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Revision of Moran Scatterplot Approach for More Effective Forest Fire Detections

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Abstract: - As spatial outliers in remotely sensed imageries are regarded as abnormal values reflecting abnormal natural or man-made phenomena, there have been continuous researches to detect such outliers. On the other hand, in statistics, methods based on spatial autocorrelations are developed to detect the outliers. These ideas may be combined to detect forest fire pixels in the satellite imageries from NASA's AQUA platform. Reasoning comes from the fact that the forest fire detection means finding spatial outliers using spatial variations of brightness temperature. Thus, in this paper, we propose a new forest fire detection approach with Moran scatterplot analysis that is based on spatial outlier detection methods. This approach is a bit revised one than the one already proposed by the same researchers last year, which is more effective in detecting the forest fire. The proposed approach was tested to evaluate its effectiveness. The evaluation was done by comparing the results with the MODIS fire product provided by the NASA MODIS Science Team, and the results of last year's research. The evaluation results showed the revised approach has a good potential in detecting the fire pixels.

Key-Words: Spatial outlier detection, Moran scatterplot, MODIS, Forest fire

1 Introduction

Throughout researches, there have been three kinds of forest fire detection methods in remote sensing; the spectral method, the spatial method and the temporal method. The spectral method uses simple thresholds for single- or multi-band data to identify fire pixels [1].

The spatial method uses statistical attributes of a local area, a mean and a standard deviation of pixel values surrounding a pixel [1] [2]. The temporal method uses temperature differences between remotely sensed imageries of different times. All of these methods have been modified according to their precise purposes and test areas to improve accuracy. Aside from these methods, on the other hand, there can be another approach to effectively detect the forest fire.

Once happens, forest fire in an imagery brings rapid change in brightness temperature of the corresponding pixels compared to its surroundings [3], [4]. Thus, forest fire pixels can be treated as thermal anomaly in an image that represents land surface temperature [4]. From this reasoning, forest fire detection becomes a process of finding spatial outliers that reflect local instability or extremity with respect to its neighboring pixel values [5], [6], [7]. So far, continuous researches to detect such spatial outliers have been done especially in the statistics.

From the statistical viewpoint, the Moran scatterplot algorithm is the one effective in detecting the spatial outliers, which uses correlations of attributive values of locations with its neighboring values and the entire data values [6],[8],[9],[10]. This algorithm may be applied in detecting the pixels indicating forest fire from the remotely sensed imageries.

From such backgrounds, there was another approach adopting the Moran scatterplot analysis, which was also called the graph-based analysis, to detect the forest fire [11]. In this approach an ordinary scatterplot and Moran scatterplot were introduced and tested. The results showed the possibility of such approach in detecting the fire pixels [11]. Though it is proven to be useful, the approach still has some margins to be improved as is discussed [11].

Therefore, in this research, some revisions of the Moran scatterplot approach were carried out. Thus, ideas such as a spatial weight matrix using a quartic kernel and a least square regression line are introduced and applied. Throughout this study, we wanted to know whether such revision has a meaning in terms of applicability in detecting forest fire. Consequently in the following section, Moran scatterplot analysis is introduced along with the ideas for revisions. Then, an evaluation of the new approach was conducted by comparing the results with the MODIS fire product provided by the NASA MODIS Science Team, and the results of the Moran scatterplot approach [11].

For the test imagery, a MODIS (Moderate Resolution Imaging Spectro-radiometer) satellite data from the AQUA covering the South Korean peninsula is used.

2 Methodology

Once happens, forest fire causes different changes in brightness temperature in 4 μm and 11 μm wavelengths, respectively [1]. Thus, brightness temperature in 4 μm changes significantly compared to the changes in 11 μm [3]. Accordingly, the corresponding brightness temperature in 4 μm (T_4) is used as a single spatial variable in the Moran scatterplot. The following sections explain the detailed ideas on the proposed approach.

2.1 Spatial weight matrix

The spatial weight matrix W reflects the relationship between each *(i,j)* pair of observations. In this research, we construct a spatial weight matrix using a quartic kernel. For revising the Moran scatterplot approach in the following paragraphs, a row-standardized spatial weight matrix W is used, which assumes the spatial effects decrease as the distance between observations increases. The elements w_{ij} of spatial weight matrix are defined as

$$w_{ij} = \begin{cases} \frac{3}{\pi}\left(1 - \frac{{d_{ij}}^2}{\tau^2}\right)^2 & d_{ij} \le \tau \\ 0 & otherwise \end{cases} \tag{1}$$

Where, d_{ij} is the distance between pixel i and pixel j, τ indicates threshold of kernel size. The weight of pixels within a distance τ drops smoothly as the distance d_{ij} increases. We let $\tau = 3$ to construct the spatial weight matrix in the Moran scatterplot algorithm. The row-standardized spatial weight matrix is created through the process of dividing the each element in the weight matrix by its row sum.

2.2 Moran scatterplot

Moran's I is a simple translation of a non-spatial correlation measure into a spatial context and is one of the oldest indicators of spatial autocorrelation. Spatial autocorrelation is based on the first law of geography: near things are more similar than are more distant [9].

Positive spatial autocorrelation is yielded when neighboring areas are similar or the same. The Moran statistics can measure both the global trend and the local trend of data set. The global Moran's I measures global spatial autocorrelation of a data set while local Moran's I measures local spatial autocorrelation of a data set. The global Moran's I is defined as

$$I = \frac{n}{\sum_i^n \sum_j^n w_{ij}} \frac{\sum_i^n \sum_j^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i^n (x_i - \bar{x})^2} \tag{2}$$

Where, n indicates a total data count, $\bar{x}$ the mean of total data, x the spatial variable (T_4), and w_{ij} the element of spatial weight matrix. By dividing the numerator and denominator of equation (2) with n^2, and using row-standardized spatial weight matrix, the global Moran's I can be expressed in Z statistics as in equation (3).

$$I = \frac{n}{\sum_i^n \sum_j^n w_{ij}} \frac{\sum_i^n \sum_j^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i^n (x_i - \bar{x})^2} = \frac{1}{n} Z^T \tilde{Z} \tag{3}$$

The local Moran's I decomposes the global Moran's I into contribution of each location. Therefore, the local Moran's I can be used to identify fire pixels [10]. The local Moran's I for an observation of i may be defined as

$$I_i = z_i \times \sum_j^n w_{ij} z_j \tag{4}$$

Where the observations z_i, z_j are in deviations from the mean, and the w_{ij} is an element from a spatial weights matrix W.

The Moran scatterplot is a plot of normalized brightness temperature value against the neighborhood of normalized brightness temperature value ($W \cdot Z$) [10]. Where, W is the row-standardized spatial weight matrix. The Moran scatterplot contains four quadrants. The upper left and lower right quadrants of figure 1 indicate a spatial association of dissimilar values. Spatial outliers can be identified form theses two quadrants.

However, in this research it is decided that pixels in lower right quadrants (a) (Fig. 1), which are surrounded by low value neighbors in Moran scatterplot, are highly potential fire pixels because forest fire areas have a higher brightness temperature than their neighbors.

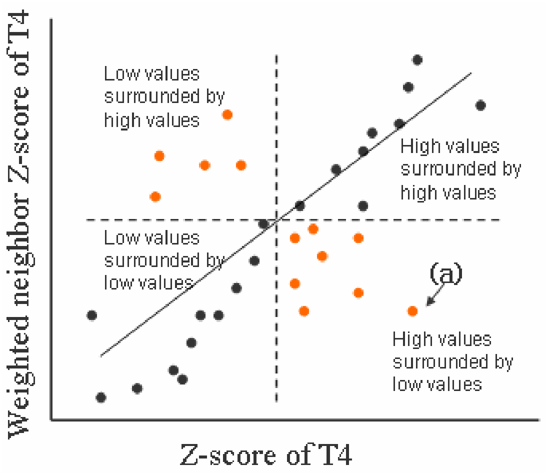

Fig 1. Moran scatterplot

Finally, a least square regression line is used to identify final fire pixels among the highly potential fire pixels. The final fire pixels show significant standardized errors from the least square regression line [5].

Assuming that errors are normally distributed, a standardized residual $s\varepsilon = |(\varepsilon - \mu_{\varepsilon})/\sigma_{\varepsilon}| > \theta$ is a common test, in which μ_{ε} and σ_{ε} represent the mean and standard deviation of the distribution of the error term ε , respectively. Pixels with standardized residuals that are greater than θ or less than $-\theta$ are flagged as possible fire pixels. In figure 1, point (a) turned out to be the farthest from the regression line and thus have a high potential to be a fire pixel. As a threshold, we let θ =3 to detect the final fire pixels.

3 Implementation Details

In the previous section, ideas to revise the Moran scatterplot approach are developed. Fig. 2 presents a flowchart of this research for implementation, which can be divided into two parts, a preprocessing of MODIS L1B data and an analysis and assessment of the proposed approach.

At first, as pre-processing, geometric corrections, subset extractions of study area, and transformations of data from radiance to temperature were done.

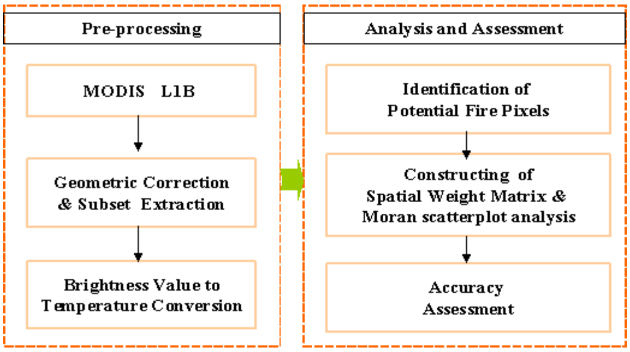

Fig. 2 Workflow of the study

Then, some tests to identify potential fire pixels were conducted, of which results reduce the execution time as well as make the detection process more effective. This is done by removing obviously non-fire pixels such as clouds or cold land pixels. Generally, clouds have low radiance value in 4 μm and 12 μm band compared to land surface. This fact allows detecting cloud pixels. In this research, potential fire pixels are decided using two criteria:

$$\begin{aligned} &Criterion\,1: R_4 > \max(\overline{R}_4, \overline{R}_{4w}) \quad and \quad R_{12} > \max(\overline{R}_{12}, \overline{R}_{12w}) \\ &Criterion\,2: \nabla T = (T_{12} - T_4) > 8K \end{aligned} \tag{5}$$

Where, R_4, R_{12} indicate radiance of 4 μm and 12 μm bands respectively, $\overline{R}_4, \overline{R}_{12}$ indicate mean radiance of 4 μm and 12 μm bands in full image respectively, and $\overline{R}_{4W}, \overline{R}_{12W}$ indicate mean radiance of 4 μm and 12 μm bands in local window. Such simple criteria screen out more than half of the pixels to be processed and eliminate cloud and sun glint pixels [4].

After this step, the proposed approach was applied to the potential fire pixels. Then, the user accuracy and producer accuracy are calculated by comparing their detection results with the ground data provided by the Korea Forest Service (KFS) [13]. KFS has built a forest fire database in terms of igniting and extinguishing times, locations, burnt areas, and other related information. Consequently, the performance of the approach is evaluated through the comparison of the resulting accuracy with that of the MODIS fire product provided by the NASA MODIS Science Team and the results of the Moran scatterplot approach [11].

4 Experiments and Results Analysis

The data used in this research is a set of MODIS L1B imageries covering the South Korean peninsula taken by NASA's AQUA satellite. A metadata of these imageries is shown in Table 1. We used seven imageries taken on April of 2003, February and March and April of 2004, and April of 2005.

Table 1 Meta data of imageries used

Satellite Name	AQUA
Sensor Used	MODIS
Spatial Resolution	250m(Band 1-2) 500m(Band 3-7) 1km(Band 8 – 36)
Number of Band	36
Area Covered	South Korea

The MODIS bands used in this research are listed in Table 2. In detecting forest fire from the MODIS imagery, band 21 as well as band 22 was used to solve the problem of sensor saturation. Sensor saturation takes place when radiance that reaches the sensor is beyond the upper limit of the sensor's sensing range [12]. The problem of sensor saturation was solved by using band 21 when sensor saturation took place in band 22.

Table 2 Specification of MODIS bands for fire detection

Band number	Bandwidth(μm)
21	3.930-3.989
22	3.930-3.989
31	10.780-11.280
32	11.770-12.270

As for the reference data for accuracy assessment, data from the KFS forest fire information system was used. The KFS data include locations of forest fires, the time of breakout and extinction, the size of damaged areas, and the cause of forest fires. In making use of the data, it was troublesome because the data was not referenced to geographic coordinates but addresses. Considering the spatial resolution of MODIS (1km on ground), we expected that there would be little possibility of misclassification from converting the addresses to approximate geographic coordinates. Thus, it was done as such. Regarding the time of image acquisition, the AQUA satellite scans Korea at around 13:30pm that forest fires that were running through this time was recorded. The size of actual damaged area recorded in the KFS system can be larger than the scanned area. Theoretically, MODIS can sense the forest fire with the temperature over at least 800~1000K and the area over 0.01ha ($100m^2$), and the detection accuracy is about 50% [2]. Therefore, the forest fire recorded in Korea Forest Service system was selected only when the size of damaged area was over 0.1ha.

As previously mentioned, the resulting user accuracy and producer accuracy are compared with the one from the MODIS Fire Product. The NASA team used the contextual algorithm to detect thermal anomalies, such as forest fires or volcanic eruptions [2].

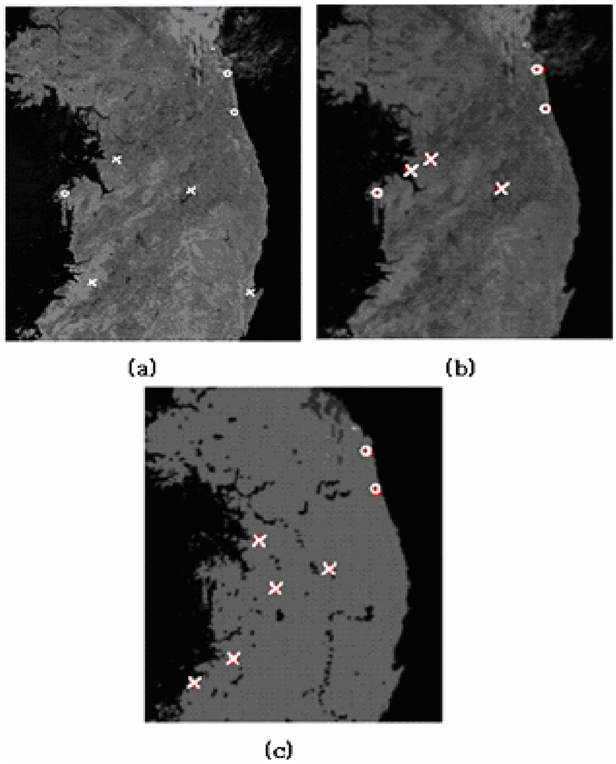

Fig 3. Detection results of Revised Moran scatterplot approach (a), Moran scatterplot approach (b) and MODIS fire product (c) (o: True fire pixels in detected pixels, x: True false fire pixels in detected pixels)

The accuracy assessment was done by checking the classified fire pixels against the data from the KFS. To understand mechanisms between the commission and omission error, both the producer accuracy and user accuracy were calculated. Then, the same imageries were used by the Moran scatterplot approach, as well as the method provided by the NASA MODIS Science Team and both the producer and user accuracy are calculated. The test results are shown in Table 3.

Table 3 Accuracy test results

	Revised Approach	Moran Scatterplot	MODIS Fire Product
Total Number of Detected Fire Pixels	33	40	35
Number of True Fire Pixels in Detected Pixels	15	15	11
Number of Omission Error	11	11	15
Number of Commission Error	19	25	24
User Accuracy(%)	45.5	37.5	31.42
Producer Accuracy(%)	57.6	57.6	42.3

As shown in Table 4, the revised approach shows about 8% higher user accuracy than that of the Moran scatterplot approach, resulting in lower commission error. It shows 14% higher user accuracy and about 15% higher producer accuracy than that of the MODIS fire product.

From the above results, the proposed ideas to revise the Moran scatterplot approach is considered as applicable in detecting forest fire pixels for it yielded higher accuracies than the Moran scatterplot approach as well as the MODIS fire product.

5 Conclusions

In this paper, ideas to revise the Moran scatterplot approach are proposed and tested for more effective forest fire detection in MODIS L1B imagery. The idea adopted spatial weight matrices using a quartic kernel as well as least square regression lines to effectively reflect spatial variation. After applying and testing the new approach, the following results are acquired.

The newly introduced approach yielded higher user and producer accuracies than those of the MODIS fire product provided by the NASA MODIS Science Team, and higher user accuracy than that of the Moran scatterplot approach. Such a result does not mean that the proposed approach works better than the Moran scatterplot or traditional fire detection methods developed so far in all case. Rather, it implies the proposed algorithm has potentials to be applied in detecting the fire pixels and thus we need to put more intention on it. One thing to note is that comparing to the traditional methods, the proposed approach is easier to use because it does not need the step for determining the threshold empirically according to the target regions.

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