

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

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## Introduction

### ❖ Objectives

- To evaluate the feasibility of the machine learning based classification method, i.e., SVM, with MNDWI for monitoring the suspicious nuclear proliferation activities in a restricted AOI (Area of Interest)

### ❖ Need for the computer-based image analysis (classification) to support imagery analysts' interpretation

- To minimize time and cost for analysts' interpretation, the computer-based image analysis has been indispensable in recent years.
- If a land cover of AOI can be classified according to its use, it is possible to determine whether or not a suspected facility regarding nuclear proliferation is in operation.

### ❖ SVM (Support Vector Machine)

- **Based on machine learning with training sets of the user-defined classes, SVM separates the classes with the optimal hyperplane** which maximizes the margin between the classes (C.-W. Hsu et al., 2010).
- Further, eCognition®, which is the representative software solutions for image analysis, offers machine-based classifier including the decision tree and the SVM.

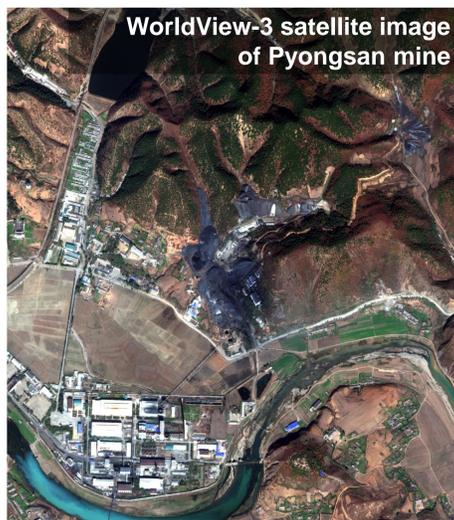
### ❖ MNDWI (Modification Normalized Difference Water Index) (Xu, 2006)

- With the multispectral satellite image including the short-wave infrared (SWIR), MNDWI can describe the spectral characteristics of open water bodies.

## Methodology

### ❖ AOI: Pyongsan uranium mine and concentration plant

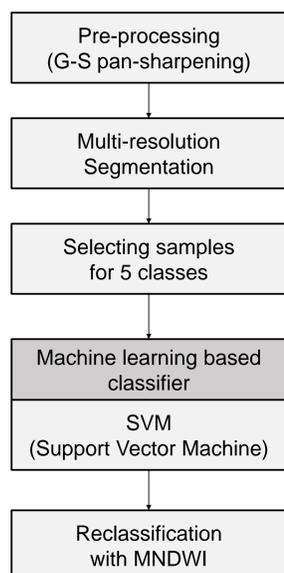
- The Pyongsan uranium mine and concentration plant in one of North Korea's largest declared uranium ore concentrate facilities, where uranium ores are mined and milled to yellowcake ( $U_3O_8$ ).
- With analyzing satellite imagery, J. Bermudez (CSIS Beyond Parallel, 2020) estimated that the plant had still in operation by detecting some changes around the facilities.



#### Characteristics of satellite image

Satellite sensor	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	3500×4000

### ❖ Object-based land cover classification methodology using the SVM classifier and MNDWI



- 1) To correct the radial and the geometric distortions, pre-processing was performed using **the Gram-Schmidt pan-sharpening and the image-to-image registration.**

(※ Spatial resolution was improved from 1.24 m and 3.70 m to 0.31 m.)

- 2) **Multi-resolution segmentation** was applied to segment the pre-processed satellite image.

(※ Scale: 100, shape: 0.5, and compactness: 0.5)

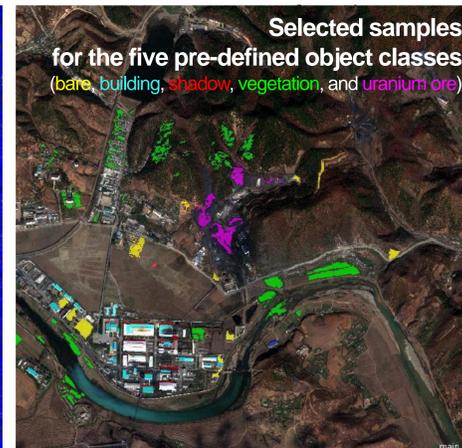
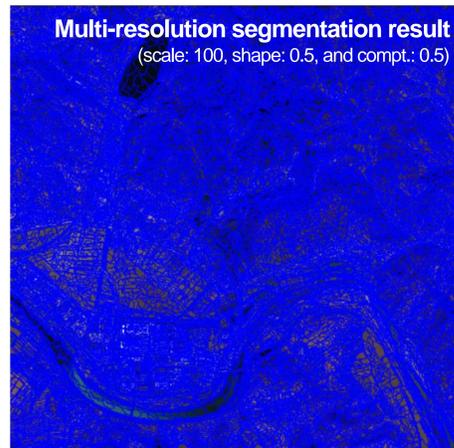
- 3) **Samples for training of the SVM classifier were selected** among the image objects according to the pre-defined object classes.

- 4) **SVM algorithm (machine learning based classification) embedded in eCognition®** were utilized to classify the image objects to 5 classes with the samples.

- 5) **Reclassification with MNDWI of Xu (2006)** was carried out to differentiate water bodies from misclassified classes.

## Results and Conclusions

### ❖ Object-based land cover classification result for AOI

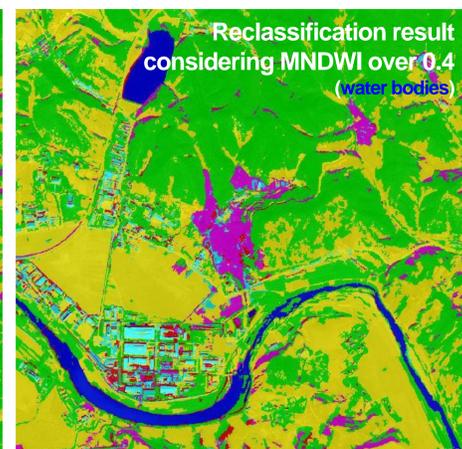
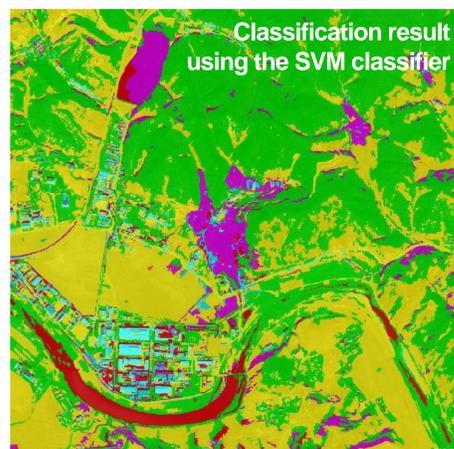


#### ➤ Multi-resolution segmentation result of AOI

- ✓ In this study, the multi-resolution segmentation algorithm in eCognition® was applied to consider all the spectral information of 16 bands of the WorldView-3 satellite image.
- ✓ The blue are **the boundaries surrounding image objects regarded as the homogeneous pixels** with the homogeneity criteria: scale (100), shape (0.5), and compactness (0.5).

#### ➤ Selected samples for the five pre-defined object classes

- ✓ Among the image objects (segments) in the segmentation result, **sample objects for training of the SVM classifier was selected according to the 5 object classes:** bare (yellow), building (sky blue), shadow (red), vegetation (green), and uranium ores (magenta).



#### ➤ Classification using the SVM classifier

- ✓ The SVM classifier trained with above samples was utilized to classify all the image object into 5 classes. (※ The soft margin parameter C was applied as the default value of 2.)

#### ➤ Reclassification with 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.
- ✓ 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.
- ✓ ∴ This study carried out the reclassification with MNDWI of Xu (2006) in the equation below. As shown in the figure above, **image objects classes indicating MNDWI over the empirical threshold, i.e., 0.4, were classified as water bodies (blue).**

$$MNDWI = \frac{Green - SWIR}{Green + SWIR}$$

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.

### ❖ Future works

- The accuracy of classification will be quantitatively analysed with the proper accuracy indices for countering nuclear proliferation.
- The change detection for the uranium ore distribution will be performed using the accumulated land cover classification results.

## Acknowledgments

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