Object-based Land Cover Classification for Pyongsan Uranium Mine and Concentration Plant using Machine Learning Based Classifier

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1. Introduction

With the significant enhancement to the spatial resolution of commercial satellite imagery, the International Atomic Energy Agency (IAEA) has applied satellite imagery analysis to verify the compliance with the Treaty on the Nonproliferation of Nuclear Weapons (NPT) [1]. Notably, in case of restricted access areas such as North Korea, various institutes regarding nuclear nonproliferation has utilized satellite imagery as the only means to monitor the suspected nuclear proliferation activities.

However, the greater number of areas monitored for nuclear nonproliferation increased, the more time and cost for image analysts to interpret the satellite imagery of those areas will be consumed [1]. In recent times, the computer-based image analysis using commercial software solutions has been indispensable to support image analysts by rapidly extracting features in the areas of interest (AOI). Furthermore, the software solutions such as eCognition® offers machine learning based classifiers (or algorithms), e.g. the decision tree and the support vector machine (SVM), which have been widely used in the field of image processing due to its high accuracy.

Therefore, this paper performed the object-based land cover classification for the Pyongsan uranium mine and concentration plant to detect North Korea's ongoing mining and milling activities using the SVM classifier in eCognition® [2]. Further, the modification of normalized difference of water index (MNDWI) was considered to reclassify the misclassified objects.

2. Methods and Results

2.1 Pyongsan Uranium Mine and Concentration Plant

The Pyongsan uranium mine and concentration plant is one of North Korea's largest declared uranium ore concentrate facilities, where uranium ores are mined and milled to yellowcake (U_3O_8) [2]. With analyzing satellite imagery, 38 North (2018) estimated that the plant had been still in operation by detecting some changes of the spoil piles and the waste tailings of uranium ores around the facilities [2]. Therefore, from the perspective of nuclear nonproliferation, the Pyongsan uranium mine and concentration plant was selected as the monitored AOI of this study.

Fig. 1 shows the WorldView-3 satellite image (0.31 m spatial resolution) of the Pyongsan uranium mine and concentration plant, which was acquired on 29 October 2017. Table 1 summarizes the specification of the satellite image resized as 4700 × 4700 (pixels) by using the ENVI® software. Specially, this study utilized all 16 sensor bands including the visible and infrared (VNIR) and the short-wave infrared (SWIR) bands for the classification.

Fig. 1. Pyongsan uranium mine and concentration plant in North Korea (38°19'N, 126°25'E).

Table I: Characteristics of satellite image utilized in this study

Satellite sensor type	WorldView-3
Acquisition date	2017.10.29.
Sensor bands	VNIR: 8 bands* SWIR: 8 bands
Spatial resolution	0.31 m
Mean off-nadir angle	28.4 °
Subset image size (pixel)	4700 × 4700

* Coastal, blue, green, yellow, red, red edge, NIR-1, and NIR-2 bands.

2.2 Pre-processing

To rectify the radial or the geometric distortions in raw data, the satellite image on AOI was pre-processed by the Gram-Schmidt pan-sharpening and the image-to-image registration.

By applying the Gram-Schmidt pan-sharpening method, the spatial resolution of VNIR and SWIR bands of the satellite image was improved from 1.24 m and 3.70

m to 0.31 m. Next, with the rational polynomial coefficient and the nearest neighbor interpolation, the image-to-image registration were carried out to less than one pixel.

2.3 Segmentation and Selection of Samples

Prior to the object-based classification, the pre-processed satellite image was segmented into the image objects by applying the multiresolution segmentation algorithm embedded in eCognition®, which can consider all the spectral information of 16 bands of the satellite image.

Fig. 2 describes the multiresolution segmentation result of AOI. The blue are the boundaries surrounding image objects regarded as the homogeneous pixels. The image objects were merged with the homogeneity criteria which are a shape factor (0.5), a compactness factor (0.5), and a scale parameter (100).

Then, as shown in Fig. 3, samples for training of the SVM classifier were selected among the image objects according to the pre-defined object classes: bare (yellow), building (sky blue), shadow (red), vegetation (green), and uranium ores (magenta).

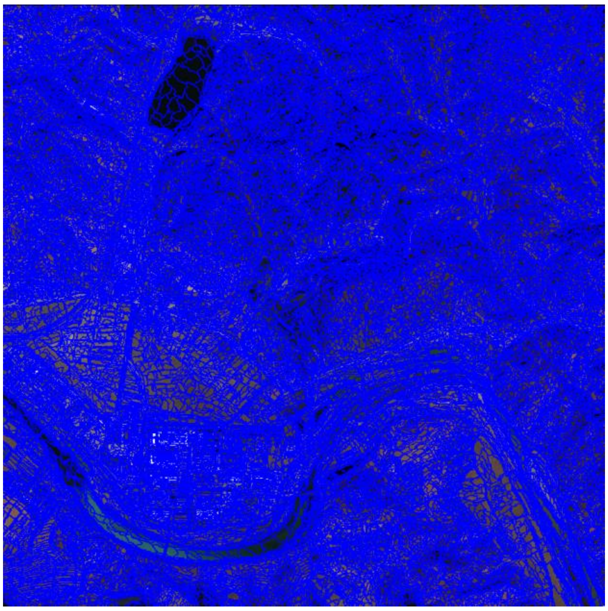

Fig. 2. Multi-resolution segmentation result where the shape factor, the compactness factor, and the scale parameter were 0.5 (default), 0.5 (default), and 100, respectively.

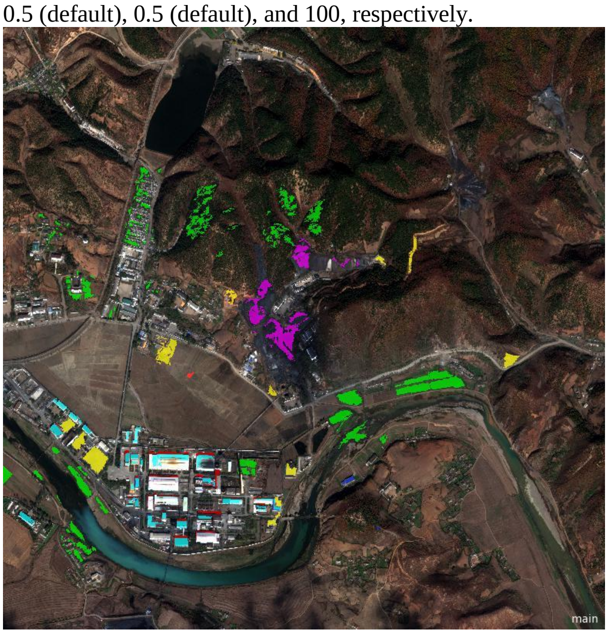

Fig. 3. Samples for the five pre-defined object classes: bare (yellow), building (sky blue), shadow (red), vegetation (green), and uranium ore (magenta).

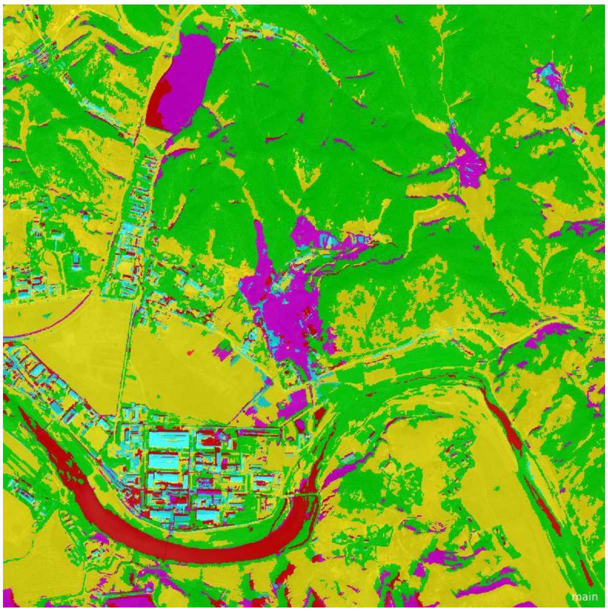

Fig. 4. Object-based land cover classification result using the SVM classifier trained by the selected samples of the pre-defined classes.

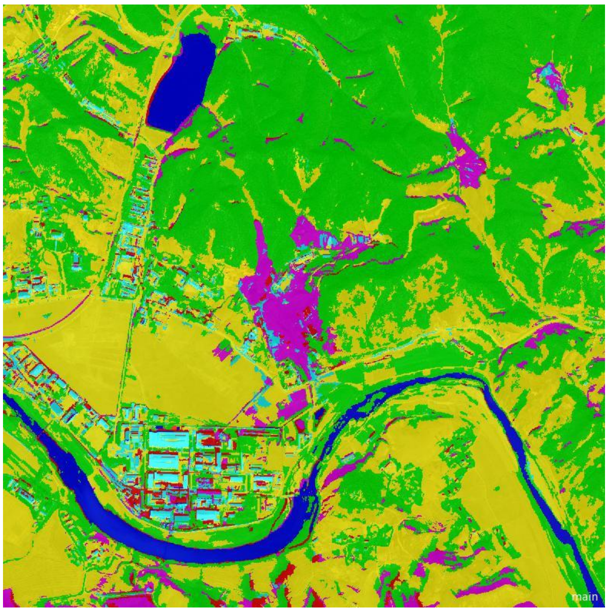

Fig. 5. Reclassification result where water classes (blue) was assigned from the misclassified objects considering MNDWI over 0.4.

2.4 Classification using Support Vector Machine (SVM)

In the object-based land cover classification, the linear SVM classifier trained with samples from object classes was applied as described in Fig. 4. SVM is the representative of the machine learning based classifiers, which constructs a hyperplane of the largest margin between training data [3]. In this study, the default value of 2 was applied to the soft margin parameter *C*.

2.5 Reclassification with the Modification Normalized Difference Water Index (MNDWI)

However, there were misclassified object classes of uranium ores (magenta) and shadows (red) including water bodies in the reservoir in the upper left part and the Ryesong liver in the lower part in Fig. 4. Since North Korea's uranium ore has been mainly estimated a black anthracite coal containing uranium and vanadium, it is difficult to distinguish uranium ores from other black objects such as shadows and open water features using the SVM classifier only.

Therefore, this study carried out the reclassification with MNDWI of Xu (2006) in Eq. (1) to differentiate water bodies from misclassified classes [4]. As shown in Fig. 5, image objects classes indicating MNDWI over 0.4 were classified as water bodies (blue).

$$MNDWI = \frac{Green - SWIR}{Green + SWIR} \quad (1)$$

where Worldview band 3 (green band, 510 to 580 nm) and band 11 (SWIR-3 band, 1,640 to 1,680 nm) was used for *Green* and *SWIR* in this study, respectively.

3. Conclusions

In this study, the object-based land cover classification for the Pyongsan uranium mine and concentration plant was carried out using the SVM classifier in eCognition®.

First, the satellite image of AOI was pre-processed by the Gram-Schmidt pan-sharpening and the image-to-image registration. Second, the pre-processed image of AOI was segmented by the multiresolution segmentation algorithm to utilize all spectral information of 16 bands. Third, samples of the five pre-defined classes was selected as training data for the SVM classifier. Fourth, the classification using the SVM classifier was performed. Fifth, MNDWI was applied to distinguish water bodies from misclassified object classes.

Consequently, even if there are limited or trivial information on AOI, this study confirmed the feasibility of a computer-based image analysis to support image analysts monitoring nuclear proliferation activities. As a future work, the accuracy of classification will be quantitatively analyzed with the proper accuracy index for countering nuclear proliferation. In addition, the change detection for the uranium ore distribution will be performed using the accumulated land cover classification results.

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REFERENCES

[1] B. Jasani et al., International safeguards and satellite imagery, issi, 2009.
[2] F. V. Pabian, P. Makowsky, and I. Buck, North Koreas's Uranium Mining and Milling Operations Continue at Pyongsan, 38 North, 2018.
[3] V. Vapnik, The nature of statistical learning theory, Springer, New York, 1995.
[4] H. Xu, Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. International Journal of Remote Sensing, Vol.27(14), p.3025-3033, 2006.