Comparative Analysis of Extraction Accuracy of Fire Detection Algorithms in Northern of China

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ABSTRACT: Forest fires are sudden and destructive natural disasters, which have an irreversible impact on ecological environment. Therefore, it is of great significance to master forest fires in a timely manner. To analysis the accuracy of absolute fire hotspots identification algorithm, MODIS fire detection algorithm and fire hotspots recognition algorithm based on variance between-class method, three forest fires in northern China since 2019 were selected. The real-time received MODIS data from the satellite ground receiving station was used as the data source. Take fire hotspots interpreted of Sentinel-2A/B and GF-6 as the comparison standard, algorithms and product accuracy comparison analysis were carried out. The results indicated that the absolute fire hotspots identification algorithm monitors three times; compared with the MODIS fire detection algorithm one time and the improved algorithm one time. Furthermore, absolute fire hotspots identification algorithm misjudged high temperature ground object or omitted low temperature fire hotspots is sensitive to the change of threshold. Considering the background pixel, MODIS fire detection algorithm, with poor geographical applicability, has lower accuracy, due to the uniform global threshold. The fire hotspots recognition algorithm based on variance between-class method has the lowest accuracy, which have many false alarm pixels and omission pixels. In general, combined with the absolute fire hotspots identification algorithm, data from satellite ground receiving station can apply to near real-time fire hotspots supervision.

1. INTRODUCTION

Forests are the main body of land ecosystems. The fierce forest fires threaten the forest ecological environment and biodiversity. It is important to accurately and timely grasp the fire to reduce disaster losses and protect forest resources (Qingyun Xu, 2017). The traditional way of monitoring forest fire not only wastes resources, but also can not provide timely information about forest fires. Satellite remote sensing technology is widely used in monitoring forest fires due to its macroscopic large-scale and rapid observation of the earth. The technology to monitoring fire hotspots is achieved by identifying the brightness temperature changes before and after the fires (Hantson S, 2013) (Jiaguo Li, 2010). At present, the algorithms of forest fire hotspots extraction mainly includes fixed threshold method (Flannigan M D, 1986), absolute fire hotspots identification method (Yoram J, 1998), contextual algorithm (Shimabukuro Y E, 1991), MODIS fire hotspots extraction method (Louis Giglio, 2003), fire detection algorithm based on variance between-class method (Xia Xiao, 2010) and so on.

Based on the north American forest area, the fixed threshold model was proposed (Flannigan M D, 1986). Using the absolute fire hotspots identification algorithm and improved algorithm, nine forest fires in China were verified and analyzed (Xiaocheng Zhou, 2006); Based on contextual algorithm, combined with satellite monitoring data and meteorological observation data, the fire hotspots of Jiangsu Province from June 2010 to June 2015 were extracted (Xin Hang, 2017); By using the MODIS fire detection algorithm to analyze the fires in the southeastern United States, a fire hotspots monitoring method for low-intensity fire areas was proposed (Wanting Wang, 2009); To extract Amazon forest fires, the threshold of the MODIS fire detection algorithm was modified, which reduced the false detection rate (Chen Yang,2013). Fire hotspots from Fujian and Heilongjiang provinces in China were extracted by using an infrared spectrum fire hotspots detection algorithm based on variance between-class method (Xia Xiao, 2010). In general, the fixed threshold method is based on the regional and seasonal experience thresholds, simple and efficient, but the algorithm is less adaptable. Researchers had proposed an absolute fire hotspots recognition algorithm based on the fixed threshold method to improve the extraction accuracy in different regions and seasons. The concept of background pixels was introduced based on the contextual algorithm, and the background pixel information around the fire hotspots was fully considered. The MODIS fire detection algorithm evolves on the basis of contextual algorithm.

The TERRA and AQUA satellite are equipped with MODIS sensor, which have taken the needs of fire monitoring into account. The satellites have higher accuracy and shorter return time than meteorological satellites. It can analyze fire hotspots in more detail and more efficient way, which have special functions and application prospects in fire monitoring. In this paper, based on the MODIS data received real time by the land satellite receiving station, the fire hotspots algorithms were adopted to extract three forest fires in northern China in 2019, which include the absolute fire hotspots identification algorithm, the MODIS fire detection algorithm and the fire hotspots identification algorithm based on the variance between classes. Finally, the image of Sentinel-2A/B and GF-6 WFV were used to verify the accuracy of three algorithm. The fire extraction results of the three algorithms were compared and analyzed, and the accuracy of the algorithm was evaluated to predict forest fires in northern of China.

2. ALGORITHM INTRODUCTION

Fixed threshold method, absolute fire hotspots identification method, contextual algorithm, MODIS fire detection algorithm and fire detection algorithm based on variance between-class method are universal method to monitor fires hotspots. Absolute fire hotspots identification algorithm and MODIS fire detection algorithm are developed based on fixed threshold methods and context algorithms for neighboring background pixels respectively. The principle of absolute fire hotspots identification algorithm, MODIS fire detection algorithm and the fire hotspots recognition algorithm based on variance between classes are described as follows:

2.1 Absolute fire hotspots identification algorithm

Based on the fixed threshold algorithm, the algorithm mainly includes four parts: cloud detection, extraction potential fire hotspots pixels and background pixels, identify fire hotspots and remove misjudgment points.

Cloud detection: If the pixel meets the condition (1), it will be judged as the cloud pixel. $\rho_{0.66}$ represents a channel reflectance of 0.66μm.

$$\rho_{0.66} > 0.2 \qquad (1)$$

Extract potential fire pixels hotspots and background pixels: The pixel that satisfies the condition (2) is judged to be the potential fire hotspots pixel, otherwise, judged as the background pixel. T_4 corresponds to the wavelength of 4μm channel brightness temperature. T_{11} corresponds to the wavelength of 11μm channel brightness temperature. ΔT_{411} is the difference between the channel brightness temperature of the wavelength 4μm and 11μm.

$$\Delta T_{411} = T_4 - T_{11} \geq 20K \& T_4 > 320K \qquad (2)$$

Identify fire hotspots: The pixel satisfies the condition (3) is the non-fire hotspots pixel, and if the pixel satisfies one of the conditions (4), (5), and (6), it is determined as a fire hotspots. Among them, T_{4b} and ΔT_{4b} are the mean and variance of the background pixels brightness temperature of the 4μm channel respectively. Similarly, T_{411b} and T_{411b} are the mean and variance of the difference between the brightness of the background pixels of the 4μm channel and the 11μm channel. If the variance is less than 2, the variance will be calculated as 2.

$$T_4 < 315K \text{ or } T_{411} < 5K \qquad (3)$$

$$T_4 > 360K \qquad (4)$$

$$T_4 > 320K \, \& \, T_{411} > 20K \qquad (5)$$

$$(T_4 > T_{4b} + 4 * \Delta T_{4b}) \& (T_{411} > T_{411b} + 4 * \Delta T_{411b}) \qquad (6)$$

Remove misjudgment hotspots: During the daytime, if the reflectance of both channels of 0.64μm and 0.86μm are more than 0.3, it will take as the flare. The final fire hotspots should exclude these false fire hotspots.

2.2 MODIS fire detection algorithm

The MODIS fire detection algorithm is also divided into four parts: cloud pixel detection, land pixel classification, fire hotspots classification and elimination of false fire hotspots. The algorithm is as follows:

Cloud pixel detection: If the pixels satisfy the conditions (7) or (8) respectively, this pixel is a cloud pixel. In the formula, $\rho_{0.65}$ and $\rho_{0.86}$ correspond to the band 1 and band 2 channel reflectance respectively, T_{12} corresponds to the wavelength of 12μm channel brightness temperature.

$$Daytime: ((\rho_{0.65}+\rho_{0.86}) > 0.9 \cup (T_{12} < 265K)) \cup ((\rho_{0.65}+\rho_{0.86}) > 0.7 \cap (T_{12} < 285K)) \quad (7)$$

$$Nighttime: T_{12} < 265K \quad (8)$$

Land pixel classification:

$$Daytime: (T_4 > 310K) \cap (T_{411} > 10) \cap (\rho_{0.86} < 0.3) \quad (9)$$

$$Nighttime: (T_4 > 305K) \cap (T_{411} > 10K) \quad (10)$$

Absolute fire hotspots classification:

$$Daytime: T_4 > 360K\text{；} Nighttime: T_4 > 320K \quad (11)$$

Potential fire hotspots classification:

$$Daytime: (T_4 > 325K) \cap (T_{411} > 20K)\ Nighttime: (T_4 > 310K) \cap (T_{411} > 10K) \quad (12)$$

If the land pixel satisfies the condition (9) or (10), the land pixel will be judged as the suspect fire hotspots pixel, otherwise it is a non-fire hotspots land pixel. When the suspect fire hotspots pixel meets the condition (11), the suspect fire hotspots pixel will be judged as an absolute fire hotspots pixel and will not participate in subsequent operations; If the suspect fire hotspots pixel does not meet the condition (11), but satisfy the condition (12), the pixel is judged as a potential fire hotspots pixel, otherwise it is a valid background pixel. In the formula, T_4 is the brightness temperature of the wavelength of 4μm channel, T_{411} is the difference between the brightness temperature between the wavelength of 4μm channel and 11μm channel.

Fire hotspots classification: By changing the window size of the center potential fire hotspots pixel and analyzing the brightness temperature difference between the potential fire hotspots pixel and the surrounding background pixel to determine whether the potential fire hotspots pixel is a real fire hotspots pixel or not, the window size n*n is expanded from 3*3 cycles to 21*21.

When the number of valid background pixels N in the window is satisfied (N≥n*n*25%) ∩ (N≥8), the window is no longer expanded and the valid background pixel statistics in window are calculated. If the potential fire hotspots pixels satisfy the discrimination condition of (7)-(11), the potential fire hotspots pixel is classified into the fire hotspots pixel; If the discrimination condition is not satisfied, the potential fire hotspots pixel is classified as the non-fire hotspots pixel, and the next potential fire hotspots pixel is determined. If the number of valid background pixels does not satisfy the condition, the window size will expand and repeat the above process until the conditions are satisfied; If the window size expanded to 21*21 and the requirements are still not satisfied, the potential fire hotspots pixel will be classified as an indeterminate pixel.

Discriminant condition：

$$T_4 > \overline{T_4} + 3 * \overline{\delta_4} \quad (13)$$

$$T_{411} > \overline{T_{411}} + 6 \quad (14)$$

$$T_{411} > \overline{T_{411}} + 3.5 * \overline{\delta_{T411}} \quad (15)$$

$$T_{11} > \overline{T_{11}} + \overline{\delta_{11}} - 4 \quad (16)$$

$$\delta'_4 > 5 \quad (17)$$

$$Daytime: (13) \cap (14) \cap (15) \cap ((16) \cup (17)); \quad Nighttime: (13) \cap (14) \cap (15)$$

In the equations (13)-(17), $\overline{T_4}$ and $\overline{T_{11}}$ are the average brightness temperature of valid background pixels of 4μm wavelength and 11μm wavelength. $\overline{\delta_4}$ and $\overline{\delta_{11}}$ are the average absolute deviation of the bright temperature of the valid background pixels of 4μm wavelength and 11μm wavelength. $\overline{T_{411}}$ is the average brightness temperature of valid background pixels of difference between 4μm wavelength and 11μm wavelength. $\overline{\delta_{411}}$ is the average absolute deviation of the bright temperature of the valid background pixels of difference between 4μm wavelength and 11μm wavelength. δ'_4 is the average absolute deviation of bright temperature of the background fire hotspots pixel for the wavelength 4μm channel.

Elimination of false fire hotspots: The fire hotspots obtained do not rule out the possibility of false fire hotspots. Strong reflection on the surface, water and land junctions, and desert edges may cause false alarm. These false fire hotspots can be further filtered by other auxiliary band information.

2.3 Fire detection algorithm based on variance between-class method

The principle of the fire detection algorithm based on the variance between-class is to extract the fire hotspots according to the variance between the fire hotspots pixels and the background pixels. At the same time, the algorithm considers the influence of the smoke plume on the threshold setting, and validly distinguishes the general fire hotspots pixel from the smoulder fire hotspots pixel. The algorithm is mainly divided into four parts: cloud, water and smoke plume classification, potential fire hotspots pixel discrimination, fire hotspots extraction and elimination of false fire hotspots. The content of the algorithm is as follows:

Cloud, water and smoke plume classification: When the pixels in the image satisfy the conditions (18)-(20) respectively, the pixel is recognized as cloud or water, which will not perform subsequent operations.

Cloud pixels detection:

$$Daytime: ((\rho_{0.65} + \rho_{0.86}) > 0.9 \cup (T_{12} < 265K)) \cup ((\rho_{0.65} + \rho_{0.86}) > 0.7 \cap (T_{12} < 285K)) \quad (18)$$

$$Nighttime: T_{12} < 265K \quad (19)$$

Water pixels detection:

$$R_2 < 0.15 \cap R_7 < 0.05 \cap ((R_2 - R_1)/(R_2 + R_1)) < 0 \quad (20)$$

Smoke plume detection:

$$0.5 \geq (R_8 - R_9)/(R_8 + R_9) \geq 0.15 \quad (21)$$

$$(R_9 - R_7)/(R_9 + R_7) \geq 0.30 \quad (22)$$

$$(R_8 - R_3)/(R_8 + R_3) \leq 0.09 \quad (23)$$

$$R_8 \geq 0.09 \quad (24)$$

$\rho_{0.65}$ and $\rho_{0.86}$ correspond to the band 1 and band 2 channel reflectance respectively, T_{12} corresponds to the wavelength of 12μm channel brightness temperature, and R represents the reflectance of the corresponding band.

Potential fire hotspots pixel discrimination:

$$T_4 > 305K \cap T_{411} > 10K \cap R_{16} < 0.3 \quad (25)$$

For the land pixels, without cloud pixels and water pixels, the potential fire hotspots pixel is discriminated by condition(25). If the land pixel that satisfies the condition, the pixel is classified as a potential fire hotspots pixel, otherwise it is a valid background pixel. In the formula, T_4 is the brightness temperature of the wavelength of 4μm channel, T_{411} is the difference between the brightness temperature between the wavelength of 4μm channel and 11μm channel, and R represents the reflectance of the corresponding band.

Fire hotspots extraction: Traverse the potential fire hotspots pixels obtained in the above steps and calculate the pixels whether meet the condition(28) or not. If the pixel that satisfies the condition is judged as the absolute fire hotspots pixel. Otherwise, take this potential fire hotspots pixel as the center pixel continue to calculate the variance between-class of the potential fire hotspots pixel and the valid background pixel in the 21×21 window. When the potential fire hotspots pixel is not a smoke pixel and the condition (27) is meet, the potential fire hotspots pixel is classified as a general fire hotspots pixel; when the potential fire hotspots pixel is a smoke pixel and the condition (29) is satisfied, then the fire hotspots pixel is classified as a smoulder fire hotspots pixel; Otherwise, this potential fire hotspots pixel is judged as a non-fire hotspots pixel.

The formula for the variance between-class σ^2 between the fire hotspots and the surrounding background pixels:

$$\sigma^2(t) = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 = \omega_0\omega_1(\mu_0 - \mu_1)^2 \quad (26)$$

$$\sigma^2_{T4} > 8 \cap \sigma^2_{T411} > 6 \quad (27)$$

$$T_4 > 360K \quad (28)$$

$$\sigma^2_{T4} > 4 \cap \sigma^2_{T41} > 3 \quad (29)$$

If n is the number of valid background pixels in the 21×21 window, then ω_1 is the probability of the potential fire hotspots in the total number of pixels; ω_0 is the probability of the valid background pixel; μ_1 is the average value of the potential fire hotspots pixel feature; μ_0 is the average of the valid background pixels values. T_4 is the brightness temperature of the wavelength of 4μm channel, T_{411} is the difference between the brightness temperature between the wavelength of 4μm channel and 11μm channel. σ^2 is the variance between-class between the fire hotspots and the valid background pixel of corresponding channel.

Elimination of false fire hotspots: The pixel is a misjudgment fire hotspots pixel, if the fire hotspots pixels satisfy condition $(R_{0.65}>0.3) \cap (R_{0.86}>0.3)$.

3. COMPARATIVE ANALYSIS OF ALGORITHM

3.1 Data source and data processing

The study selects the MODIS data received from the ground satellite receiving station, which have good time resolution, spatial resolution and spectral resolution. The data covers the range from visible to far-infrared, and band 21 and band 31 are sensitive to temperature changes. Through collecting forest fires in 2019, the data of Table 1 are determined as data sources for fire detection. Use the band 21, band 22, band 31, and band32 of MOD021KM data to monitor the fire hotspots. Fire hotspots extraction technology route is shown in Figure 1.

The pre-processed data was synthesized in the order of band 7, band 2, and band 1, and the fire hotspots could be identified by visually interpreting from true color image. Sentinel-2A/B and GF-6 image corresponding to the forest fire were used to verify algorithm precision. Superimposing fire hotspots and the verification images, the number of fire hotspots and the spatial distribution of fire hotspots were analyzed. At last, the accuracy of three algorithms were compared.

Table 1. Information of data source and verification image

No.	Phase	Tensor	Verification image	Place of fire
1	20190319	TERRA	Sentinel-2B	Boli County, Heilongjiang Province,China
2	20190401	TERRA	Sentinel-2A	Wuyuan County, Shanxi Province,China
3	20190506	TERRA	GF-6	Chengde County, Hebei Province,China

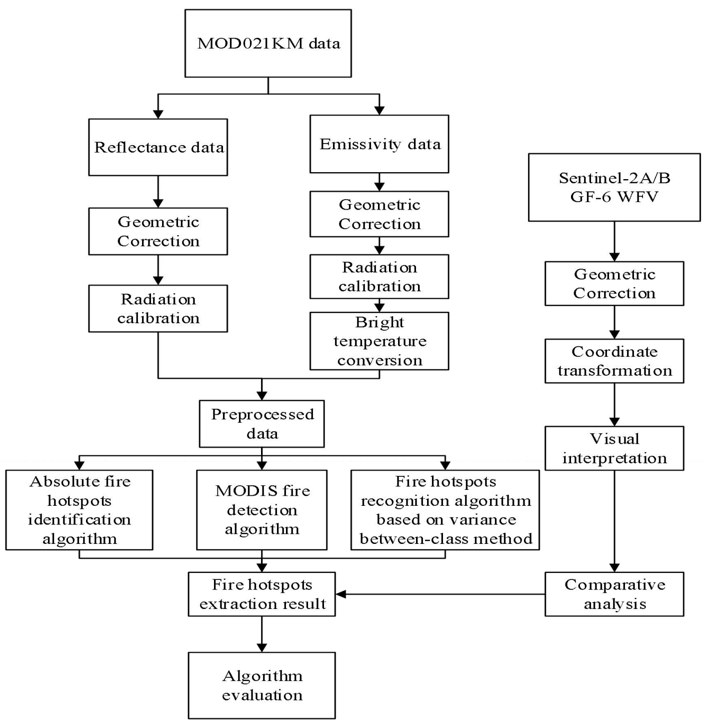

Figure 1. Technology roadmap of fire hotspots extraction

3.2 Analysis of results

Centering on the location of the three fire occurrences, each selected 727*560 km^2 as the study area, and fire algorithms were used to perform fire hotspots. The absolute fire hotspots identification algorithm detected all three fires, and the MODIS fire detection algorithm only detected one. No forest fires were detected in Boli County and Wuyuan County. The fire hotspots detection algorithm based on the variance between classes could not detect two forest fires on April 1 and May 6 of 2019, moreover there existed other areas misdetection on May 6th. Fire detection algorithm based on variance between-class method had lowest accuracy, and there were a large number of forest fires that were missed or misdetected.

Comparative analysis of the number and spatial distribution of fire hotspots: According to the location information of fires and the verification image of Sentinel-2B MSI, sixteen fire hotspots pixels were interpreted visually (Figure 2). Absolute fire hotspots recognition algorithm extracted eleven fire hotspots pixels and missed five fire hotspots pixels, and there were three false detection pixels. MODIS fire detection algorithm failed to detect all the fire pixels. The fire hotspots recognition algorithm based on the variance between classes had more false pixels, compared to the absolute fire hotspots recognition algorithm. The left picture showed the extraction results of the absolute fire point recognition algorithm. The right was fire hotspots recognition algorithm based on variance between classes. The red point in picture was the result of visual interpretation.

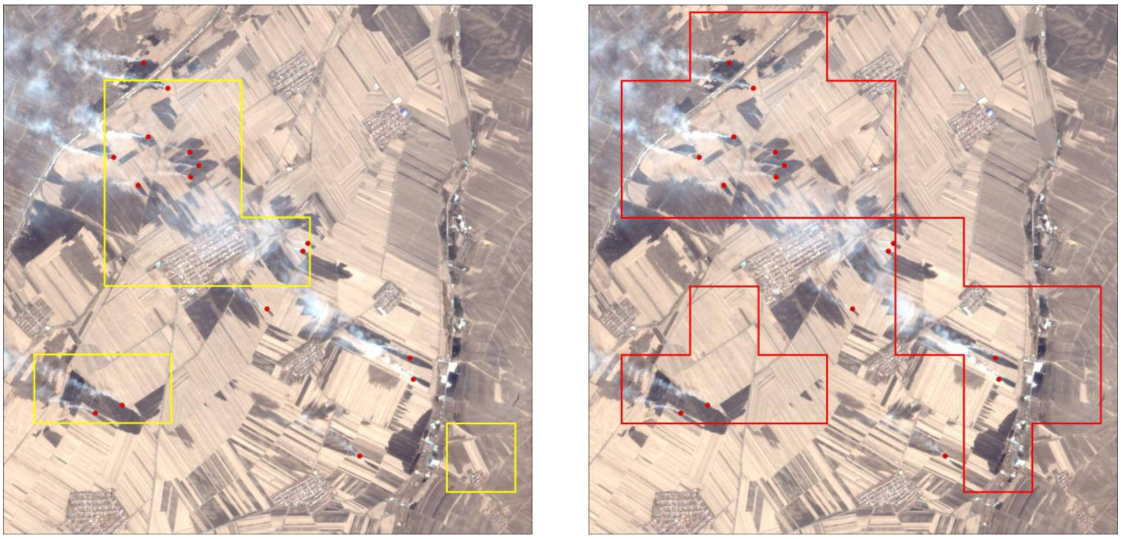

Figure 2. The spatial distribution of fire hotspots in Boli County on March 19, 2019

The Sentinel-2A image was used to visually interpret the forest fire in Wuyuan on April 1, 2019. The results extracted by the three algorithms were shown in Figure 3. The absolute fire hotspots identification algorithm had one pixel misdetection and one fire hotspots pixel missed detection. The MODIS fire detection algorithm and the fire hotspots recognition algorithm based on the variance between classes did not detect the fire. By calculating the area of the miss detection hotspots, it was found that the area of the fire was less than $50m^2$. The minimum area of the MODIS sensor that can detect the fire hotspots is $50m^2$ (Liming He, 2007).

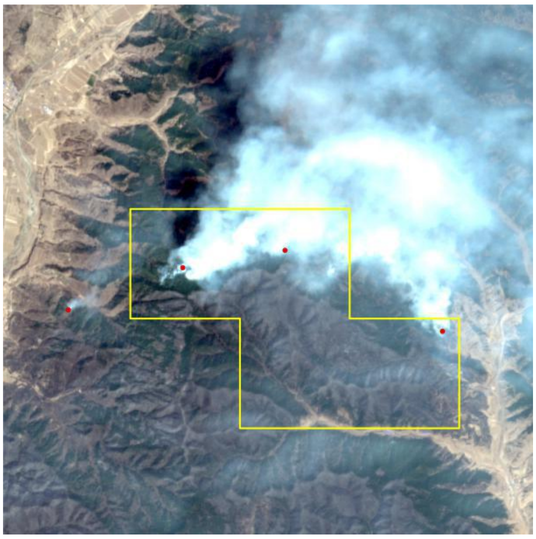

Figure 3. The spatial distribution of fire hotspots in Qinyuan County, Shanxi Province on April 1, 2019

The GF-6 WFV image was used to visually interpret the forest fire in Pingquan county on May 6, 2019. Sixteen fire hotspots pixels were detected by the absolute fire hotspots identification algorithm. The MODIS fire detection algorithm detected three fire hotspots pixels. Twelve fire hotspots pixels were detected by fire hotspots recognition algorithm based on the variance between classes, which were superimposed on the visual interpretation results of the verification image as shown in Figure 4. The absolute fire hotspots recognition algorithm could detect all fire hotspots pixels, but there existed a certain number of non-fire hotspots pixels false detections. The MODIS fire detection algorithm had one pixel false detection and one pixel omission detection. The fire hotspots recognition algorithm based on the variance between classes also failed to identify the forest fire in Pingquan County, and there were a large number of non-fire hotspots pixel false detections in the upper right corner of Figure 4. The left picture showed the extraction results of the absolute fire point recognition algorithm. The middle picture showed the results of the MODIS fire detection algorithm. The right was result of fire hotspots recognition algorithm based on variance between classes. The red point in picture was the result of visual interpretation.

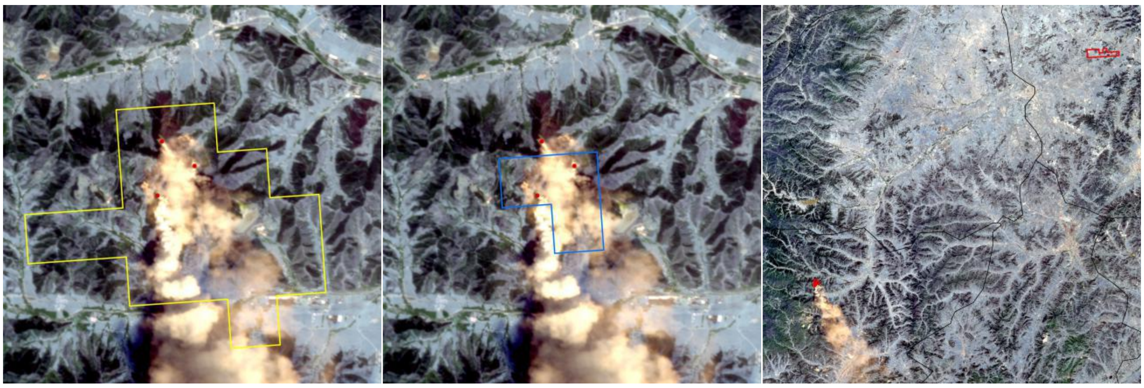

Figure 4. The spatial distribution of fire hotspots in Pingquan County, Hebei Province on May 6, 2019

The above comparison analysis results showed that the absolute fire hotspots identification algorithm detected all three forest fire events, which miss detected a small number of fire hotspots pixels and false detected few non-fire hotspots pixels. MODIS fire detection algorithm and fire detection algorithm based on variance between-class method only detected one fire event, indicating that there existed a large miss detection rate of the two algorithms. The conclusion that the MODIS fire detection algorithm had omission detection rate. The MODIS fire detection algorithm also had a small number of pixel false detections. The fire hotspots recognition algorithm based on the variance between classes did not detect two fires on April 1 and May 6, which was also same as the MODIS fire detection algorithm. There were many false detections of non-fire hotspots pixels, especially shown in the result on May 6.

Cause Analysis: According to the principle of the algorithm, the absolute fire hotspots recognition algorithm consists of three parts: First, the pixel with a sufficiently high temperature is classified as the absolute fire hotspots; Second, there exist surface temperature differences in different locations and reasons. The relationship between underlying surface temperature and the already fixed threshold is another reason why the detection result exist the rate of omission and false pixels. When the background pixel temperature of the underlying surface is relatively high and reaches the fixed threshold, the non-fire hotspots land pixels may be falsely detected as fire hotspots pixels. When the background temperature of the underlying surface is low, the low temperature or small area fire hotspots is easy to miss; Thirdly, according to the brightness temperature statistical relationship of the background pixels of the whole image, the relative threshold is set, and the change of threshold has little influence on it. Although considering the use of brightness temperature relationship between the suspected fire hotspots pixels and the background pixels, the absolute fire hotspots recognition algorithm extract the fire hotspots by setting relative threshold in the third part, which is impossible to avoid the presence of false detection or omission detection in the second part. In addition, the absolute fire hotspots identification algorithm is relatively sensitive to the change of the threshold value, which is easy to cause false detection of the fire hotspots. Raising the threshold value will miss the low temperature or small area fire hotspots; Lower the threshold value can misdetect the high temperature ground object as a fire hotspots.

The fire hotspots of MODIS fire detection algorithm consists of two parts: First, the pixel with a sufficiently high temperature is the absolute fire hotspots. Second, the fire hotspots is extracted by the contextual algorithm. The core of the contextual algorithm is the brightness temperature relationship based on the potential fire hotspots pixels and the valid background pixels, which can reduce the influence on the fire hotspots extraction result. Although the MODIS fire detection algorithm reduces the false rate of the absolute fire hotspots identification method, it also has a high omission detection rate. The main reason is that the threshold of the algorithm is globally, which makes the algorithm poor versatility. In the process of extracting potential fire hotspots pixels and no-fire land pixels, the pixel with low temperature is classified as a non-fire hotspots land pixel. This part of the pixels will not participate in the subsequent operations, forming omission detection of fire hotspots; Secondly, in the process of extracting the potential fire hotspots pixels and the valid background pixels, it is also possible to classify the pixel with lower brightness temperature as the background pixels, which reduce the number of potential fire pixels, leading omission detection of fire hotspots.

By setting variance threshold values of the fire hotspots pixels and the background pixels, the fire hotspots recognition algorithm based on the variance between classes can realize the process of extracting fire hotspots. The larger variance between the classes, the better distinguishment of the classes. When the variance between the fire hotspots and the surrounding valid background reaches a certain value, the fire can be accurately extracted from the background. The fire hotspots extracted by the algorithm is mainly composed of three parts. The first part is the absolute fire hotspots pixel, the second part is the smoulder fire hotspots pixel under the smoke plume, and the third part is the general fire hotspots pixel. Combining the smoke plume mask identify the fire hotspots pixels, the process can divide into two categories. Using different thresholds to detection, further classify the fire hotspots pixels into the smoulder fire hotspots pixel and the general fire hotspots pixels. In theory, the fire hotspots identification algorithm based on the variance between classes can accurately extract the fire hotspots. Whereas, combined with the analysis of research result, it can be known that using this method has a large false detection rate and omission detection rate. If the threshold value set too high, it will cause omission detection of the fire hotspots pixels, in contraries, it will raise the rate of false detection.

4. CONCLUSION

In order to obtain the fire hotspots information of northern China by satellite remote sensing, the MODIS data received by the ground satellite receiving station in real time is used as the data source. The absolute fire hotspots identification algorithm, MODIS fire detection algorithm and fire hotspots identification based on inter-class variance are used to detection fire hotspots. The image of Sentinel-2A/B andGF-6 WFV satellite are used as the standard fire hotspots by visual interpretation. Comparative analysis the fire detection rate, false detection rate and omission detection rate of three algorithms. The results show that the absolute fire hotspots identification algorithm, the MODIS fire detection algorithm and the fire hotspots identification algorithm based on the variance between classes have fire hotspots detection rates of 100%, 33.3% and 33.3% respectively. The false detection rate of absolute fire hotspots identification algorithm is high, which is greatly affected by the threshold change. If the threshold is too high or too low, the fire detection will be missed or misdetected. The threshold of the MODIS fire detection algorithm is globally. In the process of extracting potential fire hotspots pixels and valid background pixels, it is possible to classify the pixels with lower brightness temperature as background pixels, thus causing omission detection of fire hotspots. The fire hotspots identification algorithm based on the variance between classes uses different threshold to classify potential fire hotspots pixels into the smoulder fire hotspots pixel and the general fire point pixels. But the actual application effect of the algorithm is hardly satisfied, need further improvement.

In the final analysis, the three algorithms inevitably have the fixed threshold problem, which lead to the omission detection or false detection of the fire hotspots. The fire hotspots recognition algorithm based on the variance between classes is combined with the detection of the smoke plume pixels, which provides a new idea for fire hotspots extraction. The next study will focus on how to scientifically select thresholds to improve the applicability of the algorithm in different research areas.

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