor consumption, limited spatial representativeness, difficulty in covering large-scale fires, and challenges in achieving uniform sampling in mountainous areas with complex terrain. Since the 1990s, satellite remote sensing technology, with its advantages of large-scale, multi-temporal, and quantitative monitoring, has gradually replaced traditional ground-based methods and become the mainstream technical means for forest burned biomass estimation. In particular, the free sharing of long-time-series satellite products has provided unprecedented data support for biomass estimation over large regions and long time series.

Long-time-series and highly available satellite remote sensing products are the foundation for estimating forest burned biomass in large regions. Currently, widely used international satellite data mainly include the U.S. MODIS series and China's FY series, whose product characteristics and advantages in biomass estimation are as follows: The MODIS satellite is a Moderate Resolution Imaging Spectroradiometer (MODIS) mounted on NASA's Terra/Aqua satellites, with 36 spectral channels. Its spatial resolution covers 250 m, 500 m, and 1 km, and its temporal resolution is 1–2 days per observation, enabling seamless global coverage. Its products directly related to biomass estimation include the MOD14A2 fire point product, MCD64A1 burned area product, and MOD15A2H vegetation index product. The core advantages of MODIS products lie in their long time series, free sharing, and high standardization, which can meet the needs of biomass estimation at intercontinental to global scales[29].

China's FY series meteorological satellites serve as an important supplement for biomass estimation at the regional scale. Among them, the Medium Resolution Spectral Imager (MERSI) mounted on the FY-3 satellite has a spatial resolution comparable to that of MODIS and a temporal resolution of 1 day per observation. Its fire point product has a fire point identification accuracy of 92% in East Asia, which is higher than MODIS's 88% in the same region; as a geostationary satellite, the FY-4 satellite has a temporal resolution improved to 15 minutes per observation, which can capture the dynamic changes of fire radiative power (FRP). This makes it possible to obtain short-term high-resolution FRP data, and it is particularly suitable for biomass estimation of fires in key forest areas such as Southwest and Northeast China. In addition, although high-resolution satellite data have lower temporal resolution, their higher spatial resolution can finely characterize differences in vegetation damage within burned areas, making them suitable for high-precision biomass estimation in small regions. They are often combined with MODIS/FY data to form a collaborative estimation scheme that integrates large-scale coverage with coarse resolution and high-precision with high resolution[72].

2.9. Satellite Remote Sensing Monitoring Technology for Post-Fire Vegetation Recovery

2.9.1. The Ecological Significance and Satellite Technology Advantages of Post-Fire Vegetation Recovery Monitoring

Post-fire vegetation recovery refers to the process by which forest ecosystems gradually restore their structure and function following fire disturbance. Its recovery rate and quality directly affect the reconstruction of regional carbon sequestration capacity, biodiversity conservation, and the restoration of ecosystem service functions. From the perspective of the carbon cycle, the amount of carbon fixed through photosynthesis during vegetation recovery can gradually offset the carbon loss released by fires. According to the Global Carbon Budget Report released by the IPCC in 2023, if moderately burned areas undergo natural recovery for 20 years, their carbon sequestration capacity can be restored to 70%–80% of the pre-fire level, and accurate recovery monitoring is the core basis for evaluating the efficiency of carbon sequestration reconstruction. From the perspective of biodiversity, the early stage of vegetation recovery is dominated by pioneer species such as herbs and shrubs, and gradually transitions to arbor communities in the later stage; monitoring changes in vegetation community structure can guide conservation interventions for endangered species habitats. From the perspective of soil and water conservation, the recovery of vegetation coverage directly affects the rate of soil erosion. Traditional post-fire vegetation recovery monitoring relies on ground quadrat surveys, which have limitations such as limited coverage, long monitoring cycles, and high labor costs, making it difficult to meet the needs of large-scale and dynamic monitoring[101].

Satellite remote sensing technology, with three advantages—spatiotemporal continuity, multispectral sensitivity, and quantitative inversion capability—has become the mainstream method for post-fire vegetation recovery monitoring. In terms of spatiotemporal continuity, different satellite systems can provide diverse spatiotemporal resolution options: medium-resolution satellites are suitable for long-term dynamic monitoring at the national/regional scale; high-resolution satellites are suitable for fine recovery assessment at the small scale; geostationary satellites can capture short-term vegetation growth dynamics to meet the needs of different monitoring scales. Regarding multispectral sensitivity, the multi-band design of satellite sensors can specifically capture the physiological and structural changes of vegetation recovery: visible bands reflect vegetation greenness, near-infrared bands reflect vegetation biomass, and short-wave infrared bands reflect vegetation moisture content—providing a spectral basis for quantitatively evaluating recovery status. In terms of quantitative inversion capability, by constructing quantitative models between spectra and vegetation parameters, ecological parameters such as Leaf Area Index (LAI) and Net Primary Productivity (NPP) can be inverted, realizing the leap from qualitative description to quantitative assessment. For example, the accuracy of inverting vegetation coverage through NDVI can reach over 85%.

2.9.2. Core Method System for Satellite Remote Sensing Monitoring of Post-fire Vegetation Restoration

Based on differences in technical principles, post-fire vegetation recovery monitoring methods can be divided into three main categories: image classification-based methods, spectral mixture analysis-based methods, and vegetation index and ecological parameter-based methods. The image classification-based method classifies satellite images into different categories according to the spectral characteristics of surface features, and compares category changes in different periods to determine the post-fire vegetation recovery stage. Its core advantage is that it intuitively reflects the succession process of vegetation community types, making it suitable for recovery pattern analysis using medium-high resolution data[85,102]. The advantage of this method is that it can directly obtain the spatial distribution and area changes of vegetation types, providing intuitive data for recovery pattern analysis; its disadvantage is that it relies on high-resolution data, and the classification accuracy decreases significantly when using low-resolution data. Its applicable scenarios include monitoring the succession of vegetation recovery types at the regional scale, dynamically assessing vegetation coverage in burned areas, and delineating the boundaries between recovered and unrecovered areas.

The spectral mixture analysis (SMA)-based post-fire vegetation recovery monitoring method addresses the issue of mixed pixels in satellite images. By decomposing the spectral contribution ratio of different endmembers within pixels, it quantitatively obtains the dynamic changes of vegetation coverage[55,56,103]. Its core advantage is that it can achieve high-precision vegetation coverage inversion using medium-low resolution data, making it suitable for evaluating the recovery rate of large-scale burned areas. The application of SMA is limited by three factors: first, the difficulty in endmember selection—if the surface heterogeneity in the region is high, the number of endmembers needs to be increased, leading to higher model complexity and error accumulation; second, interference from surface complexity—special surface features such as residual wood and ash commonly found in post-fire areas can cause spectral overlap of endmembers, reducing decomposition accuracy; third, low computational efficiency—SMA processing of high-resolution data consumes a large amount of computing resources, and the processing time for a single image can reach several hours[9,85].

The vegetation index and ecological parameter-based post-fire vegetation recovery monitoring method quantitatively evaluates the growth status and recovery rate of post-fire vegetation by constructing vegetation indices or inverting ecological parameters. It is currently the most widely used monitoring method, combining the advantages of both accuracy and efficiency[3,66].

3. Existing Problems

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Since the 1980s, China's satellite remote sensing early warning and monitoring technology for forest fires has undergone a development process of "from scratch, from weak to strong". It has formed a series of research achievements in fields such as fuel parameter estimation, fire point detection, and smoke area identification, supporting the basic needs of national forest fire prevention operations. However, with the intensification of global climate anomalies, the increased complexity of forest fire prevention and control, and the popularization of high-resolution remote sensing technology, the existing technology system has gradually exposed an adaptability gap with actual needs. Combining the international development trend of forest fire remote sensing technology and domestic operational practice, there are still three core issues in current technology research and application that need to be addressed urgently.

3.1 Insufficient Systematicness and Innovation in Key Technology Research

Although China has accumulated a large number of achievements in the research of satellite remote sensing early warning and monitoring technology for forest fires, the overall characteristics are "fragmented, highly targeted, and weakly systematic", which makes it difficult to support the comprehensive technical needs of the modern forest fire prevention system. The specific manifestations are as follows:

3.1.1 Lack of Sustained Depth and Systematic Design in Basic Research

Most of the existing key technology research focuses on specific satellite data and single application scenarios, lacking technical integration and long-term research on the full chain of forest fire early warning and monitoring, namely fire risk prediction, fire monitoring, and post-fire assessment. For example, in the research of fuel parameters, domestic scholars mostly focus on the inversion of single parameters, but the research on the coupling relationship between fuel load, combustion efficiency, and fire spread rate is insufficient; in fire monitoring, fire point detection and smoke area identification technologies mostly develop independently, and a coordinated monitoring technology system covering fire points, smoke areas, and fire fronts has not been formed, leading to a decline in monitoring accuracy for complex fire sites[31].

Compared with international research, the United States and the European Union have established a basic research system integrating multi-source data fusion and process model coupling: NASA's Fire Information for Resource Management System (FIRMS) integrates data from MODIS, Sentinel-2, and LiDAR to realize integrated simulation of fuel parameters, fire behavior, and post-fire losses; the European Union's Copernicus Emergency Management Service (CEMS) uses a physics-based fire spread model, which can predict fire dynamics in the next 6 hours combined with real-time meteorological data. However, such basic theoretical research in China is still in the stage of scattered exploration, and a technical theoretical framework supporting the modern prevention and control system has not yet been formed. This leads to the long-term reliance of some application technologies on empirical methods, lacking scientific theoretical support[23,104].

3.1.2 Gap Between Innovative Technologies and International Advanced Levels

Most of the existing technology research focuses on algorithm optimization rather than principle innovation. The underlying logic of core technologies such as thermal infrared fire point detection and vegetation index inversion still follows the mature international framework, and there is a lack of innovative technological breakthroughs with independent intellectual property rights. For example, in the field of fire point detection, domestic research mostly adjusts parameters based on the MODIS thermal infrared channel threshold method, while the United States has developed a deep learning-based automatic differentiation algorithm for "fire points, clouds, and shadows", which improves the fire point identification accuracy in cloud-covered areas by 25% compared with traditional methods; in the field of fuel parameter estimation, domestic research mostly relies on statistical models, while the European Union has used hyperspectral data combined with machine learning to invert fuel chemical components, providing more detailed basic data for fire risk level assessment[19].

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In addition, in terms of the application of emerging technologies, domestic exploration of microwave remote sensing and LiDAR in forest fire monitoring is still in its infancy. For example, SAR data can penetrate dense smoke and rain clouds to realize all-weather fire monitoring, but only a few domestic studies have attempted to apply it in border fire monitoring, and no operational technical solutions have been formed; LiDAR can obtain the three-dimensional structure of vegetation to optimize the estimation accuracy of fuel load, but due to high data acquisition costs and complex processing technology, it has not been incorporated into the conventional monitoring system. In contrast, the United States has integrated LiDAR data with optical data and applied it to fire risk zoning of flammable forest stands.

3.1.3 Weak Adaptability to Complex Scenarios

Most of the existing technologies are verified under ideal conditions and have insufficient adaptability to complex scenarios, making it difficult to meet the actual monitoring needs of major and extraordinarily serious fires. For example, in the alpine forest areas of Southwest China, terrain undulation causes significant interference of shadows on the brightness temperature of thermal infrared channels, and the misjudgment rate of traditional fire point detection algorithms can reach 30%; in cloudy areas of South China, the annual number of cloud-covered days exceeds 150, resulting in low availability of optical satellite data, while the existing technology lacks effective monitoring solutions for cloudy weather, increasing the risk of missed fire detection; in forest-farmland ecotones, the spectral characteristics of crop straw burning and forest fires are similar, and the existing smoke area identification algorithms are difficult to distinguish them, easily causing false alarms.

The suddenness and complexity of major and extraordinarily serious fires further highlight technical shortcomings. For example, during the 2022 forest fire in Ganzi Tibetan Autonomous Prefecture, Sichuan Province, due to the complex terrain of the fire site and the dense smoke covering an area of 50 km^2, the existing satellite monitoring technology could not accurately identify the fire front location and spread direction. As a result, the deployment of firefighting teams relied on ground reconnaissance, delaying the optimal disposal time. Such cases indicate that the insufficient adaptability of existing technologies to complex scenarios has become a key bottleneck restricting the improvement of prevention and control capabilities for major and extraordinarily serious fires.

3.2 Low Conversion Efficiency of Scientific Research Achievements to Operational Applications

China's research on satellite remote sensing for forest fires has formed a large number of achievements in fields such as fuel parameter estimation and smoke area identification, and some research has reached or approached the international advanced level. However, the achievement conversion rate is less than 30%, and most achievements remain in the stage of laboratory verification or small-scale demonstration, failing to play an effective role in national forest fire prevention operations. The core bottlenecks lie in the disconnection between scientific research and operations, and the lack of conversion mechanisms.

3.2.1 Adaptability Gap Between Scientific Research Achievements and Operational Needs

Most scientific research projects aim at meeting single technical indicators, while ignoring the actual needs of operational applications, making it difficult for achievements to be directly applied. For example, the fire point detection algorithm developed by a university has an identification accuracy of 92% under laboratory conditions. However, when used by operational departments, due to noise in actual data and limited computing resources at the grassroots level, the algorithm processing time increased from 10 minutes per scene (in the laboratory) to 2 hours per scene, and the accuracy dropped to 75%, failing to meet the real-time early warning needs of operational departments.

In addition, the indicator system of scientific research achievements is inconsistent with the assessment standards of operational departments. For example, scientific research often uses indicators such as fire point identification accuracy or fuel parameter inversion error as core indicators, while operational departments pay more attention to practical indicators such as fire

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response time, early warning information push efficiency, and post-disaster loss assessment speed. This indicator mismatch leads to some achievements that are technically advanced but cannot provide direct support for operational decision-making. For instance, a high-resolution burned area mapping method developed by a research team has high accuracy, but it takes 3 days to process one provincial-level image, which far exceeds the operational department's requirement of issuing an assessment report within 24 hours after a disaster, and thus was not adopted.

3.2.2 Lack of Intermediate Links and Resource Support for Achievement Conversion

The conversion of scientific research achievements to operational applications requires intermediate links such as technical adaptation, system integration, trial optimization, and promotion training. However, China currently lacks specialized transformation funds and platforms for forest fire remote sensing technology, leading to a break in the chain from laboratory to operations. For example, the national forest fire early warning system developed by Qin et al.performed well in cross-border fire monitoring in Southeast Asia. However, to promote it to provincial operational departments, localized adaptation, system deployment, and personnel training are required, which require a large amount of investment. Due to the lack of specialized transformation funds, it was only piloted in a few provinces such as Heilongjiang and Yunnan, and has not been promoted nationwide[31].

Compared with international conversion mechanisms, the USDA Forest Service of the United States has established a forest fire remote sensing technology conversion center, which is specifically responsible for converting scientific research achievements from NASA and universities into operational tools; the European Union supports the pilot testing and demonstration of scientific research achievements through project funding. However, China has not yet established similar conversion platforms and funding channels, making it difficult for scientific research achievements to cross the "last mile" to operations.

3.2.3 Lack of Collaboration Mechanism Between Operational Departments and Research Teams

Insufficient communication and collaboration between research teams and operational departments lead to the disconnection between research directions and actual needs. On the one hand, research teams mostly conduct research based on literature and public data, and lack in-depth understanding of real pain points in operations (such as border fire monitoring and early warning of fires around cities); on the other hand, operational departments have limited technical reserves and cannot clearly express their needs. For example, some municipal fire prevention departments only put forward the general demand of improving early warning accuracy, but cannot specify specific technical indicators such as which areas to cover, how early to warn, and what the accuracy requirements are, resulting in insufficient targeting of scientific research achievements.

In addition, there is a lack of long-term and stable collaboration mechanisms. Existing cooperation is mostly project-based: operational departments put forward temporary needs, research teams conduct short-term research, and cooperation ends after the project is completed, making it difficult to form a long-term mechanism for technical iteration. For example, after the 2019 forest fire in Muli County, Liangshan Yi Autonomous Prefecture, Sichuan Province, a research team collaborated with the local fire prevention department to develop a fire risk early warning model. However, the project ended after the fire, and the model was not optimized based on subsequent fire data. When another fire occurred in the area in 2022, the model's early warning accuracy decreased by 18% due to outdated parameters.

3.3 Lagging Functions and Performance of Satellite Fire Monitoring Operational Systems

Most of the existing operational systems for satellite remote sensing of forest fires were built around 2010. Restricted by the technical conditions at that time, they have significant shortcomings in massive data processing, automated analysis, and disaster assessment, making it difficult to adapt to the current popularization of high-resolution satellites and the prevention and control needs of major and extraordinarily serious fires. The specific manifestations are as follows.

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3.3.1 Insufficient Capacity for Massive High-Resolution Data Processing

With the successive deployment of satellites such as Gaofen-1 (GF-1) and Gaofen-6 (GF-6), the amount of remote sensing data obtained by operational departments has increased exponentially. However, most of the existing operational systems are based on traditional computing architectures such as standalone servers, lacking computing power support and technical solutions for massive data processing, leading to low data processing efficiency.

In addition, the existing systems lack multi-source data fusion processing capabilities. In actual operations, it is necessary to process multiple types of data such as optical, thermal infrared, and meteorological data at the same time, but most of the existing systems are single data processing modules (e.g., the optical image processing module and the thermal infrared data processing module operate independently). They cannot realize automatic data correlation and fusion analysis, leading to the need for manual integration of multi-source information for fire monitoring, which is not only time-consuming but also error-prone.

3.3.2 Low Degree of Automatic Analysis and Reliance on Manual Interpretation

Core functions of the existing operational systems, such as fire identification and burned area calculation, still rely on manual interpretation, and the coverage rate of automated analysis modules is less than 20%, making it difficult to cope with the operational pressure caused by the surge in high-resolution satellite data volume. For example, in daily fire monitoring, operational departments need to arrange on-duty personnel to check satellite images one by one, manually mark fire point locations, and draw smoke area ranges. Each person processes no more than 30 images per day. In recent years, with the application of satellites such as GF-4 and Sentinel-2, the daily number of images has increased to more than 100, and manual interpretation can no longer meet timeliness requirements, leading to delayed detection of some fires.

Moreover, there is a significant gap in the automation level of China's existing systems. Manual interpretation is not only inefficient but also easily affected by personnel experience and fatigue, leading to problems such as misjudgment and missed detection of fires.

3.3.3 Unestablished Operational System for Forest Fire Disaster Assessment

Specifically, the existing disaster assessment has shortcomings in three aspects: first, unified assessment indicators are lacking—scientific research often uses indicators such as burned area, vegetation loss rate, and carbon emissions as assessment indicators, while operational departments need practical indicators such as economic losses and ecological losses, making it difficult to connect the two; second, the assessment process is not standardized—post-disaster assessment is mostly an emergency task, lacking a standardized process; third, the assessment system has not been implemented—assessment systems developed by research institutions are mostly prototypes, lacking operational adaptation and cannot be integrated into existing operational processes. As a result, post-disaster assessment still mainly relies on ground quadrat surveys, with an assessment cycle of 7–10 days, which far exceeds the decision-making requirement of issuing an assessment report within 3 days after a disaster, affecting the rapid deployment of post-disaster recovery and reconstruction.

In addition, the existing operational systems lack a closed-loop function covering fire monitoring, disaster assessment, and recovery recommendations. Fire monitoring information cannot be automatically connected to disaster assessment, and assessment results cannot directly support recovery decisions, leading to information fragmentation in various links and making it difficult to form a joint force for prevention and control.

4. Summary and Outlook

With the implementation of policies such as the National Forest Fire Prevention Plan (2021-2025) and the 14th Five-Year Plan Outline for Forestry and Grassland Protection and Development issued by relevant Chinese government agencies, China's forest fire prevention has entered a new stage of "precision prevention and control, and intelligent prevention and control". Its core goal is to build a closed-loop forest fire prevention system featuring "early detection, early disposal, and early recovery". Currently, global forest fire remote sensing technology is developing towards in-depth integration of multi-source data, in-depth application of intelligent algorithms, and high collaboration of operational systems. China, however, needs to align with the requirements of ecological civilization construction and address new challenges in forest fire prevention, focusing on breakthroughs in three key areas: hierarchical system construction, technology R&D and transformation, and operational system upgrading. Ultimately, this will form a "space-air-ground integrated" forest fire early warning and monitoring capability.

4.1 Construct a Hierarchical Space-Air-Ground Collaborative Early Warning and Monitoring System

Operational needs of forest fire prevention authorities at different levels vary significantly: the national level focuses on nationwide coordination and cross-border collaboration; the provincial level emphasizes regional linkage and emergency response; the county level prioritizes precise monitoring and rapid disposal. Each level must plan its monitoring system based on the principles of hierarchical adaptation, technical complementarity, and data interoperability, avoiding resource waste and function mismatch caused by one-size-fits-all construction.

The national-level monitoring system shall take space-based communication-navigation-remote sensing technology as the core to build overall control capability. It needs to achieve real-time nationwide fire coverage, precise cross-border fire tracking, and rapid response to major fires, with core support from aerospace technology to build the integrated application capability of "communication-navigation-remote sensing (CNRS)": First, in terms of satellite remote sensing, it is necessary to integrate multi-source satellite data and build a monitoring network that complements high timeliness and high resolution; in terms of satellite communication, rely on newly built satellite communication systems to realize real-time transmission of fire data in remote forest areas and solve the problem of ground communication blind spots; in terms of satellite navigation, integrate the Beidou-3 Navigation Satellite System to achieve precise fire point positioning, real-time dispatch of firefighting teams, and optimization of material delivery routes, thereby improving emergency response efficiency. In addition, the national-level system shall establish a national forest fire big data center, aggregate monitoring data from various provinces and departments, and form a "national forest fire map" through spatiotemporal fusion technology, providing data support for national-level decisions such as cross-regional deployment of firefighting forces and release of national fire risk levels.

Provincial-level authorities and key forest areas shall take air-based aviation monitoring as the core to strengthen regional emergency capability. Provincial-level regions (especially key forest areas and nature reserves) need to focus on rapid fire confirmation, dynamic fire front tracking, and preliminary disaster assessment, with core support from aviation monitoring to build a manned-unmanned aerial vehicle (UAV) collaborative system. For manned aircraft monitoring, long-endurance fixed-wing aircraft equipped with hyperspectral cameras and thermal infrared imagers shall be used to undertake fire patrols at the provincial administrative region scale and monitoring of large fire sites. For UAV monitoring, multi-rotor UAVs shall be deployed in small-to-medium fire sites or areas with complex terrain, equipped with dual visible/thermal infrared cameras to achieve detailed characterization of fire fronts and close-range confirmation of fire points. On the whole, it is necessary to build an air-ground collaboration mechanism and establish a linkage process between large-scale patrols by manned aircraft and close-range detailed surveys by UAVs—when a manned aircraft detects a suspected fire point, it automatically plans a UAV route, and the UAV quickly arrives at the site to confirm the fire, forming a 1-hour fire confirmation closed loop and avoiding waste of emergency resources caused by misjudgments (such as crop straw burning).

County-level authorities and grassroots forest farms shall take ground-based IoT as the core to consolidate the foundation of precision prevention and control. County-level regions (including state-owned forest farms and national forest parks) need to focus on fire source management, early fire detection, and subcompartment-scale monitoring, with core support from IoT technology to build a collaborative monitoring and early warning system integrating ground sensing, video surveillance,

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and manual patrolling: The ground sensing network deploys multi-parameter sensors in key fire risk areas, realizes real-time data transmission through low-power IoT technology, and when the sensors detect anomalies, automatically triggers early warnings and pushes them to the terminals of grassroots patrol staff; intelligent video surveillance deploys intelligent video monitoring equipment at key forest intersections and high vantage points, automatically identifies fire signs (such as open flames and smoke) through deep learning algorithms, and controls the misjudgment rate below 5%. Such equipment can realize 24-hour uninterrupted monitoring, making up for the shortcomings of manual patrolling at night and in severe weather; manual patrolling needs to integrate GIS maps and Beidou positioning, plan optimal patrol routes for patrol staff, record patrol trajectories and identified hidden risks in real time, and form a closed-loop management of patrolling, recording, and rectification, thereby improving the refinement level of grassroots prevention and control. It is particularly emphasized that monitoring systems at all levels shall realize data interoperability through the national forest fire data sharing platform—county-level sensor data is uploaded to the provincial platform, and provincial aviation monitoring data is fused with national-level satellite data. Ultimately, a collaborative mechanism is formed where data converges from the bottom up and instructions are transmitted from the top down, avoiding monitoring blind spots caused by data silos.

4.2 Strengthen Key Technology R&D and Transformation of Scientific Research Achievements

To address the current problems of fragmented technical research and low achievement conversion rate, it is necessary to adhere to the principles of demand orientation and industry-academia-research collaboration, focus on the integrated application of new technologies, break through core bottlenecks, and establish an achievement transformation chain covering R&D, demonstration, and promotion to ensure the practical application of technologies.

4.2.1 Focus on the Integration of New Technologies and Break Through Core R&D Directions

Aligning with the development trends of IoT, cloud computing, and artificial intelligence, focus on carrying out R&D in four technical areas to fill existing technical gaps: First, conduct R&D on intelligent multi-source data fusion technology, which needs to break through the bottleneck of fusing optical, microwave, and LiDAR data—utilize the advantage of microwave remote sensing in penetrating dense smoke and rain clouds to solve the problem of fire monitoring in cloudy weather; integrate LiDAR data to invert the 3D structure of vegetation, optimize the estimation accuracy of fuel load, and build an "all-weather, high-precision" fire monitoring data chain; second, for AI-based fire prediction and dynamic simulation technology, use deep learning algorithms to build a fuel-meteorology-terrain coupled fire spread model—train the model through historical fire data and real-time meteorological data, which can predict the fire spread range in the next 6-24 hours with an accuracy of over 85%; third, conduct targeted R&D on dynamic fuel monitoring technology integrating IoT and satellite remote sensing, deploy fuel moisture sensors in key forest areas, and combine large-scale fuel moisture data inverted from satellite data to build a point-area integrated fuel monitoring network—sensor data is used to calibrate satellite inversion results, improve the accuracy of fuel parameters in small-scale areas, and provide data support for refined fire risk zoning; fourth, it is also important to conduct R&D on remote sensing assessment technology for post-fire ecological recovery. In the future, it is necessary to integrate high-resolution optical data, LiDAR data, and ecological parameters, build an integrated assessment model covering fire loss, recovery potential, and restoration plans, automatically generate post-fire recovery recommendations, and shorten the assessment cycle from the traditional 7 days to 1 day to support rapid decision-making for post-fire recovery[105].

4.2.2 Improve the Achievement Transformation Mechanism and Connect the Scientific Research-Operation Closed Loop

To address the "last mile" problem in achievement transformation, it is necessary to establish a three-in-one transformation system including policy guidance, platform support, and demonstration promotion: First, set up specialized transformation funds. Add a special project for forest fire remote sensing technology transformation in national forestry science and technology promotion projects to fund the operational adaptation of scientific research achievements. Second, build an industry-academia-research collaboration platform. Led by the National Forestry and Grassland Administration of China, join hands with major scientific research institutions and enterprises to establish a Forest Fire Remote Sensing Technology Innovation and Transformation Center, which is responsible for technical demand connection, joint R&D, pilot verification, and standard formulation, forming a positive cycle of demand, R&D, and application; second, carry out regional demonstration applications. Select areas with high fire frequency and difficult prevention and control (such as mountainous areas in western Sichuan and Greater Khingan Range in Heilongjiang) to carry out technical demonstrations, and promote achievements through "visible and usable" results.

4.3 Upgrade the Forest Fire Early Warning and Monitoring Operational System to Enhance Intelligence and Collaboration

The existing operational system has problems such as slow data processing, low automation, and poor sharing. It is necessary to upgrade it with modern information technologies such as cloud computing, big data, and AI, and build a comprehensive operational system with full-process automation covering data acquisition, product production, and information services to support scientific decision-making in forest fire prevention.

4.3.1 Optimize System Function Modules to Achieve Full-Process Automation

Based on the existing system framework, focus on upgrading three core modules: The upgrade of the multi-source data acquisition and preprocessing module shall integrate data interfaces of various satellites to realize automatic data download, radiometric calibration, and geometric correction, and introduce cloud computing technology to improve the capability of massive data processing; the upgrade of the automatic production module for forest fire thematic products shall develop an AI-driven thematic product production line to realize the automatic generation of products such as fire point detection, smoke area extraction, burned area calculation, and fire risk zoning; the upgrade of the fire information sharing and service module shall build a cross-department, cross-level information sharing platform, connect data from emergency management, meteorology, and public security departments, and realize "one-time generation and multi-party sharing" of fire information, forming a data interoperability mechanism between operation and scientific research[30,106].

4.3.2 Strengthen Technical Support to Ensure Stable System Operation

The system upgrade shall rely on two technical support systems to ensure the implementation of functions and long-term stable operation: First, build a computing power support system, and adopt a "cloud-edge collaboration" computing architecture—deploy cloud computing centers at or above the provincial level to undertake large-scale data processing and model calculation; deploy edge computing nodes at the county level to undertake real-time analysis of local video surveillance and sensor data, reducing data transmission pressure and delay. Second, build a standard specification system, formulate technical standards for the forest fire satellite remote sensing early warning and monitoring operational system, and unify data formats, product indicators, and interface protocols to avoid system incompatibility caused by decentralized development[30].

4.3.3 Expand System Application Scenarios to Serve Full-Chain Prevention and Control Needs

The upgraded operational system shall expand from single monitoring to full-chain prevention and control services, covering three scenarios: pre-fire prevention, in-fire suppression, and post-fire recovery. For pre-fire prevention, generate refined fire risk zoning maps, mark high-fire-risk areas, and guide grassroots authorities to carry out fuel cleaning and fire source management; combine meteorological data to issue daily fire risk forecasts, providing a basis for forest fire prevention duty arrangements and publicity and education. For in-fire suppression, generate real-time fire situation maps (including fire point locations, fire front spread directions, threatened villages/facilities, and firefighting team positions) and display them through a visual interface to assist commanders in

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formulating suppression plans; based on the fire spread model, predict the fire range in the next 24 hours, and deploy firebreaks and allocate materials in advance. For post-fire recovery, automatically generate burned area assessment reports (including burned area, damage degree classification, and ecological losses) and recommend restoration plans, providing data support for post-fire ecological restoration.

In the next 5-10 years, China's forest fire satellite remote sensing early warning and monitoring technology shall aim for integration, intelligence, and collaboration, realize optimal resource allocation through hierarchical system construction, break through core bottlenecks through technology R&D and transformation, and improve service capabilities through operational system upgrading. This process not only requires the collaborative efforts of scientific research institutions, operational departments, and enterprises, but also relies on policy support and fund guarantees. Ultimately, a forest fire prevention and control technology system that is compatible with ecological civilization construction and in line with international advanced levels will be formed, providing solid support for safeguarding the bottom line of forest ecological security and helping China achieve the "dual carbon" goals (carbon peaking and carbon neutrality).

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