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Review

Research on Progress of Forest Fire Monitoring with Satellite Remote Sensing

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Abstract: With satellite remote sensing technology blooming, satellite remote sensing has become a common tool to detect forest fires, and played an important role in forest fire monitoring. This paper sort the research status and progress on satellite remote sensing monitoring for forest fires to provide directions and insights for subsequent research and applications. Through reviewing the literature on satellite remote sensing monitoring for forest fires, we present satellites and sensors for forest fire monitoring, describe forest fire monitoring methods through brightness temperature detection and smoke detection, and summarize current problems of satellite remote sensing monitoring of forest fires. Despite forest fire satellite remote sensing monitoring algorithms are becoming increasingly mature, it is not without problems such as slow migration of cloud detection algorithms, difficulties in unifying spatial and temporal characteristics, and difficulties in detecting small fires and low-temperature fires. Finally, in response to the problems identified, we list some recommendations with a view to providing useful references for future research on forest fire monitoring with satellite remote sensing.

Keywords: satellite remote sensing; sensors; forest fire monitoring; forest fire brightness temperature; forest fire smoke

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1. Introduction

The introduction should briefly place the study in a broad context and highlight why it is important. It should define the purpose of the work and its significance. The current state of the research field should be carefully reviewed and key publications cited. Please highlight controversial and diverging hypotheses when necessary. Finally, briefly mention the main aim of the work and highlight the principal conclusions. As far as possible, please keep the introduction comprehensible to scientists outside your particular field of research. Forest fire is a worldwide natural disaster. As it can destroy forest resources and cause global environmental pollution, governments are paying more attention to it. Forest fires occur randomly and unexpectedly, therefore timely monitoring of forest fires helps to reduce the loss caused by them.

With the vigorous development of satellite remote sensing technology, satellite remote sensing has become a frequently used tool for forest fire monitoring. When monitoring forest fires, relying on "low and medium altitude" tools is not only high-cost and technically difficult, but leaves blind spots for forest fire monitoring (Shu et al., 2005). However, satellite sensors can provide information with different spatial resolutions and different spectra on a global scale (Chuvieco et al., 2020), with the advantages of large monitoring range, short response time and strong anti-interference ability. They can effectively make up for the shortcomings, regarding the small monitoring range, poor stability and high cost, of "low altitude" cameras in forest areas (Barmpoutis et al., 2020; Wu et al., 2020), and solve problems of being subject to air control, weather conditions and short range of "mid-altitude" Unmanned Aerial Vehicles (UAVs) (Howard et al., 2018). Thus, satellite sensors meet the need for timely monitoring of forest fires in large areas (Qin et al., 2015). There are currently two main ways of using remote sensing technology for forest fire monitoring. One is to obtain the brightness temperature information through the infrared band of satellite remote sensing. The flames produced by forest fires have distinctive radiative characteristics, contrasting markedly with the background radiation of surrounding areas (Sun et al., 2020). The other is to detect forest fire smoke produced during forest fires. which can detect forest fires earlier than brightness temperature detection. In the early stages of forest fires, the incomplete combustion of combustible materials can produce large amounts of smoke (Zheng et al., 2023), which can help to detect forest fires earlier than monitoring through brightness temperature detection.

This paper reviews the progress of research on satellite remote sensing for forest fire monitoring. We begin with an overview of the development and properties comparison of meteorological satellites and sensors commonly used for forest fire monitoring (Section 2). We then compared and analyzed methods of monitoring forest fires using brightness temperature detection and smoke detection (Section 3). Finally, we discuss the existing problems and future directions of satellite remote sensing monitoring for forest fires (Section 4). The above studies can provide useful references for the selection of satellites for forest fire monitoring, the adoption of monitoring methods, and the improvement of forest fire monitoring accuracy to point the way to further research.

2. Overview and Application of Meteorological Satellites and Sensors for Forest Fire Monitoring

2.1. Overview of Meteorological Satellites and Sensors for Forest Fire Monitoring

In recent years, with the advancement of remote sensing technology, the launch of a large number of remote sensing satellites and the low cost of usage, scholars worldwide have studied satellite remote sensing monitoring for forest fires.

At present, domestic and foreign mainly use meteorological satellites to monitor forest fires. According to their orbits, meteorological satellites are divided into two main categories: Polar Orbit Meteorological Satellite and Geostationary Meteorological Satellite. The capabilities' comparison of the two satellites is shown in Table 1. The Geostationary Meteorological Satellite, also known as Geosynchronous Satellite, usually orbits at an altitude of around 36,000 km, matching the speed of the Earth's rotation. The Geostationary Meteorological Satellites currently in orbit include China's Fengyun-2 (FY-2) and Fengyun-4 (FY-4), the US GEOS series, Japan's Himawari-9, Korea's GEO-KOMPSAT-2A(GK2A), etc. The Polar Orbit Meteorological Satellite, also known as Sun-synchronous Orbit Satellite, usually orbits at an altitude of around 500 to 800 km, travelling along a near-polar orbit between the North Pole and the South Pole. Due to the large inclination angle of the orbit of such satellite, it can only make earth observations during each fly-by. The Polar Orbit Meteorological Satellites presently in orbit include China's Fengyun-3 (FY-3), the US NOAA and the European Metop series, etc.

Table 1. The capability comparison between Polar Orbit Meteorological Satellite and Geostationary Meteorological Satellite.

Capability	Geostationary Meteorological Satellite	Polar Orbit Meteorological Satellite
Providing Continuous Observation Data	√	×
Temporal Resolution	High	Low
Spatial Resolution	Low	High
Enabling Continuous Monitoring of the Same Area over a Long Period	√	×
Orbital Position	Settled	Unsettled
Orbital Period	Long	Short

Satellite systems are based on sensors (Rafik et al., 2020). acquire images at multiple spatial and temporal resolutions by carrying different sensors. Satellites acquire images with multiple spatial and temporal resolutions by carrying different sensors. Sensors on board Geostationary Meteorological Satellites that are commonly used for forest fire monitoring include Advanced Himawari Imager (AHI), Advanced Baseline Imager (ABI), Advanced Geostationary Radiation Imager (AGRI), etc. Sensors on board Polar Orbit Meteorological Satellite include Advanced Along-track Scanning Radiometer (ATSR), Advanced Very High Resolution Radiometer (AVHRR), Moderate-resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer (VIIRS), etc.

The world's first meteorological satellite is the US TIROS-1, which was launched in 1960 and transmitted back the first satellite cloud images (Lv et al., 2003). From 1975-2010, the US launched four generations of the GOES series geostationary satellites. The temporal resolution, number of channels and imaging speed of the satellites have been gradually increased, and monitoring capabilities have been enhanced (Fang, 2014). Meanwhile, the third generation US Polar Orbit Meteorological Satellite, NOAA, went into operation in 1978, equipped with the AVHRR (Lu & Gu, 2016). In 2011, the SNPP satellite was successfully launched, primarily carrying the VIIRS with operational microlight detection capability.

The development of meteorological satellites in Europe began with the first Geostationary Meteorological Satellite Meteosat-1, launched in 1997. Europe's first Polar Orbit Meteorological

Satellite, Metop-A, was launched in 2006. Despite its late start, the satellite had a high technological starting point, with rapid advances in its imaging quality and the Infrared Atmospheric Sounding Interferometer (IASI) on board (Lu & Gu, 2016).

With the improvement of satellite remote sensing technology, Japan launched the Geostationary Meteorological Satellite Himawari-8 in 2014, equipped with the AHI, which is mainly used for the monitoring of natural disasters (He et al., 2020). And then the Himawari-9 was launched in 2016 and was to be in service in 2022.

China is one of the few countries in the world with both Geostationary Meteorological Satellites and Polar Orbit Meteorological Satellites (Tang et al., 2016). China has launched eight Polar Orbit Meteorological Satellites and nine Geostationary Meteorological Satellites, completing the transformation of meteorological satellites from experimental applications to operational services (Sun et al., 2020). In addition, China's High-resolution Earth Observation System was started at 2010. And GF-4 is China's first relatively high-resolution remote sensing satellite (Sun et al., 2020).

2.2. Applications of Meteorological Satellites and Sensors for Forest Fire Monitoring

As early as the 1980s, techies began being abuzz about research on forest fire monitoring using remote sensing technologies. With the advantages of the vast synchronous observation area, broad detection band and rapid sampling time, the AVHRR sensor equipped on NOAA satellite (NOAA/AVHRR), since its successful launch in 1978, has become the main data source for domestic and international scholars using satellites to monitor forest fires. Flannigan and Haar attempted to use NOAA/AVHRR to monitor the forest fire in north-central Alberta in June 1982. However, experiment results indicated that the satellite's visual field is susceptible to clouds and smoke, making it difficult to monitor forest fires (Flannigan & Haar, 1986). In 1996, Yi et al. conducted a simulation experiment based on NOAA/AVHRR data for the southwest forest of China, where forest fires occurred frequently and were difficult to monitor, and their results were basically at a practical level (Yi et al., 1996). In 1997, Pozo et al. compared forest fire information in southeastern Spain obtained by AVHRR Band 3 and 4, with real information of forest fires provided by the Andalusian Regional Government Environmental Directorate (Pozo et al., 1997). They verified the advantages of using remote sensing techniques for forest fire monitoring in forests containing complex features that are difficult to monitor fires by other tools. In 2012, to eliminate fire signal noise due to solar reflections, He et al. introduced a new test to filter forest fire detection results based on the 2004 mid-infrared band data of NOAA/AVHRR, reducing the number of false fire detections by 27.1% (He & Li, 2012). During this period, the accuracy of forest fire monitoring using remote sensing still needed to be improved, but the greater value of forest fire monitoring using remote sensing technology was initially confirmed.

At the beginning of the 21st century, the MODIS sensor began collecting remote sensing information as part of NASA's Earth Observing System (EOS) in 1999 on board the Terra satellite and in 2002 on board the Aqua satellite. MODIS sensor has specific bands and fire products for fire monitoring and has therefore become a research hotspot in the field of remote sensing monitoring for forest fires during this period. In 2002, Justice, a professor of the University of Maryland, and Kufuman, a staff of Goddard Space Flight Center, led a research team to conduct a simulation experiment on forest fire monitoring in African forests using MODIS data, and validated the results of the simulation experiment using the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data (Justice et al., 2002). In 2003, Giglio et al., members of the above research team, tested the effectiveness of MODIS data for forest fire detection and found that MODIS data were subject to interference from water et al. resulting in high false alarm rates for forest fire monitoring and difficulties in detecting small or low-temperature forest fires (Giglio et al., 2003). In 2007, they used MODIS data to compensate for the limitations of the Visible and Infrared Scanners in detecting forest fires in tropical and subtropical regions due to differences between day and night (Giglio, 2007). In 2016, Giglio et al. studied the 6th Version of MODIS data (collection 6) compiled by NASA, which improved the forest fire detection performance of MODIS by reducing false alarms caused by small bare land and missed alarms caused by thick smoke cover occurred in Version 5 data (Giglio et al., 2016). In 2004, Qin et al. detected forest fires in China, with an accuracy of 80%, based on band characteristics of MODIS (Qin & Yi, 2004). Furthermore, scholars collected information from higher spatial resolution sensors to validate the performance of MODIS for forest fire monitoring. In 2008, Schroeder et al. analyzed the MODIS fire detection product MOD14 using remote sensing imagery collected from the ASTER sensor and ETM+ sensor with the spatial resolution of 30m and showed that MODIS has difficulty detecting fires under the tree canopies (Schroeder et al., 2008). During this period, the complex environmental background of forests had a greater impact on forest fire monitoring using MODIS and required reliability verification through extensive experiments. But the feasibility and prospect of MODIS for forest fire monitoring was confirmed. Until 2019, MODIS was still used as an important tool for forest fire monitoring, for example, Ba et al. used MODIS images for scene classification to detect early forest fires (Ba et al., 2019).

With the launch of more remote sensing satellites and sensors, satellites and sensors for monitoring forest fires tend to be diversified. In 2008, Giglio et al. used data from the ASTER sensor, carried on the Terra satellite, to detect the forest fire radiative power (FRP) to measure the forest fire intensity (Giglio et al., 2008). In 2011, He et al. combined data from the same temporal phase of ASTER and MODIS for forest fire detection to eliminate the effects of solar contamination and thermal-path-radiance, improving the accuracy of forest fire detection, but with a higher rate of detecting errors in deforested areas (He & Li, 2011). European ATSR sensor, onboard ERS satellites, provides multi-angle, near real-time thermal infrared measurement information for forest fire monitoring (Arino et al., 2012). In 2012, Arino et al. analyzed the time series of night fires provided by ATSR and verified that the ATSR data correlated well with MODIS data (Arino et al., 2012). As the Sea and Land Surface Temperature Instrument (SLSTR) sensor on the Sentinel-3 has similar characteristics to the ATSR and has a wider scanning area, Arino et al. proposed the use of the SLSTR as the supplement to the night fire information collected from ATSR and MODIS to address information saturation during the day (Arino et al., 2012). In 2012, Wooster et al. developed and tested a theoretical forest fire detection algorithm for SLSTR using MODIS and ASTER data and confirmed its high detection accuracy for small or low-temperature forest fires (Wooster et al., 2012). However, this experiment lacked validation using real SLSTR images. With the launch of the Sentinel-3 satellite with the SLSTR sensor in 2014, Xu et al. collected real images from SLSTR in 2020 to complement and update previous forest fire monitoring data and compared them with fire products from MODIS and VIIRS (Xu et al., 2020). Furthermore, in 2021, they confirmed that the F1 Band of SLSTR is of great application for forest fire detection (Xu et al., 2021). And they predicted that data from Sentinel-3/SLSTR could become the main source for midday and night forest fire detection in the future.

In 2011, the first VIIRS sensor was successfully launched on board the SNPP satellite, carrying two sets of independent multispectral Bands and providing images of global coverage. In 2014, Schroeder et al. developed a fire detection algorithm using VIIRS, which has superior mapping capabilities to MODIS (Schroeder et al., 2014). In 2017, Zhang et al. jointly used I-band at a spatial resolution of 375 m and M-band of 750 m from VIIRS to detect fire and its radiated power (FRP) for the first time, and were able to effectively detect small fires (Zhang et al., 2017). The Chinese GF-4 satellite has high temporal resolution and moderate spatial resolution, making it suitable for high-frequency forest fire monitoring. In 2021, Zhou et al. discovered that the Infrared Spectrum (IRS) sensor carried by the GF-4 has a band that is sensitive to forest fires. And they used this band for spatial alignment with MODIS and carried out forest fire monitoring experiments at Qinghai Lake and Siling Lake, obtaining a high degree of radiometric calibration agreement (Zhou et al., 2021). In 2022, Zhang et al. used data from the Panchromatic and Multispectral (PMS) sensor and IRS sensor carried by GF-4 to eliminate high-temperature anomalies when forest fires were not occurring, and used MODIS data to verify feasibility (Zhang et al., 2022). During this period, greater progress was made in forest fire monitoring using new satellites and sensors.

To achieve real-time monitoring of forest fires and improve the accuracy, scholars at home and abroad have devoted to research on multi-source satellite remote sensing monitoring for forest fires. In 2022, Tian et al. considered that remote sensing data from a single source could not meet the needs of forest fire monitoring, thus they combined Planet, Sentinel-2, MODIS, GF-1, GF-4 and Landsat-8 satellites to validate forest fires that occurred in March 2020 in Liangshan Yi Autonomous Prefecture, Sichuan Province, and the monitoring efficiency was significantly improved (Tian et al., 2022). In 2023, Yin et al. used GF-6 Wide Field of View (WFV) data and FY-3D Medium-Resolution Spectral Imager (MERSI) data to effectively identify forest fires in Anning, Yunnan Province, on 9 May 2020 (Yin et al., 2023).

3. Forest Fire Monitoring Methods with Satellite Remote Sensing

Nowadays, many countries have established satellite remote sensing systems for forest fire monitoring (He et al., 2022), and scholars have developed and improved a variety of forest fire monitoring algorithms for different remote sensing satellites. Forest fire monitoring algorithms can be mainly classified into Brightness Temperature detection-based forest fire monitoring methods and forest fire smoke detection-based forest fire monitoring methods.

3.1. Forest Fire Monitoring Methods Based on Brightness Temperature

The most common and basic method used in research on forest fire monitoring with satellite remote sensing technology is Brightness Temperature (BT) detection method. This method uses BT differences between forest fires and other categories of land cover in the Middle Infrared (MIR) and Thermal Infrared (TIR) channels of remote sensing imagery to construct forest fire detection algorithms, and then combines the reflective properties of the visible or Near-infrared (NIR) channels to exclude spurious detections of forest fires.

3.1.1. Brightness Temperature Detection Based on Bi-spectral Method

Remote sensing infrared is highly sensitive to thermal radiation (Li & Jia, 2018). Forest fires occur at high temperatures, therefore the use of remote sensing infrared to discriminate the BT anomaly of land covers can be effective in detecting forest fires.

In 1981, Dozier (1981) proposed the bi-spectral detection method to calculate the temperature and area of sub-pixel fire points using MIR and TIR data from AVHRR, paying the way for forest fire monitoring using remote sensing infrared data. However, this method is premised on the assumption that there are only two temperature fields, the flame and the background, and both temperature fields have the same temperature (Dozier, 1981). This assumption is usually unrealistic and limits the applicability of the method. On this basis, scholars have made further improvements to the bi-spectral detection method. In 1990, Kaufman et al. (1990) improved the bi-spectral method by using AVHRR data to deal with the problem of high environmental impact during forest fire detection in the daytime. In 2006, Zhukov et al. (2006) used Dozier's bi-spectral method to summarize and analyze the mission experience of the bi-spectral infrared detection (BIRD) experimental small satellite and confirmed that it is more reasonable to quantitatively evaluate forest fires in terms of FRP than the effective fire temperature or the effective fire area. In 2008, Eckmann et al. (2008) proposed the multiple endmember spectral mixture analysis (MESMA) based on the bi-spectral method to address the uncertainties in the detection of fire size and temperature using MODIS et al. They estimated the size and temperature of each fire sub-pixel by pre-generating a library of fire end-members and background end-members at different temperatures to decompose the fire pixels (Eckmann et al., 2008). In 2013, Peterson et al. (2013) used MIR and TIR data from MODIS to develop a sub-pixel-based FRP algorithm, which incorporated a radiative transfer model to eliminate solar effects and was applied to monitoring large forest fires in California, bridging the gap of earlier studies (Dozier, 1981) where the algorithm effect could not be verified due to the lack of real data. Given the rapid replacement of satellites and sensors, this algorithm was designed to be suitable for other sensors with similar spectral properties (Peterson et al., 2013). In 2014, Giglio and Schroeder (2014) proposed a rejection test before using the bi-spectral method. They filtered detection errors caused by background interference on the basis of prior knowledge and performed a feasibility assessment using MODIS data over 10 years (Giglio & Schroeder, 2014) to further improve the application of the bi-spectral method in forest fire detection.

3.1.2. Brightness Temperature Detection Based on Threshold Method

The threshold method is based on the analysis and study of prior knowledge of an area or season to select the threshold for fire point identification. When the BT of one or more spectral channels exceeds the pre-selected threshold, it is considered to be the fire point pixel. The threshold methods used for forest fire monitoring can be divided into single-channel threshold (SCT) method and multi-channel threshold (MCT) method.

The SCT method relies only on the BT value T_4 in the MIR channel. If the BT value T_4 of a pixel is greater than the pre-selected threshold, this pixel is defined as having the fire point. In 1991, Setzer and Pereira (1991) carried out a study of forest fire detection in tropical forests, using a digital non-supervised clustering algorithm to set pixels in Band 3 of AVHRR with the radiometric temperature above 460°C as fire points. As AVHRR lacks a dedicated channel designed for fire detection, scholars attempted to migrate SCT to other sensors and demonstrated its feasibility, for example, Arino and Rosaz (Arino et al., 1999) applied SCT to ATSR for forest fire detection. SCT is better suited to areas with low temperatures or low solar reflection (Hua & Shao, 2017). And it is more effective in detecting forest fires at night, but during the day there are more detection errors due to the influence of solar reflection caused by surface bright objects.

To solve the problems of SCT, MCT is pre-processed by eliminating clouds, compensating for solar radiation generated by ground reflections et al. to improve the effectiveness of MIR and then rules out spurious forest fires by comparing the BT difference in channels between MIR and TIR (Li et al., 2001). In 1990, Kaufman et al. (1990) demonstrated that if in a pixel, the channel 3 (MIR) temperature T_3 and the channel 4 (TIR) temperature T_4 acquired from AVHRR simultaneously satisfy the following criteria, fires are defined in this pixel.

$$T_3 \geq 316K,\ T_3 \geq T_4 + 10K,\ T_4 > 250K \tag{1}$$

In Equations (1), T_3 represents the MIR temperature value, T_4 represents the TIR temperature value, and K represents the unit of temperature.

In 1994, Kennedy et al. (1994) upgraded the forest fire monitoring system in West Africa, based on Kaufman's study (Kaufman et al., 1990), by optimizing the threshold value for channels 3 and 4 and increasing the difference between T_3 and T_4 to further eliminate spurious forest fires. In 2004, Pu et al. (2004) used a series of threshold tests to eliminate spurious fire alarms caused by warm backgrounds (e.g. bare ground), highly reflective clouds, and surface bright objects.

The threshold method is highly territorial and is only applicable to local areas, which is difficult to cope with forest fire monitoring in different geographical areas or different seasons. Therefore, scholars need to select appropriate thresholds according to characteristics of different areas. For example, in 2004, Li et al. (2000) developed a forest fire monitoring threshold method for the unique environment of northern Canada, which discriminated all potential forest fire pixels while removing spurious forest fire pixels. This algorithm can detect most real forest fires without thick cloud interference, laying the foundation for local forest fire satellite monitoring systems. In response to the problem of poor adaptability of fixed-threshold methods, scholars have investigated forest fire monitoring algorithms with adaptive thresholds (He & Liu, 2008; Liu et al., 2020). However, the missed detection rate of forest fires was high.

3.1.3. Brightness Temperature Detection Based on Contextual Method

The threshold method uses multi-spectral information to detect forest fires step by step for individual pixels without taking into account the effect of surrounding pixels, i.e. the environmental background changes, on forest fire detection.

To solve this problem, in 1990, Lee and Tag (1990) proposed a contextual method, based on MCT, extending to spatial information. They set up a 3x3 pixel matrix centered on the target pixel, calculated the background temperature according to surrounding pixels, and compare it with the mean BT value within the matrix to discriminate the presence of fires in the target pixel (Lee & Tag, 1990). This method can be flexibly and effectively applied to scenes where the surface temperature varies considerably. In 1996, Flasse and Ceccato (1996) proposed a fire detection contextual algorithm. They used the threshold method to detect potential fires using AVHRR data, analyzed the neighboring pixel background, and then compared the potential fires and their backgrounds by the BT properties of background pixels to confirm the real fires (Flasse & Ceccato, 1996). This method was tested in tropical rainforests and proved to be suitable for detecting forest fires in different areas at different times. However, a limitation revealed by this study is that in 1999, Nakayama et al. (1999) found that when this method was applied to large burning areas of fire, the central point was wrongly detected as a non-fire point. In 2007, Li et al. (2007) proposed an enhanced contextual algorithm for detection of forest fire (ECFDA), which improved the neighboring pixels confirmation algorithm of potential fires by optimizing the size of the background matrix, and improved the criteria selection algorithm for real fires by introducing the concept of BT gradient. The ECFDA is sensitive to the detection of small-scale fires, but cannot be applied to large-scale forest fires.

MODIS has dedicated fire detection channels and is used more often in forest fire monitoring studies. In 2003, Giglio et al. (2003) proposed an improved contextual fire detection algorithm for MODIS, known as version 4, which provides considerable improvement over previous versions. The version 4, improving the detecting sensitivity to small fires and cold fires, classified pixels examined by MODIS as one of the following classes: missing data, cloud, water, non-fire, fire, or unknown (Giglio et al., 2003). In 2008, Schroeder et al. (2008) tested the performance of the MODIS fire product using ASTER and ETM+ images in Brazilian Amazonia by quantifying commission and omission error and improved contextual detection algorithms using BT profiles to reduce the commission error rate in tropical forests. To exclude the detection errors caused by small forest bare areas, smoke obscuration, etc. and to reduce the commission error rate of fire detection (Wang et al., 2009; Wang et al., 2007), in 2016, Giglio et al. (2016) improved the detecting algorithm using collection 6 MODIS data by introducing the forest clearing rejection test.

However, in 2006, Zhou and Wang (Zhou & Wang, 2006) demonstrated that the theoretical algorithm for forest fire detection using MODIS data, when applied to Chinese forests, misidentified non-forest fire areas with image noise interference as forest fires. Therefore, they used the contextual method to analyze fire points and their neighboring pixels of nine forest fire events in China, and improved the noise point filtering criteria to effectively eliminate the noise interference points (Zhou & Wang, 2006).

As the performance of satellites and sensors continues to improve, scholars have attempted to address problems of MODIS in forest fire detection using newer satellites and sensors. In 2014, Schroeder et al. (2014) proposed an improved contextual method based on VIIRS to eliminate spurious fire identification caused by daytime water bodies, sun glints, bright objects, etc. In 2017, Lin et al. (2017) proposed the use of infrared channel slope to analyze the difference between TIR and MIR information collected from FY-3/VIRR and combined the contextual fire detection method and dynamic threshold fire detection method for selecting fire pixels. This method could better suit the global environment for fire detection. In 2020, Yin et al. (2020), based on the FY-3/MERSI data, improved the dynamic threshold method and the contextual method for forest fire detection, by setting the threshold criteria for the BT value in the MIR, which achieved the fast and effective detection of both large and small-scale fires. The contextual method detects forest fires based on the difference between the target and the background within the adaptive window. It expands the application range of algorithms and improves the accuracy of forest fire detection, but the application flexibility is limited by regional differences in monitoring.

3.1.4. Brightness Temperature Detection Based on Deep Learning Method

In recent years, scholars have paid increasing attention to the application of Deep Learning methods in various fields, including the field of forest fire monitoring, and have made great progress. The more commonly employed methods include Neural Networks (NN), Decision Tree and its ensemble learning algorithms, and Support Vector Machine (SVM), etc. In 2000, Arrue et al. (2000) constructed the "False Alarm Reduction System" for forest fire monitoring using Back Propagation (BP) NN, Radial Basis Function Network, and Dynamic Learning Vector Quantizer to calculate the probability values of forest fires using satellite infrared images. In 2009, Maeda et al. (2009) used the BP algorithm to train artificial neural networks (ANN) of different structures to detect forest fires in high-danger areas of the Brazilian Amazon using MODIS imagery, achieving 90% accuracy. This algorithm allowed for fast training of samples while maintaining detection accuracy for forest fires (Abid, 2021).

The BT detection method for forest fires is mainly implemented by satellites and sensors with TIR channels, such as MODIS, AVHRR, FY series, etc., but it is not suitable for satellites and sensors with only a single MIR channel for forest fire detection.

3.2. Forest Fire Monitoring Methods Based on Forest Smoke Detection

In the early stage of forest fires, the low temperatures from combustion make it difficult for satellites to receive sufficient infrared radiation for imaging. However, insufficient burning of combustible materials produces large amounts of smoke, and detection of forest fire smoke by satellite can lead to earlier detection of forest fires. Currently, there are fewer domestic and international studies on smoke detection using satellites to detect forest fires.

3.2.1. Forest Smoke Detection Based on Visual Identification Method

The visual identification method is the early forest fire smoke detection method. It uses computers to generate true-color or false-color images of forest fire smoke to visualize the shape and scale of forest fire smoke (Chung & Le, 1984; Ferrare et al., 1990), and then manually interprets the area and diffusion direction of the forest fire smoke. The visual identification method is intuitive and convenient, but it relies on artificial operation, which is not conducive to the automatic processing of forest fire smoke information, and the accuracy of smoke identification is low. To improve the accuracy of smoke detection and reduce the subjective dependence of the visual identification method, scholars have used infrared information in combination with the threshold method for forest fire smoke detection.

3.2.2. Forest Smoke Detection Based on MCT Method

MCT detects smoke pixels by utilizing the rich land cover information in remote sensing images, setting criteria based on characteristics of land covers such as clouds, water bodies, vegetation, etc., combining the spectral features of multiple infrared channels (Xie et al., 2007), and excluding non-smoke pixels by different thresholds.

In 2007, Chrysoulakis et al. (2007) identified the center of forest fire smoke, based on multi-temporal and multi-spectral features of remote sensing imagery, by comparing the anomalous pixels in the NIR channel and combining them with the Normalized Difference Vegetation Index (NDVI) index, and then used spectral and spatial filters to spatially extend the center to the entire area covered by the forest fire smoke plume. The proposed algorithm provided accurate estimates of the spatial characteristics of the forest fire smoke plume (Chrysoulakis et al., 2007). To improve the sensitivity of detecting small fires and low-temperature fires, in 2007, Wang et al. (2007) identified smoke pixels using the smoke mask technique based on information from the TIR channel and solar reflectance channel, and used the contextual method to detect missed forest fire events accompanied by significant smoke plumes. In addition, in 2008, Peng et al. (2008) set a forest fire smoke discrimination threshold based on the characteristics of tropical rainforests, and improved forest fire monitoring algorithm based on version 4 MODIS data by using the adaptive window adjustment technique of the smoke plume mask. This algorithm improved sensitivity to detection of small forest fires at low-temperature forest fires, especially fires with large scan angles (Peng et al., 2008).

However, smoke has no fixed spectral characteristics and shows similar features to clouds, dust and haze on the satellite spectral bands, thus making it difficult to distinguish them, resulting in the MCT method not being able to effectively employ smoke detection for early warning of forest fires.

3.2.3. Forest Smoke Detection Based on Deep Learning

With the continuous launch of satellites, real-time access to remote sensing data has become a reality, and there is an urgent need to develop more effective and intelligent algorithms for the automated detection of forest fire smoke based on massive remote sensing data. In 2014, Li et al. (2014) separated smoke from other land cover types in satellite imagery and developed a smoke identification algorithm combining Fisher linear Discrimination and K-means clustering, which was validated using forest fire events in Greater Khingan Mountains (China), Amur Region (Russia), Australia and Canada, confirming that the algorithm could capture both heavy and dispersed forest fire smoke. In 2015, Li et al. (2015) trained and debugged the BPNN with samples acquired from MODIS data of three forest fire events occurring in China, Northeast Asia, and Russia, and verified that the algorithm was effective in capturing thick and thin smoke over land. In 2020, Qin et al. (2020) constructed a Decision Tree Identification model for forest fire smoke based on the reflectance of forest fire smoke in the visible and NIR channels of GF-1 and GF-2 satellite imagery. In 2023, Li et al. (2023) improved the subpixel mapping method based on the Random Forest model for identifying and locating forest fire smoke.

Scholars have further improved deep learning algorithms to address problems that have arisen in forest fire smoke detection research. The uneven spatial distribution of smoke and the complexity of its background result in smoke being difficult to detect due to its inconspicuous features in satellite imagery. To distinguish forest fire smoke from the background scene, in 2019, Ba et al. (2019) optimized the CNN, which improved the recognition accuracy of CNN for forest fire smoke based on remote sensing imagery, by introducing spatial and channel-wise attention mechanisms, and sorting out the spatial characteristic information of remote sensing images collected from medium- and high-resolution satellites. The acquisition of remote sensing image data containing forest fire smoke is limited by the constraints of satellite lifetime in orbit, geographical coverage, etc., which makes it difficult to collect a sufficiently large-scale dataset of forest fire smoke (Zheng et al., 2023). In 2018, ZHANG et al. (2018) performed forest fire smoke detection experiments based on the Faster R-CNN model, inserting real and simulated smoke into forest images to generate synthetic forest fire smoke samples. The results demonstrated that the method solves the problem of insufficient data while eliminating the need for sample labeling. In 2023, Sathishkumar et al. (2023) selected the Xception model as the optimal model, and fine-tuned it using the Learning Without Forgetting (LwF) algorithm to suit the new task. As a result, they investigated Transfer Learning of pre-trained models for forest fire smoke monitoring, which increased the data amount and decreased the long training time (Sathishkumar et al., 2023). In 2023, Zheng et al. (2023) used Himawari-8 satellite remote sensing images to construct a small-scale dataset and proposed a forest fire smoke detection model (SR-Net) combining CNN and Lightweight Vision Transformer (Lightweight ViT). The model employed CNN for inductive bias and the Global Attention Mechanism of Lightweight ViT to generate a lightweight forest fire smoke detection model with higher accuracy while consuming fewer training resources (Zheng et al., 2023).

4. Discussion and Conclusion

This study statistics and analyses research on satellite remote sensing for forest fire monitoring in recent decades based on bibliometric analysis, using the co-occurrence frequency of textual data located in titles, abstracts and keywords. We extracted data from the Web of Science search tool which contains a full range of papers. The input qualifiers were “remote sensing” and “forest fire monitoring”, and a total of 999 papers were retrieved (the data obtained up to 20 July 2023). We then used VOSviewer software to visually represent extracted data from 999 papers (Figure 1).

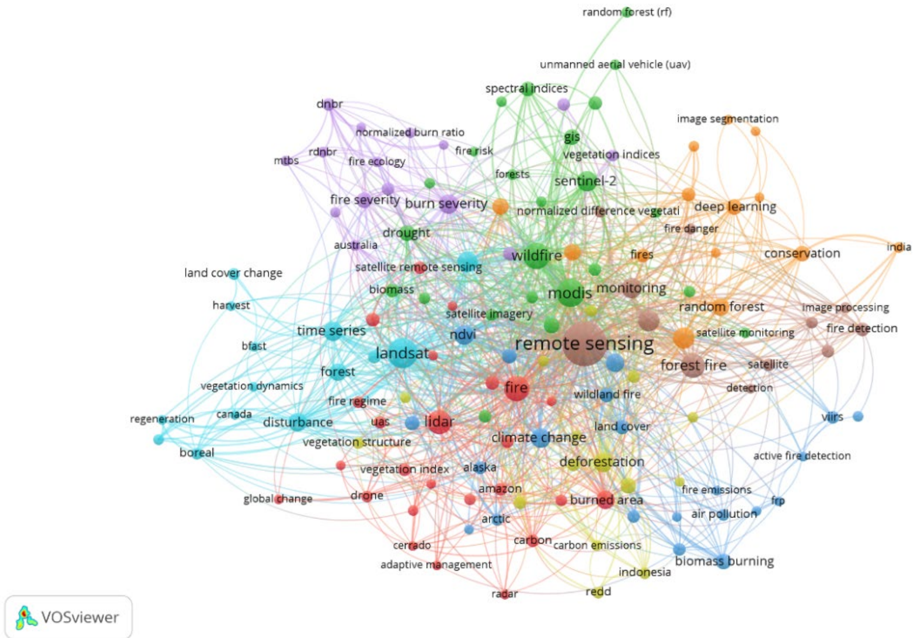

Figure 1. Data visualization based on keywords collected from Web of Science.

The results of the data network visualization show that satellites used more in forest fire satellite monitoring studies are Landsat, MODIS, Sentinel, etc., which all have obvious advantages and limitations in forest fire detection. Landsat provides detailed information on the spatial distribution of fires, but has a long revisit period (every 16 days) and a small geographical coverage area. MODIS has channels and products specifically designed for fires, with a resolution of the highest 250m and high detection accuracy, but the temporal resolution is not high enough to detect fires in time and then alarm it. Moreover, the methodology for satellite monitoring of forest fires shown in Figure 2 involves more terms such as “machine learning”, “time series” and “spectral indices”. It indicates that the research hotspots in forest fire monitoring focus on the introduction and development of Deep Learning in forest fire monitoring (machine learning), the improvement of the temporal efficiency of medium- and high-spatial-resolution satellites and sensors (time series), the improvement of monitoring algorithms for forest fires using the information of infrared channels (spectral indexes), and so on.

Figure 2. Publication numbers of research on satellite monitoring for forest fires in the Web of Science Core Collection database from 2009 to 2023. (The data obtained up to 20 July 2023.)

As the systems of satellites, sensors and forest fire monitoring technology, such as time series techniques to process data, deep learning methods, etc. (Santos et al., 2021), advance by leaps and bounds, and the free remote sensing imagery springing up, the attention to satellite remote sensing monitoring of forest fires has gained a strong momentum. From the data provided by Web of Science, it can be seen that 2018 to 2023 (the data obtained up to 20 July 2023) are the most representative five years for domestic and international research on forest fire satellite remote sensing monitoring. Over these five years, satellite remote sensing monitoring algorithms for forest fires have become increasingly mature, but the current algorithms still have their own advantages and disadvantages, as shown in Table 2.

Table 2. Advantages and disadvantages of satellite remote sensing monitoring algorithms for forest fires.

Algorithms	Advantages	Disadvantages
Bi-spectral Method	Laying the theoretical foundations.	Based on unrealistic assumptions and lack of validation by actual data.
SCT Method	Simple technology.	Large daytime error.
MCT Method	High stability.	Not adapted to diverse environmental backgrounds.
Contextual Method	Highly adaptable to the environment.	High rate of missed and wrong judgements for small fires and low-temperature fires.
Deep Learning Method	Highly automated.	Relatively complex methods and techniques.

The review of literature revealed the following characteristics of satellite remote sensing monitoring of forest fires:

(1) Satellite remote sensing monitoring of forest fires is strongly influenced by the temporal and spatial resolution of satellites and sensors. It is difficult for current satellites and sensors to simultaneously fulfill the requirements of high temporal resolution and high spatial resolution for forest fire monitoring. Geostationary Meteorological Satellites have high temporal resolution but low spatial resolution, while Polar Orbit Meteorological Satellites have low temporal resolution but higher spatial resolution. Therefore, scholars at home and abroad have improved various algorithms for satellite remote sensing monitoring for forest fires, and are dedicated to making up for shortcomings of forest fire monitoring in time and space. For example, Himawari-8 can acquire surface information every 10 minutes, which is suitable for real-time monitoring of forest fires (Zhang et al., 2023), but suffers from the problem of low spatial resolution of pixels and large differences in the information contained in pixels. Therefore, Himawari-8 is more suitable to use deep learning algorithms for forest fire monitoring (Kang et al., 2022). On the contrary, MODIS has low temporal resolution and cannot rapidly detect forest fires, but it has high spatial resolution and can more accurately detect forest fires (Feng & Zhou, 2023).

Cloud masking impacts the effectiveness of forest fire monitoring. Current cloud identification algorithms have evolved to automatically and intelligently identify clouds using machine learning algorithms (Bing et al., 2023), but there are fewer studies applying them to data preprocessing for forest fire monitoring. Cloud masking can increase the satellite's reflectance in the visible band and decrease the BT value in the infrared band (Xie et al., 2018). Current cloud identification algorithms in forest fire monitoring mainly use the threshold method (Xu & Zhong, 2017), but the method is greatly affected by different time points and environments. Cloud identification using machine learning algorithms is more flexible than the threshold method, which has a simpler structure and higher accuracy, however, it requires manual extraction of training samples from different scenes (Tsagkatakis et al., 2019), and it is difficult for a single satellite or sensor to meet the number requirement of training samples.

Satellite monitoring algorithms for forest fire work to improve the sensitivity of monitoring small fires and fires with low bright temperatures. Due to the small burning area, insufficient combustion, low flame temperature and other features at the early stage of forest fires, and canopy shading, it leads to missed judgment and false judgment when using satellites and sensors to detect small fires or low-temperature fires.

Given the above characteristics, the future development trends of satellite remote sensing monitoring for forest fires are as follows:

(1) Using multi-source satellites and sensors to improve the spatial and temporal efficiency of forest fire monitoring. For instance, the combination of GF-6 WFV and FY-3 MERSI enables multi-aspect capture of forest fire information (Yin et al., 2023). The spatial resolution of GF-6 WFV data is 16m, the radiometric resolution is 12bit, its coverage is wide, and its imaging quality is high. FY-3 MERSI's monitoring scope is broad, observation frequency is dense, and it is sensitive to high-temperature heat reservoirs on the ground (Zheng et al., 2013). In addition, recent years have witnessed a spurt of progress in satellites and sensors. Research could incorporate an increasing number of advanced satellites for forest fire monitoring, such as China's HJ-1A and 1B satellites which can provide data up to 30m resolution (Sun et al., 2010), and South Korea's GK2A

satellite carrying an AMI sensor, which can provide a spatial resolution of up to 500m in the visible band, has a comparatively higher radiometric and spectral resolution, and has improved imaging time up to 10 minutes (Chen et al., 2022).

(2) Migrating and improving deep learning-based cloud detection algorithms to make them suitable for data preprocessing of forest fire monitoring. Deep learning captures more comprehensive and deeper features of cloud on remote sensing imagery, which can also be improved to be trained with small sample datasets (Zheng et al., 2023). Among the deep learning algorithms, CNN can classify and detect clouds with high accuracy (Segal-Rozenhaimer et al., 2020; Yu et al., 2020). U-Net can identify thin clouds, broken pieces of clouds (Segal-Rozenhaimer et al., 2020; Yu et al., 2020) and clouds in snow and ice regions (Jeppesen et al., 2019), distinguish between clouds and their shadows, and capture cloud boundaries (Bing et al., 2023). And BP NN are suitable for remote sensing imagery data containing complex underlying surfaces (Gao et al., 2018). However, the training time for cloud recognition using deep learning models is long and the model structure is complex, so they need to be migrated and improved to increase the computational efficiency when they are applied to forest fire monitoring.

(3) Increasing the accuracy of spatial positioning for satellite remote sensing monitoring of forest fires. Remote sensing imagery contains abundant feature types, but the spatial resolution of the highly temporal satellite data used in forest fire monitoring is low. The use of hybrid pixel decomposition combined with sub-pixel localization methods can effectively improve the spatial positioning accuracy during forest fire monitoring (Xu et al., 2022). There have been studies applying sub-pixel localization methods to other areas (Ling et al., 2010), but fewer use it in satellite remote sensing monitoring of forest fires.

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