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Multi-temporal remote sensing fire detection based on GBDT in Yunnan area

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***Abstract*: How to detect forest fire on time is an important social problem. Remote sensing detection with large detection areas and high time resolution has become a popular method in detecting forest fire. Therefore, we propose a new method of detecting forest fire based on Himawari-8 geostationary satellite data. The detection algorithm used is the GBDT(Gradient Boost Decision Tree) machine learning combined with multi-temporal information referred to as MT-GBDT algorithm. Considering the characteristics of Yunnan Province, the algorithm of this paper uses contextual algorithms to filter potential fire points. Then, combined with multi-temporal information, we processed the potential fire point by using the diurnal temperature cycle (DTC) model. Finally, we used GBDT machine learning model to process the information obtained in the above steps. Result shows that the fire point information with high accuracy is obtained. The probability of false detection is 18%, and the probability of detection is 86%. Compared with the existing three methods, MT-GBDT algorithm successfully detects most forest fires, while other algorithms omit many forest fires, and the probability of detection is 40% to 50%.**

Keywords: fire detecting; Remote sensing; Himawari 8; machine learning

I. INTRODUCTION

Forest fires have tremendous destructive power on human society and ecosystems. In recent decades, forest fires have frequently appeared, and forest resources have been lost in large quantities. Since the 1980s, there have been 255,000 recorded forest fires worldwide every year. There exist many ways to detect and prevent forest fires. Among them, satellite detection has become an important method for detecting and preventing forest fires due to its wide detection range and timely detection. However, satellite detection of fires still requires immense improvement.

Satellite remote sensing detection of forest fires began in the 1980s. The current mainstream detection methods include threshold based, contextual, adaptive threshold based, and multi-temporal algorithms. Dozier [1] and Matson [2] used the 4/11 micron infrared data of NOAA satellite AVHRR to perform sub-pixel temperature inversion and fire spot monitoring research and proposed hotspot sub-pixel area and its temperature inversion algorithm. Flasse [3] proposed a fire point background recognition algorithm on the basis of AVHRR 4/11 micron infrared band background parameters. Kaufman [4,5] proposed the MODIS fire spot identification method on the basis of numerous AVHRR hot spot recognition research results. S.P.FLASSE and P.CECCATO [6] proposed the contextual algorithm of using the brightness temperature of neighboring pixels instead of the background brightness temperature of the target pixel to detect fire. Van den Berfh [7] used a multi-temporal algorithm of comparing multiple historical images

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with existing images to obtain changes in fire information. Peng Zhang [8] conducted a detailed comparison and analysis on the geostationary meteorological satellite Himawari-8/9 AHI sensor and the Fengyun-4. Weijie Chen [9] proposed an adaptive dynamic on the basis of Himawari-8 satellite forest fire detection methods to identify fire points. Jie Chen [10] analyzed the fire point identification method of Himawari-8 geostationary meteorological satellite and used it to conduct grassland fire monitoring research.

The current new generation geostationary weather satellite Himawari-8 has a higher time resolution than Modis, which significantly helps detect fires on time. This paper is based on the GBDT machine learning method, combined with the multi-temporal information obtained by the DTC model to establish a fire point recognition algorithm on the basis of the Himawari-8/9 AHI sensor in the geostationary satellite suitable for Yunnan, and used Yunnan's May to June 2019 wildfire data to verify the algorithm.

II. HIMAWARI-8 AHI

Himawari-8 is a geostationary satellite sensor system constructed in Japan. It was launched on October 4, 2014. Himawari-8 has 16 observation bands. The spatial resolution of infrared band is 2 km, and that of visible and near-infrared bands is 0.5 or 1 km. Himawari-8 encompasses East Asia to Australia and the sensor collects data every 10 minutes. The time resolution of Himawari-8 is high, which is conducive to detecting fire points on time. For fire detection, the system is better than polar orbit satellite data with higher spatial resolution but lower temporal resolution.

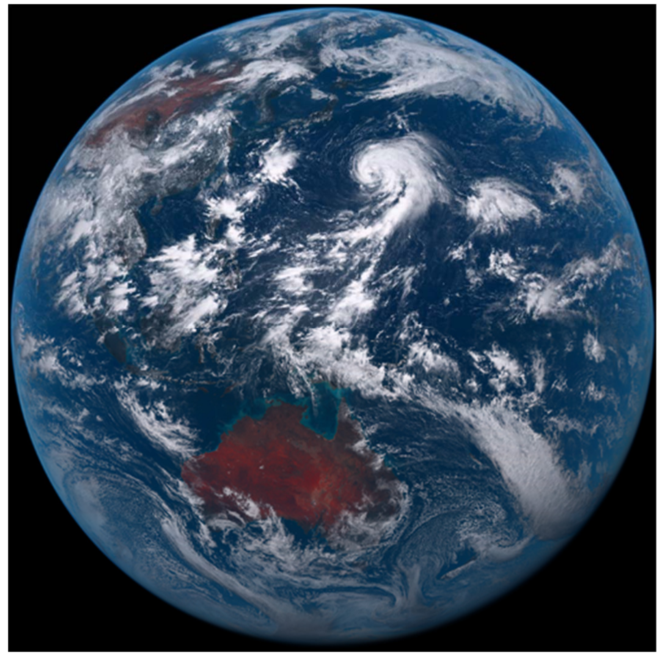

Figure 1. Himawari-8 color picture

TABLE I. SPECTRAL CHARACTERISTICS OF THE AHI THERMAL BANDS

band	1	2	3	4	5	6	7	8
Wavelength/μm	0.47	0.51	0.64	0.86	1.6	2.3	3.9	6.2
Resolution/km	1	1	0.5	1	2	2	2	2
band	9	10	11	12	13	14	15	16
Wavelength/μm	6.9	7.3	8.6	9.6	10.4	11.3	12.4	13.3
Resolution/km	2	2	2	2	2	2	2	2

III. FOREST FIRE DETECTION ALGORITHM

A forest fire detection method called GBDT-based multi-temporal algorithm (MT-GBDT algorithm) is proposed in this paper, which includes the following steps. First, the contextual algorithm is used to filter pixels that may appear as forest fires. The purpose of this step is to identify potential fire pixels and find all real fire points as much as possible.

However, there will be many false fire points. Then, with the help of multi-temporal information, the DTC model is used to preliminarily rule out false potential fire spots. Finally, the trained machine learning model is used to identify the real fire point from the potential fire point pixels. Figure 2 shows the process flow chart of MT-GBDT algorithm.

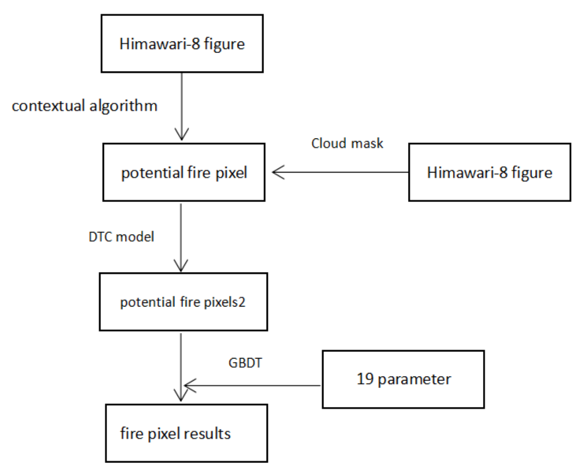

Figure 2. Flow chart of multi-temporal algorithm based on GBDT

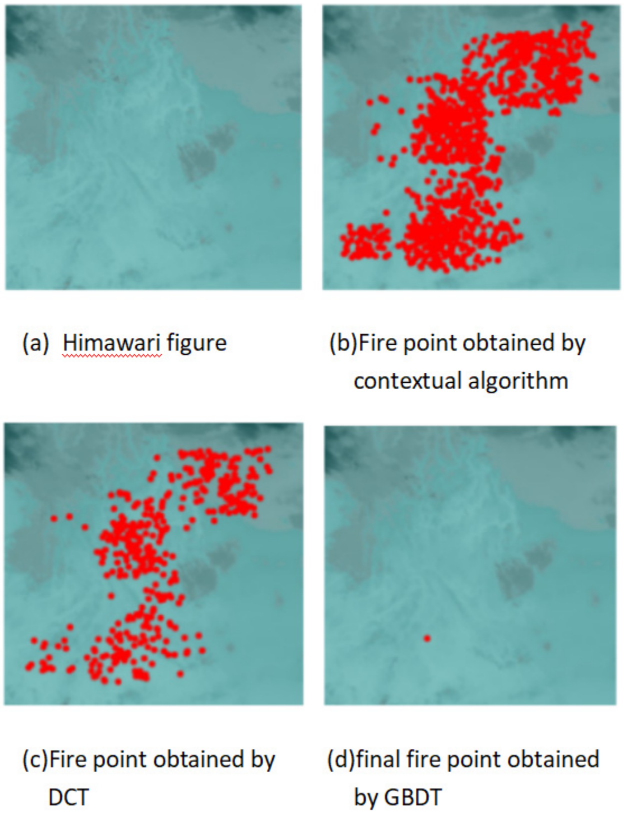

Figure 3. Fire point results of each step

A. *Contextual algorithm*

Different areas of Yunnan Province significantly vary in brightness temperature values. Many non-fire pixels in areas with high brightness temperature values are higher than fire pixel in low brightness temperature areas. Therefore, if a fixed threshold method is used, the excessive number of potential fire points will be filtered out. This article uses the contextual algorithm to obtain potential fire points. According to the actual situation of fires in Yunnan, active fires can be detected with high-intensity mid-infrared and thermal bands. In the contextual algorithm of this article, the data of 5, 7, and 14 bands of Himawari-8 are used.

Band 7 can effectively reflect the temperature of the object. The high temperature brought by forest fires will make the radiation of Band 7 in the area significantly high. Concurrently, the difference between Bands 7 and 14 has much to do with fire. Many existing fire detections types of data are used in the algorithm. In the contextual algorithm of this paper, if the difference between the T7 (7-band value) and ΔT (the difference between Bands 7 and 14) of the pixel and the T7 and ΔT of the surrounding pixels is greater than a certain threshold, the pixel may be a potential fire spot. The threshold is judged by the experience of multiple tests.

Another important step in the contextual algorithm is cloud mask. In existing fire-detection algorithms, the short wave infrared band (1.58 μm–1.64 μm) is used to distinguish clouds, solar scintillation, and water, and band 5 belongs to this range. In this paper, the criteria given by Xu[11] for cloud masking is adopted.

B. *DCT model*

The DTC is a model of various brightness temperatures in a certain area within 24 hours. G ü ttsche and Olesen[12] proposed a model which is approximate to the shape of the curve. The model takes the brightness temperature as a function of time dependent variable, and the formula is as follows.

$$T(t) = T_0 + \delta\mathrm{T} + \begin{cases} \mathrm{T_a}\cos(\frac{\pi}{\omega}(t - t_m)) - \delta T, & t \ge t_s \\ (\mathrm{T_a}\cos(\frac{\pi}{\omega}(t - t_m)) - \delta T)e^{-\frac{t-ts}{T}}, & t < t_s \end{cases} \tag{1}$$

T_0 is the residual temperature before sunrise, T_a is the temperature amplitude, δT is $T_0\text{-}T_{(t\to\infty)}$, t_s is the time of maximum temperature, t_m is when the temperature begins to decay, and τ is the attenuation constant.

Using Kalman filter, the expected brightness temperature is modeled as a linear process:

$$\mathrm{X_k} = \mathrm{A_{k\text{-}1}}\mathrm{X_{K-1}} + n_{k-1} \tag{2}$$

$\mathrm{X_k}$ is the system state (expected brightness temperature value) of time k, $\mathrm{A_{k\text{-}1}}$ is the state transition coefficient, and n_{k-1} is the process noise.

After obtaining the expected brightness temperature of each target pixel through DCT, the error potential fire point can be eliminated by comparing the difference between the actual brightness temperature value of a potential fire point and the predicted brightness temperature value. If the difference is not significant, it means that the temperature in the area is not far from usual, which is unlikely to be the fire point. If the actual brightness temperature value is significantly greater than the expected brightness temperature value, it is likely that a fire will lead to abnormal temperature rise. Using the multi-temporal information provided by the DTC model can improve the detection rate of fire spots and reduce false fire points. Meanwhile, the realistic background brightness temperature provided by DTC model will be an important parameter of the GBDT mode.

C. *GBDT*

GBDT is an enhanced integration method that iterates the new regression decision tree to fit the classification errors of each step. GBDT collects numerous relatively weak simple models, so the estimated results are usually more robust and accurate than those obtained by a simple model. The enhancement method generates many simple models by changing the weight of module samples in each step.

GBDT has two main advantages. First, it can be used as a feasible method to calculate the complex nonlinear interaction between variables and responses without using direct physical modules. Second, GBDT has almost no overfitting problems, which leads to the ideal performance of the algorithm in the training phase.

The steps of establishing the GBDT model are as follows:

Initialize the estimates of all samples on K categories;

The learning and updating process under the cycle is m times;

Use the logistic transformation to estimate the function without samples;

The probability of traversing each category of all samples;

Calculate the probability of each sample in the K class;

Learn the regression tree of J leaf nodes through the gradient method;

Calculate the gain of each leaf node;

Update the estimates of all samples under class K.

In this paper, 81 forest fire reference cases in 2019 are divided into two categories according to the damaged area, time, and location: 60 fire cases are used to train the GBDT model, and the remaining 21 cases are used to verify the model.

According to the importance of relative variables provided by iterative testing, we selected 19 parameters (Table 1), which we used as inputs to the GBDT model.

TABLE II. INPUT PARAMETERS OF THE GBDT MODEL

Band radiance	Ch07	Ch07 （DTC）					
Band differences	Ch05-Ch07	Ch06-Ch07	Ch04-Ch07	Ch07-Ch15	Ch12-Ch15		
BT ratios	BT13/BT15	BT07/BT13	BT07/BT14	BT07/BT11	BT07/BT12		
BT differences	BT07-BT13	BT07-BT14	BT13-BT15	BT07-BT11	BT07-BT15	BT07-BT12	BT12-BT16

IV. RESULTS AND DISCUSSION

Yunnan has an area of 394,100 square kilometers and 24.76 million hectares of forest

lands (about 64.7% of the total area). Yunnan is one of the key forest areas in China where forest resources are extremely rich, but it is also prone to forest fires. This paper uses the data of forest fires in situ provided by the Yunnan power grid as reference data. Each forest fire case contains information on date/time, location, area of damage, and cause. The wildfire data used are mainly forest fires from May to August in 2019. Among 131 fire data of Yunnan power grid, 81 cases that are not covered by clouds are selected as reference data.

Among the 81 reference cases, 21 reference forest fire cases were used to evaluate the MT-GBDT algorithm. Only two cases of forest fire detected by context based algorithm are detected given that detecting these two cases is difficult detect because of their small damage areas. Although the detection results are complete, the number of false detected pixels is large, so the DCT model is used for further screening. In the calibration cases, 57 of 60 cases occurred, and 21 cases of 21 cases were found in the verification cases.

In evaluating accuracy, this article compares the results obtained through the MT-GBDT algorithm with three existing algorithms. Among the 21 verified forest fire cases, AHI-FSA[13], AHI-FIRE [14], and COMS[15] algorithms detected 12, 9, and 11 forest fires, while MT-GBDT detected 18 of them. The detection rate of MT-GBDT algorithm proposed in this paper is higher than the existing three algorithms. This means that compared with existing algorithms, the proposed method is effective for small-scale fire. All of them use Himawari-8 to detect these forest fire cases in Yunnan, but the result of MT-GBDT algorithm is better than ahi-fsa and ahi-fire algorithms.

TABLE III. NUMBER OF FOREST FIRE DETECTION, PROBABILITY OF FALSE DETECTION, AND THE PROBABILITY OF DETECTION OF MT-GBDT, AHI-FSA, AHI-FIRE, AND COMS ALGORITHMS

	number of forest fire detection	**probability of false detection**	**probability of detection**
MT-GBDT	21	18%	86%
AHI-FSA	21	14%	57%
AHI-FIRE	21	18%	42%
COMS	21	21%	52%

V. CONCLUSIONS

Given the climatic and topographic characteristics of Yunnan, existing forest fire satellite-detection algorithms have low accuracy in detecting forest fires in Yunnan. This paper proposes a combined algorithm on the basis of the geostationary satellite Himawari-8 to detect forest fires in Yunnan. This algorithm combines the characteristics of Yunnan area, uses the contextual algorithm to conduct preliminary screening, combines the multi-temporal information provided by the DTC model, and uses GBDT machine learning training to obtain a fire detection model. Given the high time resolution of geostationary satellite data, using Himawari-8 to detect fires can quickly respond to forest fires and prevent its spread immediately. Concurrently, the GBDT-based multi-temporal algorithm can provide forest fire data for other forest fire monitoring tasks, such as calculating fire spread rate. the GBDT-based multi-temporal algorithm is locally optimized, but for areas with similar characteristics to the Yunnan area, after adjusting all three steps, the algorithm can be extended to this area.

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