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BASIC STUDY OF LAND COVER CLASSIFICATION USING RAPIDEYE DATA TO ESTIMATE THE AMOUNT OF DISASTER WASTE

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Abstract. *To draw reconstruction plans following great earthquakes, it is necessary to quickly estimate the amount of disaster waste using remote sensing data. However, the digital number (DN) of each pixel represents the average land cover conditions, i.e., the information provided by a pixel should be represented as a one-pixel mixed-class ("mixel") instead of a one-pixel one-class. In a previous study, we proposed a method for unmixing mixels using the DNs and texture features from THEOS data. However, to detect collapsed buildings, at least a 2.0 m ground resolution is required. In this paper, we propose a method of land cover classification using RapidEye data, whose effectiveness was confirmed by our results. That is, the ground resolution of the RapidEye data is improved 6.5 meters to about 2.0 meters by unmixing mixels.*
Keywords: Remote sensing, Mixel, Land cover classification, RapidEye, Great East Japan Earthquake

1. **Introduction.** To draw reconstruction plans following great earthquakes, the amount of disaster waste must be quickly estimated [1]. Disaster waste estimation using remote sensing data is a first priority that will affect all subsequent processing. Although remote sensing data of high ground resolution contain detailed information, they have a narrow scanning width and high costs. On the other hand, remote sensing data of 5-30 m ground resolution can cover wide areas in one time at low costs. However, the digital number (DN) of each pixel represents the average land cover conditions, i.e., the information provided by a pixel should be represented as a one-pixel mix-class instead of a one-pixel one-class. This pixel is referred to as mixel [2] and both mixels and pure pixels should be considered to accurately classify land cover conditions. It is also necessary to develop a method to extract detailed information from remote sensing mixels. [3] proposed a method of unmixing mixel for improving the ground resolution of data. However, only three classes (rice field, soil, and vegetation) were classified by the method, and complicated land cover conditions like a disaster area have not been classified yet. In our previous study, we proposed a method for unmixing mixels that uses the DNs and texture features from THEOS data which observed the stricken area [4]. However, to detect collapsed buildings, at least a 2.0 m ground resolution is required. In this paper, we propose a method of

land cover classification using RapidEye data, which has a higher ground resolution than THEOS data. This paper consists of five sections. The background and purpose of this study are described in Section 1. Section 2 explains the study area and the data used for analysis. Section 3 outlines our method of land cover classification using RapidEye data. Section 4 shows the results of land cover classification and evaluates the results using a manually classified map. Section 5 discusses the conclusion of this study.

2. Study Area and Data Used.

2.1. Study area. In the Great East Japan Earthquake from March 11, 2011, 29,742,000 tons of disaster waste (18,794,000 tons of disaster waste and 10,948,000 tons of Tsunami deposit) were disposed in the Iwate, Miyagi, and Fukushima Prefectures, which suffered the most serious damage [5]. In the Miyagi Prefecture, 19,295,000 tons (11,710,000 tons of disaster waste and 7,585,000 tons of Tsunami deposit) were disposed, corresponding to about 65% of the total [5]. Although the waste disposal in this prefecture is finished, it was the fastest among the three prefectures. The purpose of this study was to identify land cover changes within an area circumference before and after an earthquake and to estimate the amount of disaster waste, using the Miyagi Prefecture coastal area as a study area.

2.2. Data used. The ground resolution of the RapidEye is 6.5 m for bands 1-5, with a scanning width of 77 km and a regression period of 5.5 days [6]. Table 1 lists the details of RapidEye data. In this paper, data from March 19, 2011, with 900 × 900 pixels size was used for analysis (Figure 1).

Table 1. Wavelength range of the RapidEye

Band	Wavelength range
1	440-510 nm Visible range (blue)
2	520-590 nm Visible range (green)
3	630-690 nm Visible range (red)
4	690-730 nm Red-edge region
5	760-880 nm Near-infrared region

Figure 1. Data used around Wakabayashi-ku, Sendai, Miyagi, Japan (RGB; band 3, 2, and 1) (including material ©2011 RapidEye S.á r.l. All rights reserved)

3. Proposed Method.

3.1. Outline. The proposed method involved five steps. First, classification groups and classes were set. Second, the RapidEye data were divided in similar feature domains. Third, we calculated the supervised data using the DNs. Fourth, the class mixture proportion was estimated using the supervised data. Finally, the mixels were estimated using the class mixture proportion and unmixed.

3.2. Estimation of the class mixture proportion.

(a) **Group and Class Classification:** The study area corresponded to a coastal area impacted by a Tsunami and covered by Tsunami deposits, which complicated its land cover classification. However, it could be classified using the THEOS data [4], given its low ground resolution (15 m), in opposition to the high ground resolution (6.5 m) of the RapidEye data, which complicates its pixel information. In this paper, we set five classification groups: water, buildings, flooded soil, vegetation, and soil, and 24 additional classes (e.g., "sea" and "marsh" were set in water group).

(b) **Domain Division:** To enable a detailed classification, the RapidEye data was clustered in five similar domains, specifically:

- A water-containing domain (Domain A), extracted with band 5 for low water reflectance;
- A vegetation-containing domain (Domain B), extracted using the normalized difference vegetation index (NDVI), which shows the vegetation activity, calculated by Equation (1).

$$NDVI = \frac{(NIR - VIS(Red))}{(NIR + VIS(Red))} \tag{1}$$

  Here, *NIR* as the DN of band 5 of high vegetation reflectance and *VIS (Red)* as the DN of band 3 of low vegetation reflectance from the RapidEye data;
- A vegetation-free domain (Domain C), also extracted using the NDVI;
- A domain with similarly distributed features (Domain D), extracted based on the homogeneity, one of the texture features calculated by Equation (2) and the concurrent occurrence matrix.

$$homogeneity = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\left(\frac{1}{1+(i-j)^2}\right)P_\delta(i,j) \tag{2}$$

  The co-occurrence matrix was a matrix using the element of probability $P_\delta(i,j)$ of the density of a pixel with a constant displacement $\delta = (\gamma, \theta)$ from a pixel (j) of density i $(i, j = 0, 1, \ldots, n-1)$;
- And other domains (Domain E), not classified within the above four.

(c) **Generation of Supervised Data:** In each class set described by Section 3.2 (a), 50 points were sampled referring to actual conditions. Moreover, their average values and variance values were calculated, and were used as supervised data.

(d) **Calculation of the Class Mixture Proportion:** Based on the supervised data, the class mixture proportion was calculated by the method of estimating class mixture proportion [2], which proved to accurately estimate mixels on an actual image [7].

3.3. Mixel unmixing. Mixels are not independent of the adjacent pixels and can be considered relevant to their surrounding pixels. Therefore, it is possible to decompose a target pixel in the pure pixel from a composition class corresponding to the class mixture proportion. When a target pixel is located in a class boundary, the DN of that pixel is expressed by a linear combination of the DN of the pure pixel whose weight coefficient is the class mixture proportion of each class in the mixel [7]. In this study, the original pixels were divided in 3×3 pixels using the class mixture proportion.

The mixel unmixing involved three steps (Figure 2). First, the pure pixels and mixels were classified. When the class mixture proportion was above the threshold value T_P, the pixel was classified in the class characterized by the largest value. Subsequently, when the sum of the class mixture proportion of the top two classes was above the threshold value T_M, the pixel was classified as a mixel consisting of these classes. Table 2 lists the thresholds for each divided domain. Second, the class mixture proportion of the top two classes was re-estimated and the pure pixels and mixels re-classified. Finally, the mixels were unmixed based on their class mixture proportion and location information [3].

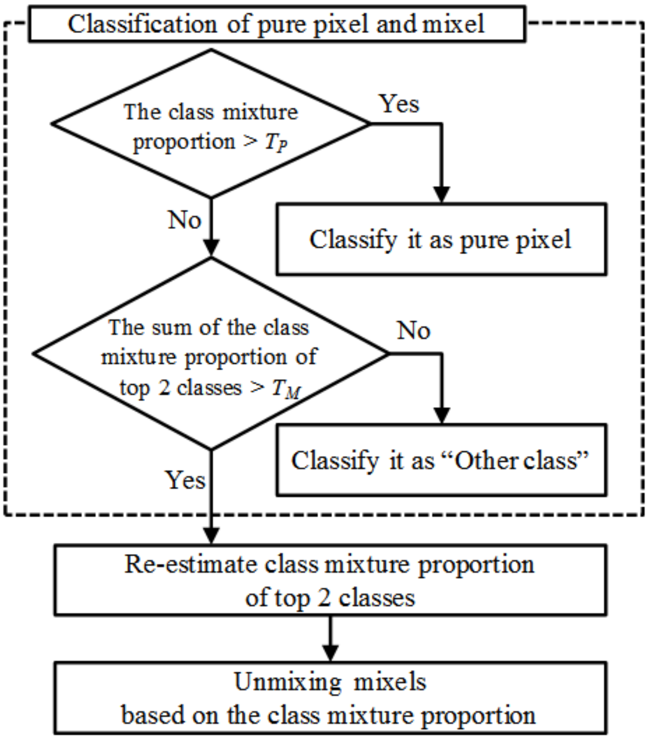

FIGURE 2. Flow-chart of the unmixing mixel process

TABLE 2. Thresholds for each divided domain

	T_P	T_M
Domain A	0.55	0.45
Domain B	0.55	0.55
Domain C	0.55	0.50
Domain D	0.45	0.50
Domain E	0.50	0.45

3.4. **Calculation of the matching rate.** To quantitatively evaluate the results from the proposed method, the matching rate was calculated in the following two steps. A classification map was manually created referring to the map [8] and aerial photograph [9] (Figure 3), after calculating the matching rate between the land cover classification and the manually classified map.

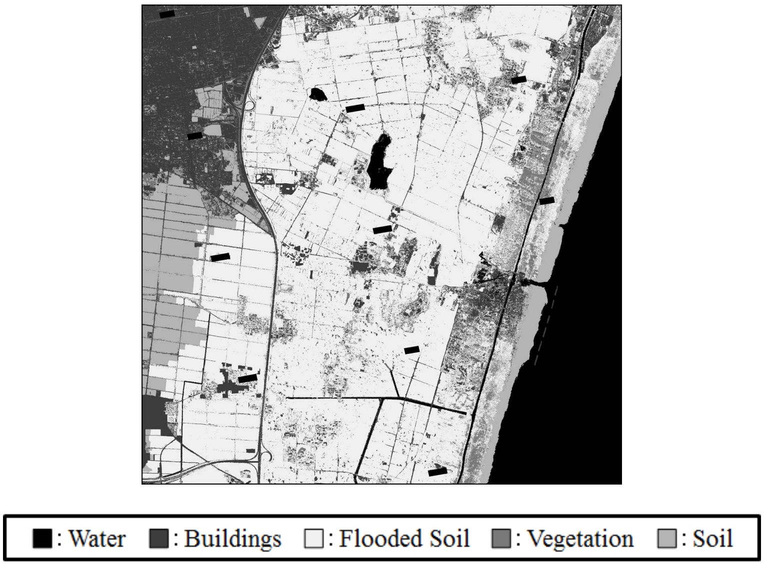

Figure 3. Manually classified map

4. Results and Discussion.

4.1. Proposed method results. Figure 4 shows the land cover classifications by the proposed method, with all pixels expressed as pure pixels and image size had changed from 900×900 pixels to 2700×2700 pixels. That is, the ground resolution of data used was improved 6.5 m to about 2.0 m by the proposed method. However, part of the flooded soil group was classified as a water group (circle in Figure 4), suggesting that the results reflect the actual situation, with accumulation of Tsunami water in that area. Therefore, when the water group pixel from the proposed method was in the flooded soil group of the manually classified map, the pixel was considered as a flooded soil pixel. In addition, since the acquisition date of the aerial photograph used to manually create the classification map differed from the RapidEye data, the land cover conditions may have changed in the flooded soil region. Therefore, the soil group pixel was included in the flooded soil group. In order to solve this problem, we have to select data without the difference in the date of acquisition in each data. However, it has not come to acquire the data that has resolution

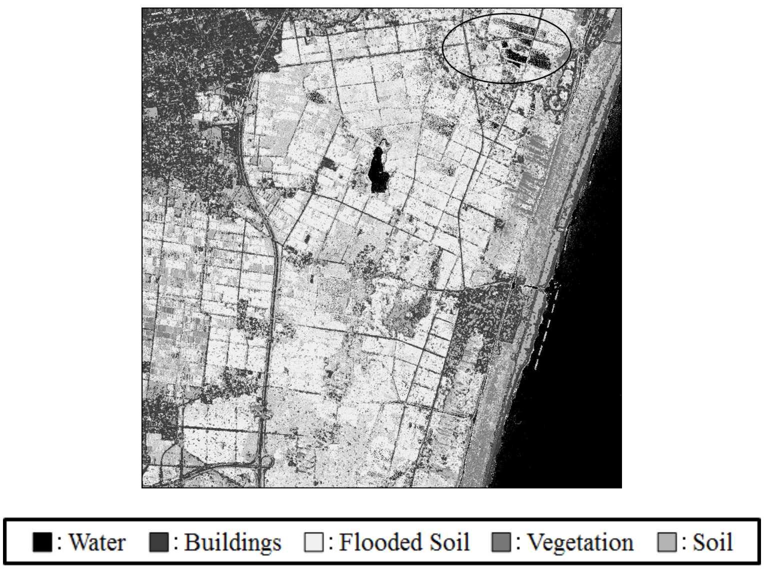

Figure 4. Land cover classification using the proposed method

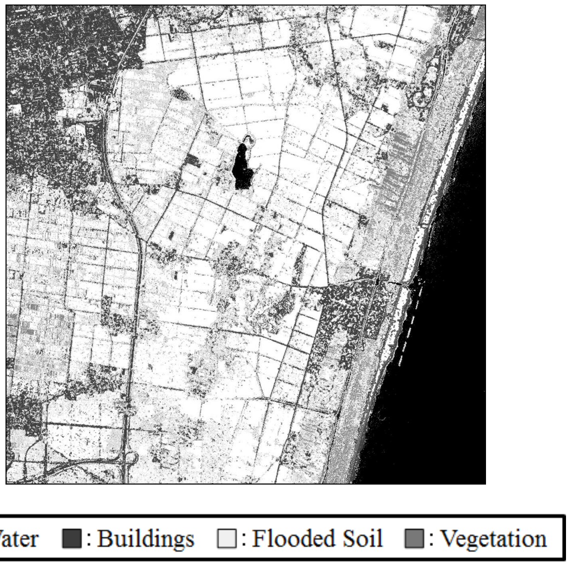

Figure 5. Land cover re-classification

Table 3. Calculated matching rates

	Matching rate (%)	Composition rate (%)
Water	91.4	12.5
Buildings	87.5	19.0
Flooded soil	90.5	61.3
Vegetation	87.0	7.2
Total	89.9	–

comparable as the resolution of RapidEye data. The low of the matching rate between the soil and the flooded soil region is a problem in the future.

Figure 5 shows the re-classification results and Table 3 lists the calculated matching rate for the above conditions. The matching rate was 89.9%, with a good agreement between the land cover classification and the manually classified map.

4.2. **Proposed method evaluation.** To examine the usefulness of the proposed method, the classifications were also obtained using the maximum likelihood method ("the comparative method") (Figure 6). In this result, some pixels in the sea region were classified as the buildings group, and many pixels in the wind break forest region were classified as the flooded soil group. That is, its classification could not reflect the actual conditions. Table 4 lists the comparison of the matching rates for the proposed and comparative method. The matching rates using the comparative method were 21.3%, 17.6%, and 77.7% lower for the water, buildings, and vegetation groups than using the proposed method. In addition, the total matching rate using the comparative method was 8.2% lower than the proposed method. The proposed method proved to be effective for land cover classification using RapidEye data.

5. **Conclusions.** This paper proposed a land cover classification method using RapidEye data to estimate the amount of disaster waste. We concluded that the ground resolution of the RapidEye data was improved, since all mixels were unmixed. In addition, the total matching rate compared to the manually classified map was 89.9%. The total matching rate of the proposed method was 8.2% higher than that for the maximum likelihood, suggesting its effectiveness.

■: Water ■: Buildings □: Flooded Soil ■: Vegetation

Figure 6. Comparative method classification

Table 4. Matching rates using the proposed and comparative methods

	Proposed method (%)	Comparative method (%)
Water	91.4	70.1
Buildings	87.5	69.9
Flooded soil	90.5	91.5
Vegetation	87.0	9.3
Total	89.9	81.7

In the future, we will investigate the land cover condition before an earthquake and develop a method to estimate the amount of disaster waste using RapidEye data.

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