Analysis of the moderate resolution imaging spectroradiometer contextual algorithm for small fire detection

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Abstract. In the southeastern United States, most wildland fires are of low intensity. A substantial number of these fires cannot be detected by the MODIS contextual algorithm. To improve the accuracy of fire detection for this region, the remote-sensed characteristics of these fires have to be systematically analyzed. Using an adjusted algorithm, this study collected a database including 6596 remote-sensed fire pixels in 72 MODIS granules, of which 3809 fire pixels are missed by the MODIS contextual algorithm. The statistical distributions of the sensor-observed fire reflectance and brightness temperature at relevant spectral channels are analyzed. The study explains the reasons that the detection of low intensity fires by the MODIS contextual algorithm is significantly influenced by view angles, especially when view angles are greater than 40 degrees. This paper discusses and suggests several aspects which could improve regional detection of low intensity fires. The results indicate that 1) the R_2 threshold $R_2 < 0.3$ is still valid for detecting low intensity fires omitted by the MODIS contextual algorithm; 2) the threshold $T_4 > 310$ K is too high, and a lower threshold of $T_4 > 293$ K should be adopted instead; 3) the threshold $\Delta T > 10$ K is also too high, and both algorithms that use it risk omitting small fires because of this threshold.

Keywords: algorithm, MODIS, regional fire detection, small fire.

1 INTRODUCTION

Fire statistics provided by U.S. Fish & Wildlife Service (http://www.fws.gov/fire/program_statistics/) show that from 1995 to 2006 over 90 percent of wildland fires have burn area less than 1000 acres (405 hectares) in the United States. Because of the special regional wildland fire patterns, environmental factors, and frequent activities of prescribed fires in the southeastern United States [1,2], wildland fires are commonly small in burn size and low intensity, thus low in brightness temperature when observed with the MODIS sensors. The dominant fire pattern in the southeast is the understory fire [3], which are less intense and less severe than crown fires dominant in the West. Understory fires are usually smaller size and lower temperature than crown fires, and are more difficult to detect using remote sensing.

Research on small fire detection by Wang et al. [4] found a substantial number of low intensity fires in the southeastern United States are omitted by the MODIS contextual algorithm. They suggested attenuating two thresholds of the MODIS contextual algorithm for detecting potential fire pixels. Their algorithm provided a useful tool for identifying small fires omitted by the MODIS contextual algorithm. In this paper, we adjusted the MODIS contextual algorithm based on their results.

This research collected 6596 sample fire pixels from 72 MODIS granules to analyze the performance of the MODIS contextual algorithm for detecting small fires, observed by

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MODIS (Moderate Resolution Imaging Spectroradiometer) sensors onboard NASA's Terra and Aqua satellites. It analyzed several reasons that the MODIS contextual algorithm omits small fires, and addressed several aspects on how to improve the MODIS contextual algorithm, which provided the necessary knowledge on improving the accuracy of small fire detection in the southeastern United States.

2 DATA AND METHODS

2.1 Datasets

We selected 72 MODIS granules with substantive numbers of missed fire spots. All these granules, observed from 2001 to 2004, were downloaded from the Earth Observing System Data Gateway, Land Processes Distributed Active Archive Center (DAAC), including the MODIS Level 1B Radiance product (MOD02/MYD02), the geolocation product (MOD03/MYD03), and the thermal anomalies, fires, biomass burning product (MOD14/ MYD14). The MODIS Direct Readout (DR) software package MODISNDVI_DB_V2.1 is used to calculate atmospherically corrected solar reflectance at red, green, blue channels for generating true color images. The DR software is provided by the Direct Readout Laboratory at http://directreadout.gsfc.nasa.gov/. MATLAB is used to implement the adjusted algorithm. We identified 6596 fire pixels in these 72 granules, of which 3809 fire pixels were missed by the MODIS contextual algorithm. The spatial distribution of the 2787 fire pixels that were identified by both algorithms, and 3809 fire pixels missed by the MODIS contextual algorithm are displayed in Fig. 1 panel (a) and (b), respectively.

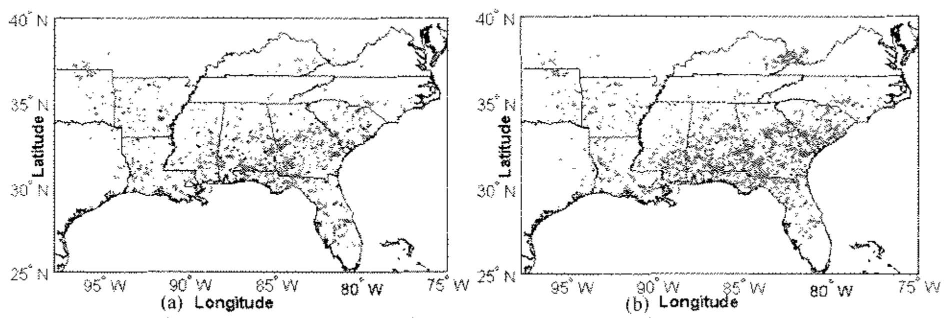

Fig. 1. Spatial distribution of the fire pixels. (a) Fire pixels detected by the MODIS contextual algorithm; (b) Fire pixels omitted by the MODIS contextual algorithm.

These fire pixels are broadly distributed in seven southeastern states, including South Carolina, Georgia, Florida, Alabama, Louisiana, Mississippi, and Arkansas. All these fire samples are validated using the MODIS contextual algorithm [5] and visual examination of MODIS 1 km resolution true color images, so that all identified fire spots are confirmed to be real fire pixels.

2.2 Methods

The MODIS version 4 contextual algorithm [5] is an optimized algorithm for global fire detection. This algorithm, designed for operational global fire monitoring, has limitations for regional fire detection in the southeastern states, where the understory fire regime is dominant. These limitations include problems caused by large view angles, the over-high fixed threshold for identifying potential fire pixels, and the impact of undetected fire pixels that are falsely counted as valid background pixels.

The accuracy of small fire detection decreases with the increase of view angles. Giglio et al. [6] evaluated three global fire detection algorithms using simulated AVHRR infrared data, including a fixed threshold algorithm [7], and two contextual algorithms [8,9]. They found that the detectability of low intensity fires decreases with increasing view angles. For scan angles up to ~45 degree this shift is gradual, but for larger scan angles the curve of difficulty increase rapidly. The brightness temperature T_4 and T_{11} decrease as scan angles increase for small fires (~100 m^2), where T_4 and T_{11} represent brightness temperature at AVHRR 3.75 μm and 10.8 μm channels, respectively, or at MODIS 3.96 μm and 11.0 μm channels, respectively. However, T_4 decreases more rapidly than T_{11}. This results in a reduction in ΔT, which is the difference of T_4 and T_{11}, so that detection becomes less likely as scan angles increase.

These three issues in the MODIS contextual algorithm are interrelated. Preliminary thresholds ($T_4 > 310$ K and $\Delta T > 10$K) which are too high, falsely excludes many low intensity fires with T_4 lower than 310 K in the first step of the algorithm, i.e. the process of identifying potential fire pixels. Of these fire pixels, some small fires observed at large view angles are mistakenly marked as non-fire pixels due to their brightness temperature T_4, and ΔT being lower than they would be at the nadir. All these missed fire pixels, in turn, are mistakenly counted as non-fire background pixels, and increase the background brightness temperature. This further falsely eliminates other fire pixels in the process of contextual tests. Therefore, when applied to regional active fire detection in the southeast, the MODIS version 4 contextual algorithm often misses low intensity fires.

A challenge to studying remote-sensed characteristics of low intensity fires is to find an algorithm that can identify small fires omitted by current algorithms. An algorithm [[4]] based on the MODIS version 4 contextual algorithm was recently developed to detect low intensity fires in the southeastern states. This algorithm is more sensitive to small fires especially at large view angles because it attenuates the T_4 threshold ($T_4 > 293$ K). In this study we use an adjusted algorithm based on the MODIS version 4 contextual algorithm and the results of Wang et al. [[4]]. This adjusted algorithm changes the MODIS contextual algorithm in three aspects to allow more small fires to be detected by relaxing the conditions of fire detection. First, the preliminary test $T_4 > 310$ K is substituted by the threshold $T_4 > 293$ K. Second, the contextual test $\Delta T > \overline{\Delta T} + 3.5\delta_{\Delta T}$ is replaced by the test $\Delta T > \overline{\Delta T} + 2.5\delta_{\Delta T}$. Last, the contextual test $T_4 > \overline{T_4} + 2\delta_4$ is used instead of $T_4 > \overline{T_4} + 3\delta_4$.

The results of the adjusted algorithm are validated by the MODIS contextual algorithm and visual examination based on MODIS 1 km true color images. Fire events detected by both the MODIS contextual algorithm and the adjusted algorithm are considered true fires, since the MODIS contextual algorithm has been validated systematically and offers a significantly lower false alarm rate. We use visual inspection to check the remaining fire pixels that can only be identified by the adjusted algorithm. If a detected 'fire' spot is accompanied by a smoke plume, we consider it as a real fire spot; otherwise comparative analysis is conducted between earlier and later observations at this location. If a previous and/or later observation of this fire spot is also identified as a fire spot, this fire spot is believed to be a true fire spot; otherwise it is identified as an uncertain pixel and excluded from further analysis. By eliminating uncertain pixels through the validation process, we obtain the database of the "ground truth" for fire spots.

3 RESULTS

Examples of fire maps derived using the adjusted algorithm are displayed in Fig. 2. Fires in the left panels, marked in red with the MODIS 1 km true color image background, are detected by the adjusted algorithm. The right panels show fire maps detected by the MODIS contextual algorithm. Panel (a) and (b) present a typical situation when sensor view angles are large. Panel (c) and (d) are examples of the MODIS contextual algorithm systematically omitting small fires in less vegetated areas, where the adjusted algorithm is able to detect more fire spots. Panel (e) – (h) represents the capability of the adjusted algorithm to identify small fires mixed with low clouds and high clouds.

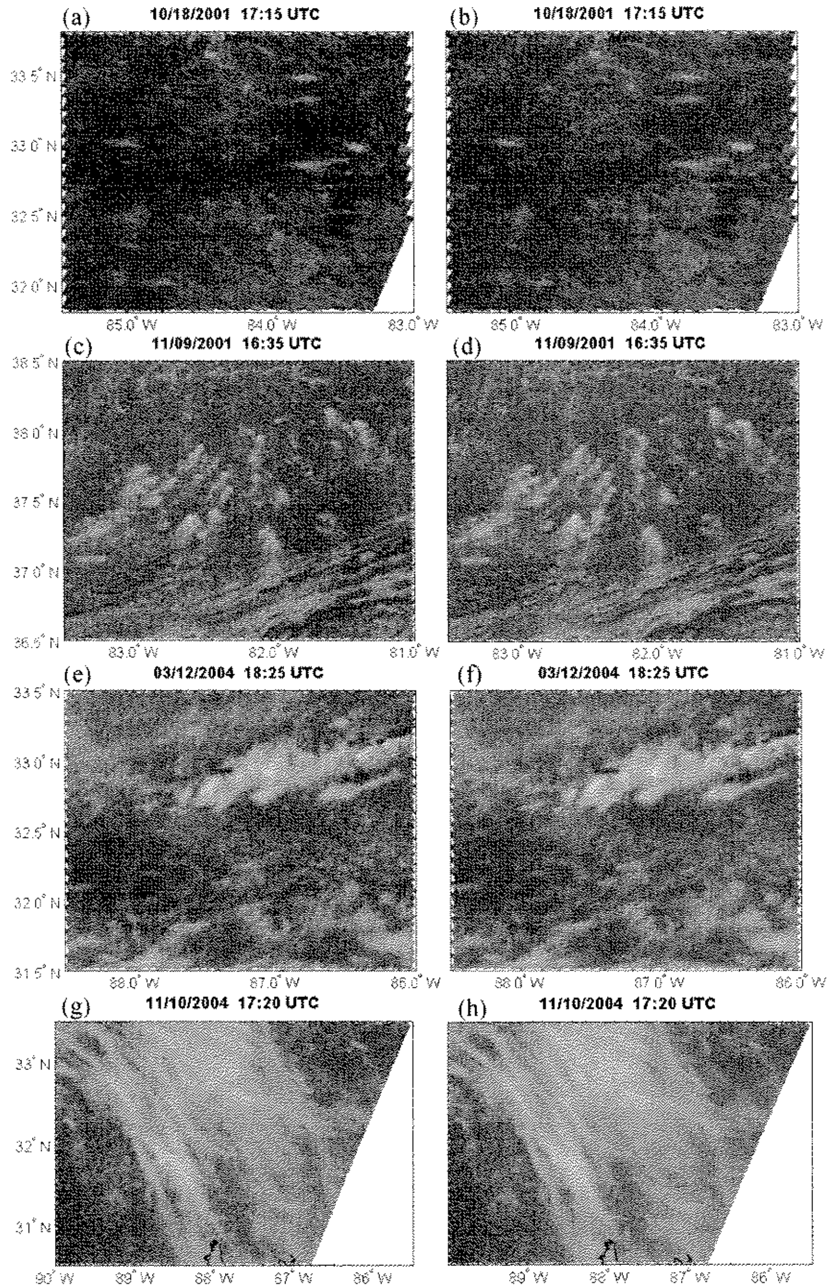

Fig. 2. Small fires detected by the adjusted algorithm and the MODIS contextual algorithm. Fires in left panels are detected by the adjusted algorithm, and fires in right panels are detected by the MODIS contextual algorithm.

Of all 6596 fire pixels, two groups are separated. The first group (MCA) includes fire pixels that can be detected by both algorithms, named as fire pixels identified by the MODIS contextual algorithm. The other group (AA) includes fire pixels that are omitted by the MODIS contextual algorithm referred as fire pixels only detected by the adjusted algorithm. Three fixed thresholds to identify potential fire pixels in the MODIS contextual algorithm are analyzed based on these two groups.

3.1 Test for the reflectance at 0.86 μm channel (R_2)

The histogram of R_2 (reflectance at band 2) (Fig. 3 Panel a) reveals that the fire pixels omitted by the MODIS contextual algorithm have similar distribution as those fire pixels detected by both algorithms. The density distribution of all fire pixels (Fig. 3 Panel b) shows that the reflectance increases slightly with view angles greater than 40 degrees. The distribution of R_2 indicates that the R_2 threshold $R_2 < 0.3$ is still valid for detecting low intensity fires omitted by the MODIS contextual algorithm. The increase of view angles does not substantially affect the validity of the R_2 threshold.

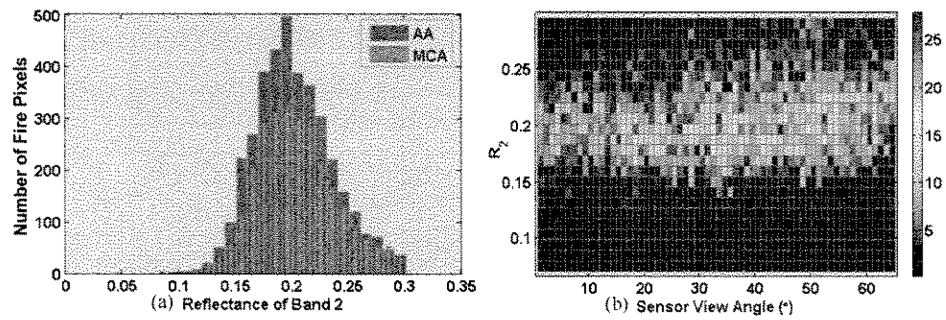

Fig. 3. The distribution of R_2. (a) The histogram of R_2. The distribution of fire pixels detected by the MODIS contextual algorithms is in brown (MCA). Blue is for fire pixels that only can be detected by the adjusted algorithm (AA). (b) The density distribution of all fire pixels (Group AA and MCA) with R_2 and the sensor view angle.

3.2 Test for the brightness temperature at 3.9 μm channels (T_4)

The histogram of T_4 (Fig. 4 Panel a) shows that a substantial number of fire pixels have T_4 values lower than 310 K. None of which are detectable by the MODIS contextual algorithm. The combination of fire pixels from Group MCA and Group AA forms a nearly intact distribution of T_4. The density distribution of fire pixels with the sensor view angle and T_4 shows a decreasing trend with increasing sensor view angles. To show this trend more clearly, the maximum densities of fire pixels at every sensor view angle in Panel b are identified, and plotted in Panel c, where the corresponding brightness temperature T_4 converges to lower T_4 values (< 310 K) as the sensor view angle increases. This shows that the sensor view angle evidently affects the remote-sensed T_4 values of fire pixels, and consequently influences the accuracy of the MODIS contextual algorithm because its fixed preliminary threshold $T_4 > 310$ K is too high. One of the reasons that the adjusted algorithm can detect so many low intensity fires missed by the MODIS contextual algorithm is that the adjusted algorithm uses a more relaxed preliminary threshold, $T_4 > 293$ K, thus avoiding the major effect of the sensor view angle on T_4 of fire pixels. The fire density distribution with R_2 and T_4 (Panel d) shows that all fire pixels cluster to the area centered at R_2 equal to 0.19 and T_4 equal to 305 K with R_2 smaller than 0.3 and T_4 greater than 293 K. This further proves that the R_2 threshold is still valid, that the threshold $T_4 > 310$ K is too high for small fire detection, and that $T_4 > 293$ K should be adopted instead. Setting the T_4 threshold to 293 K allows the detection of low intensity fires omitted by the MODIS contextual algorithm.

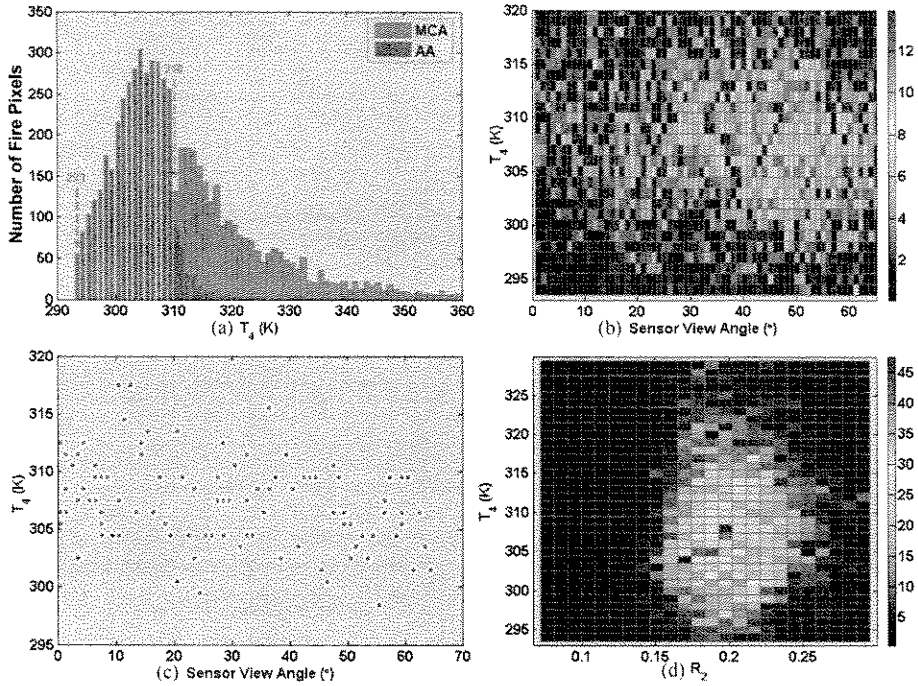

Fig. 4. The distribution of brightness temperature T_4. (a) The histogram of T_4. The distribution of the fire group MCA is in brown. Blue is for the fire group AA. (b) The density distribution of all fire pixels (Group AA and MCA) with T_4 and the sensor view angle. (c) The distribution of T_4 for maximum fire density at all sensor view angles. (d) The density distribution of all fire pixels with R_2 and T_4.

3.3 Test for ΔT

Figure 5 Panel (a) displays the histograms of ΔT for Group MCA (brown), Group AA (blue), and the combination of Group MCA and Group AA (grey). The ΔT distribution for omitted fire pixels (Group AA) is not an intact distribution curve and is cut off at $\Delta T = 10$ K, which is the ΔT threshold used by both algorithms. While the skewed distribution for Group MCA is relatively intact. The distribution of all fire pixels shows the same characteristics as the omitted fire pixels (Group AA), and is not intact. Panel (a) implies that the threshold $\Delta T > 10$ K possibly is too high to detect some small fires, and both algorithms risk omitting small fires because of this high threshold. Panel (b), the density distribution of all fire pixels with ΔT and the sensor view angle, shows that as view angles increase, ΔT converges to a low value rapidly, and is likely to drop below 10 K. The maximum densities of fire pixels at all sensor view angles in Panel b are identified, and plotted in Panel c, in which the corresponding brightness temperature ΔT converges to 10K rapidly as the sensor view angle increases. Because both algorithms use 10 K as the threshold, Panel (c) is unable to show the real converge point if the converge point is lower than 10 K, which is very possible. The fire density with ΔT and T_4 (Panel d) shows an incomplete distribution. In the previous section we found that T_4 threshold of 293 K is valid, so the primary reason of this incomplete distribution is because the ΔT threshold (10 K) is too high. In the algorithm designed for small fire detection, the ΔT threshold should be tuned to a value lower than 10 K.

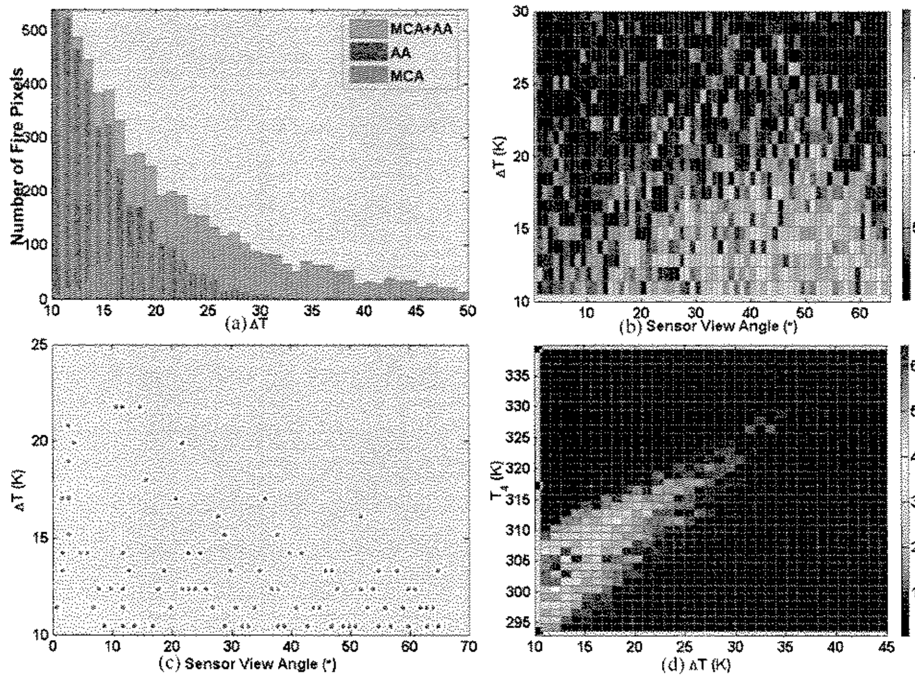

Fig. 5. The distribution of ΔT. (a) The histogram of ΔT. The distribution of fire pixels detected by the MODIS contextual algorithms (MCA) is in brown. Blue is for fire pixels that only can be detected by the adjusted algorithm (AA). All fire pixels from both groups are in grey. (b) The density distribution of all fire pixels with ΔT and the sensor view angle. (c) The distribution of ΔT for maximum fire density at all sensor view angles. (d) The density distribution of all fire pixels with ΔT and T_4.

3.4 Over-all effect of view angles on the MODIS contextual algorithm

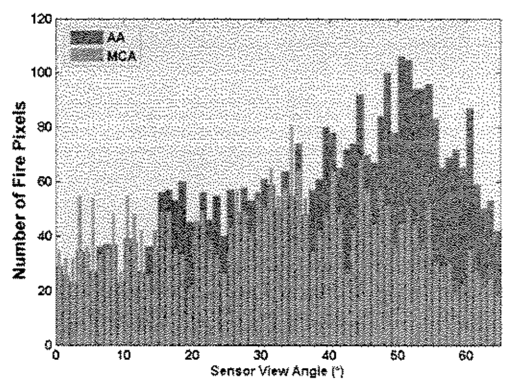

Fig. 6. The histogram of sensor view angles for fire pixels. The distribution of fire pixels detected by the MODIS contextual algorithms (MCA) is in brown. Blue is for fire pixels that only can be detected by the adjusted algorithm (AA).

The number of fire pixels detected by the MODIS contextual algorithm (Fig. 6, in brown) steadily decreases when view angles are larger than 40 degrees, because of the effect of sensor view angles as we observed in Fig. 4 c and Fig. 5 c. Fig. 6 illustrated the trend of missed fire pixels by the MODIS contextual algorithm, i.e. number of missed fires (in blue) gradually increase with the view angle when it is less than 55 degree. However, when the sensor view angle is larger than 55 degrees, number of missed fire pixels decrease dramatically. The adjusted algorithm is obviously affected by the view angle larger than 55 degrees. As analyzed in the previous sections, the T_4 and ΔT of fire pixels decrease as sensor view angle increases, which is a very important cause of omission errors in the MODIS contextual algorithm. In the adjusted algorithm, T_4 has been attenuated to a proper threshold so that it is not a major source of omission errors. Therefore, ΔT is possibly one of the causes of the drop of omitted fire curve when view angles are greater than 55 degrees.

In the design of a regional algorithm for small fire detection, merely decreasing T_4 and ΔT thresholds will probably cause false alarms to rapidly increase around the nadir region. An alternative option is to design T_4 and ΔT thresholds as the functions of view angles. False alarm rejection tests also have to be studied for those new false alarms caused by the lower T_4 and ΔT thresholds.

4 CONCLUSIONS

Using an adjusted algorithm, this study collected a database including 6596 remote-sensed fire pixels in 72 MODIS granules, of which 3809 fire pixels are missed by the MODIS contextual algorithm. We analyzed the MODIS contextual algorithm based on this database, which contains fire locations, the reflectance of the MODIS 0.86 μm channel (R_2), and the brightness temperature of MODIS 3.96 μm and 11 μm channels (T_4 and T_{11}). The study explains the reasons that the MODIS contextual algorithm omits significant small fires. One of the major reasons is because of increase of view angles, especially when view angles are greater than 40 degrees. The paper discusses several aspects that may improve the regional detection of low intensity fires.

The results indicate that the R_2 threshold of $R_2 < 0.3$ is still valid for detecting small fires omitted by the MODIS contextual algorithm. The change of view angles does not substantially affect the validity of the R_2 threshold. However, a trend was observed whereby T_4 decreases with the increase of sensor view angles. This trend demonstrates that sensor view angles evidently affect the accuracy of the MODIS contextual algorithm for detecting low intensity fires. The reason that the adjusted algorithm can detect many more small fires is because the T_4 threshold is attenuated to 293 K, which counts in the T_4 variations of fire pixels due to increased view angles. The study indicates the threshold $T_4 > 310$ K is too high for small fire detection, and that $T_4 > 293$ K should be adopted instead. We also observed a decreasing trend of ΔT with increase of sensor view angles. As the view angles increase, ΔT converges to a low value rapidly, and is highly probable to drop below 10 K, which implies that the threshold $\Delta T > 10$ K is too high for detecting small fires, and both algorithms risk omitting small fires.

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