# USES OF MULTI-DATE SATELLITE IMAGES FOR MONITORING OF LAND COVER CHANGES OVER COAL-FIRED POWER PLANT SURROUNDED AREAS IN THE QUANG NINH PROVINCE

Chu Hai Tung [1], Dang Truong Giang [1], Do Thi Phuong Thao [2], Mai Anh Dung [3], Le Anh Tai [4]

[1]National Remote Sensing Department (NRSD), Ministry of Natural Resources and Environment
No. 83 Nguyen Chi Thanh street, Dong Da District, Ha Noi, Vietnam
Email: chuhaitung@gmail.com; chtung@monre.gov.vn; dtgiang2@monre.gov.vn
[2]Faculty of Geomatics and Land Administration, Hanoi University of Mining and Geology
No. 18 Vien street, Duc Thang ward, Bac Tu Liem District, Ha Noi, Vietnam
phuongthao.mdc@gmail.com
[3] Department of Financial and Planning, Ministry of Natural Resources and Environment
No. 10 Ton That Thuyet street, Cau Giay District, Ha Noi, Vietnam
maidung@monre.gov.vn
[4] Hanoi University of Natural Resources and Environment
No. 04 Tran Phu street, Ba Dinh ward, Bim Son Town, Thanh Hoa, Vietnam
latai@hunre.edu.vn

**KEY WORDS:** Landsat 8 Operational Land Imager (OLI), Maximum Likelihood (ML), Support Vector Machine (SVM), Gray Level Co-occurrence Matrix (GLCM);

**ABSTRACT:** In the Quang Ninh province, the social-economic activities related to the Coal-fired power plants causes considerable impacts to environment features in their surrounded areas, particularly changing of land cover classes. This study aimed to use multi-date remotely sensed images to evaluate changes in land cover features over an area in Quang Ninh province (Viet Nam) where many coal-fired power plants are operating. Landsat 8 OLI images acquired at different dates from 2014 to 2020 has been collected and utilized. Land cover classes at different dates were generated using both traditional Maximum Likelihood (ML) and machine learning based Support Vector Machine (SVM) classification techniques. In order to improve the classification performance, various textured features including Gray level co-occurrence matrix (GLCM) had been integrated into classified datasets. Obtained land cover classes are then compared and analyzed to work out changing of land cover features taking into consideration operation status of existing coal-fired power plant and other social economic activities in the study area. Results revealed that the remote sensing technology with multi-date satellite analysis techniques is very effective tool for monitoring of changes of environment features such as land cover subject to social-economic activities, including the operation of power plants running by burning coal. Furthermore, it is shown that the integrating of textured features has improved classification results and the machine learning based SVM algorithm has outperformed the traditional ML algorithm when classify complex datasets.

## 1. INTRODUCTION

Coal-fired power plants contribute largest percentages of generated electricity for Vietnam. Therefore, they play very important role in various aspects of social economic development. The Quang Ninh province is leading coal mining industry in Vietnam where many coal mines are exploited and produce every year multi-million tons of coal products. Taking advantage of using local fuel source many coal-fired power plants has been built and operated in this area. However, mining activities and operation of coal-fired power plants caused significant impact to natural resources and environment, including changes of land cover features in surrounded areas. The Quang Ninh province with long coastline and famous World Heritage Ha Long Bay is also very attractive for tourism industry and highly potential economic development. Recently, the province experienced rapid development in social-economic activities. Thus, mining activities coupled with operations of coal-fired power plant and other activities caused considerable changes on land cover features over the area. Consequently, it is necessary to monitor land cover changes in this region.

Remote sensing technology which chiefly applying of satellite imagery has been considered as an efficient method for land cover mapping and monitoring changes of land features in the Earth's surface (Choudhary & Pathak 2016, Fonji & Gregory 2021, Garai & Narayana 2018, Jia et al 2014, Mishra et al 2017). Whereas traditional image interpretation method for extracting land features is very time consuming and dependent of experiences of interpreters, the digital classification approach is much faster and provide acceptable results. Many studies have been carried out using different classification techniques for land use/cover classes, including a traditional Maximum Likelihood (ML) and Machine Learning based classifiers such as Artificial Neuron Network (ANN) and Support Vector Machine (SVM) classifiers. Most of researchers claimed that the SVM classifier outperformed the traditional ML classifier (Hashim et al 2021, Kete et al 2019). Moreover, numerous researchers had incorporated spatial textured information into classified datasets and achieved improvement in classification results (Altaei & Ahmed 2018, Huang et al 2017, Lu et al 2014, Rodríguez-Galiano et al., 2011).

This study analyses capabilities of multi-date Landsat 8 OLI images incorporated with several GLCM texture measures to detect and monitor land cover changes in coal-fired power plant surrounded area using Machine Learning based SVM classification technique. Furthermore, performances of the traditional ML classifier and SVM classifier were compared using different satellite image based datasets.

## 2. DATA USES AND STUDY AREAS

The study area is located in Quang Ninh province, in North-East of Vietnam. The center coordinate is 21º04’30” N and 107º22’ E. The study area is very typical of coal mining and coal – fired power plants. There are two coal-fired power plants, namely Cam Pha and Mong Duong, have been constructed and currently operated in this study area. Beside coal mining and power plants, the area is also convenient for tourism activities since its location very near to Ha Long bay - the famous World Heritage site and facing to the Bai Tu Long bay which is smaller but no less beautiful. Recently, there has been significant changes on land surface due to growing of industrial activities as well as extensive social-economic development. The study area is consisted of various land cover/land use classes, including dense forest, planted forest, residential areas, mining activity, coal ash, coal located areas, water surfaces, bare land or newly created lands.

Four Landsat 8 Operational Land Imager (OLI) images acquired at different dates from 2014 to 2020 were downloaded from USGS/ Earth Explore Website and used for this study. Details of these remote sensing datasets are presented on the Table 1.

Table 1. Landsat 8 OLI data for study areas

| Satellite/sensors | Date | Spectral band/resolution |
|---|---|---|
| Landsat 8 - OLI | 11/10/2014 | MS: 7 bands / 30m |
| | 30/06/2016 | |
| | 06/10/2018 | PAN: 1 band/ 15m |
| | 27/12/2020 | |

Figure 1. Landsat 8 OLI image acquired at December 27, 2020 over study area
(Red: Band 4; Green: Band 3; Blue: Band 2)

Reasons to select these remote sensing data for this study were Landsat 8 is one of the most stable Earth Observation satellite which provide datasets free of charge over certain area every 16 days with large coverage, multiple bands and spatial resolution. These characteristics of Landsat 8 OLI are very useful for monitoring natural resources on Earth surface, particularly, land cover/land use mapping and changes. Each Landsat 8 – OLI dataset consisted of 7 multispectral (MS) bands with a spatial resolution of 30m and a panchromatic (PAN) band with a spatial resolution of 15m.

All of four dated Landsat 8 OLI datasets were geo-rectified to same map coordinated system (UTM projection, zone 48, WGS84) with accuracy less than 1 pixel. After geo-rectification, MS band images were re-sampled to same resolution as PAN bands with pixel size of 15m.

The post-classification method was applied for monitoring of land use/land cover classes in the study site. Firstly, each Landsat 8 OLI acquired at single date were classified to obtain land cover classification maps. Then, classification results at different dates were compared to work out changes on land cover features over time. The Machine Learning based Support Vector Machine (SVM) algorithm were employed as a main classifier. However, we also carry out classification using a traditional Maximum Likelihood (ML) classifier on the most recent dataset (27/12/2020) to compare performances of both classifiers.

Nine land cover classes are defined for mapping, including Residential Areas (RA), Water Surface (WF), Dense Forest (DF), Planted/Sparse Forest (PF), Mining Sites (MS), Industrial-Factories (IF), Bare land or Newly created Land (BL), Coal-ash dumped ground (CS), Coal Storage Field (CF). Sampled areas were carefully selected based on referent maps and high resolution satellite images available on Google Earth. Two sets of samples were used for training and evaluating classification results.

In order to improve classes separability as well as obtained results texture measures were generated and integrated in combined datasets for classification.  The Gray Level Co-occurrence Matrix (GLCM) textures which are commonly used has been generated from PAN imaged band with window size of 5x5 for each single date Landsat 8 OLI dataset. In this study we select four (4) textured measures, namely Data range, Variance, Homogenety and Correlation because they are relatively less correlated with others. Hence, there are two type of datasets used for classification, the first set consisted of 7 Landsat 8 OLI multi-spectral bands and the second consisted of 7 Landsat 8 OLI multi-spectral bands + 4 textured measures.

## 3. RESULTS AND DISCUSSIONS

### 3.1 Classification results and performance of ML, SVM classifiers

Results of classification using ML and SVM classifiers on 2 different datasets (7 multispectral bands and combination of 7 spectral bands + 4 GLCM texture measures) are given in the Figure 2 and Table 2.

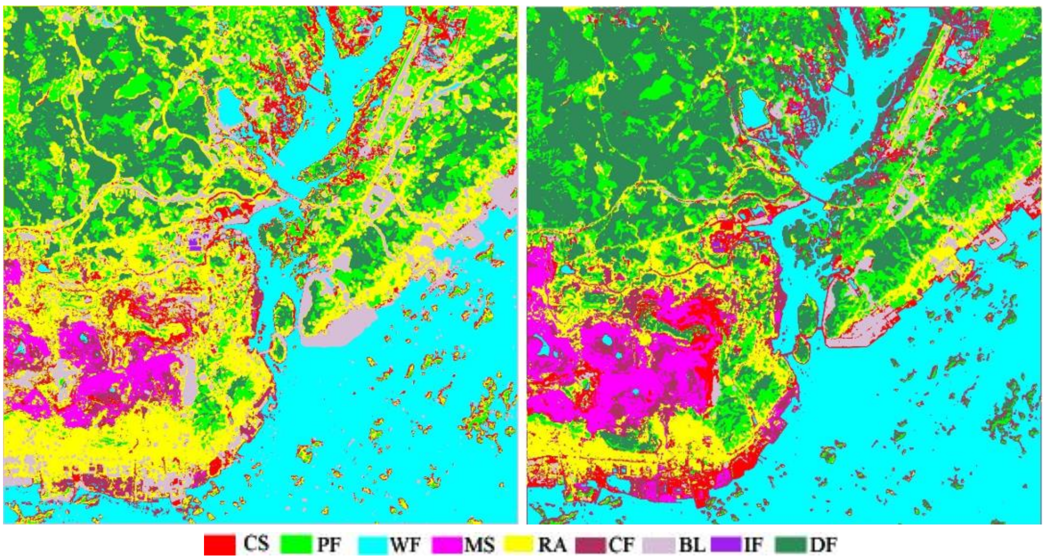


Figure 2. Results of Land cover classification using ML and SVM classifiers on combined multispectral + GLCM textured datasets of Landsat 8 OLI image acquired at 27/12/2020

Table 2. Overall classification accuracy for ML and SVM classifiers for two different datasets generated from Landsat 8 OLI image acquired on 27/12/2020

| Landsat 8 OLI Datasets | Maximum likelihood classification (ML) Accuracy (%)/Kappa coefficient | Support Vector Machine Classification (SVM) Accuracy (%)/Kappa coefficient |
|---|---|---|
| Multispectral 7 bands | 91.11/ 0.90 | 90.69/ 0.89 |
| Multispectral 7 band + 4 GLCM textured measures | 87.57/ 0.86 | 94.79/ 0.94 |

It is revealed that the ML and SVM algorithm produced similar results when classifying pure composed Landsat 8 OLI multispectral dataset with overall classification accuracy (and Kappa coefficients) were 91.11% (0.90) and 90.69% (0.89), respectively. However, the SVM classifier produced much better results than the traditional ML classifier when classifying the combined datasets consisting of 7 band multispectral + 4 GLCM textured measures with overall classification accuracy for each algorithm were 94.79% (0.94) and 87.57% (0.86), respectively. We have found that the ML algorithm did not work well with the complex dataset which comprised of different types of spatial data, such as a combination of multispectral and textured data. The classification accuracy generated by ML classifier on this combined dataset was even reduced to 87.57% in comparison with the case of purely composed multispectral dataset (91.11%). In contrary, the SVM classifier provided higher classification accuracy for combined dataset with an increase of classification accuracy by 2.88%. It is also illustrated that introduction of textured information can enhance classification accuracy with the Machine Learning based SVM classifier but it might not be the case of the traditional ML classifier. This also indicated that the SVM algorithm with its nature of non-parametric classifier is more suitable for handling complex datasets consisting of different type of data.

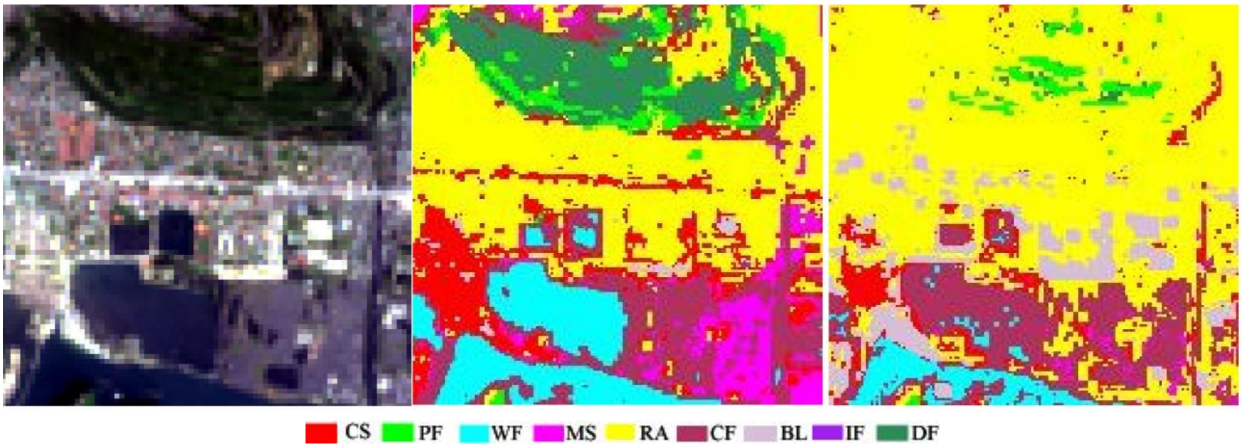


Figure 3. Compared classification results of SVM (middle) and ML classifiers (right)

More typically, SVM classifier outperform ML classifier on separating between Residential Areas and Forest (both Dense and Plantation/Sparse Forest) as well as water surface from other land cover classes. As shown in the figure 3, while the SVM can classify Residential Areas, Forest and Water Surface rather well, ML classifier produced misclassification of Forest to Residential Areas. The Water Surface at lower left has been wrongly classified as Coal storage Field.

### 3.2 Monitoring land cover changes

Results of land cover classification using SVM classifier and 4 different dated Landsat 8 OLI + Textured measures datasets were shown in the figure 4. After that, classified classes at 4 different dates were then compared to monitor changes of land features over study areas. The table 3 shown changes of different land cover features in the study area during the period from 2014 to 2020. It is clear that using SVM classifier and Landsat 8 OLI satellite images can classify existing land cover/classes and detect their changes over time very well. The comparison upon classified results has revealed that all of studied land cover features experienced significant changes from 2014 to 2020. These changes related closely with increase of social-economic activities in the area, particularly the operation of coal-fire power plants, mining, tourism activities and growing of residential areas.

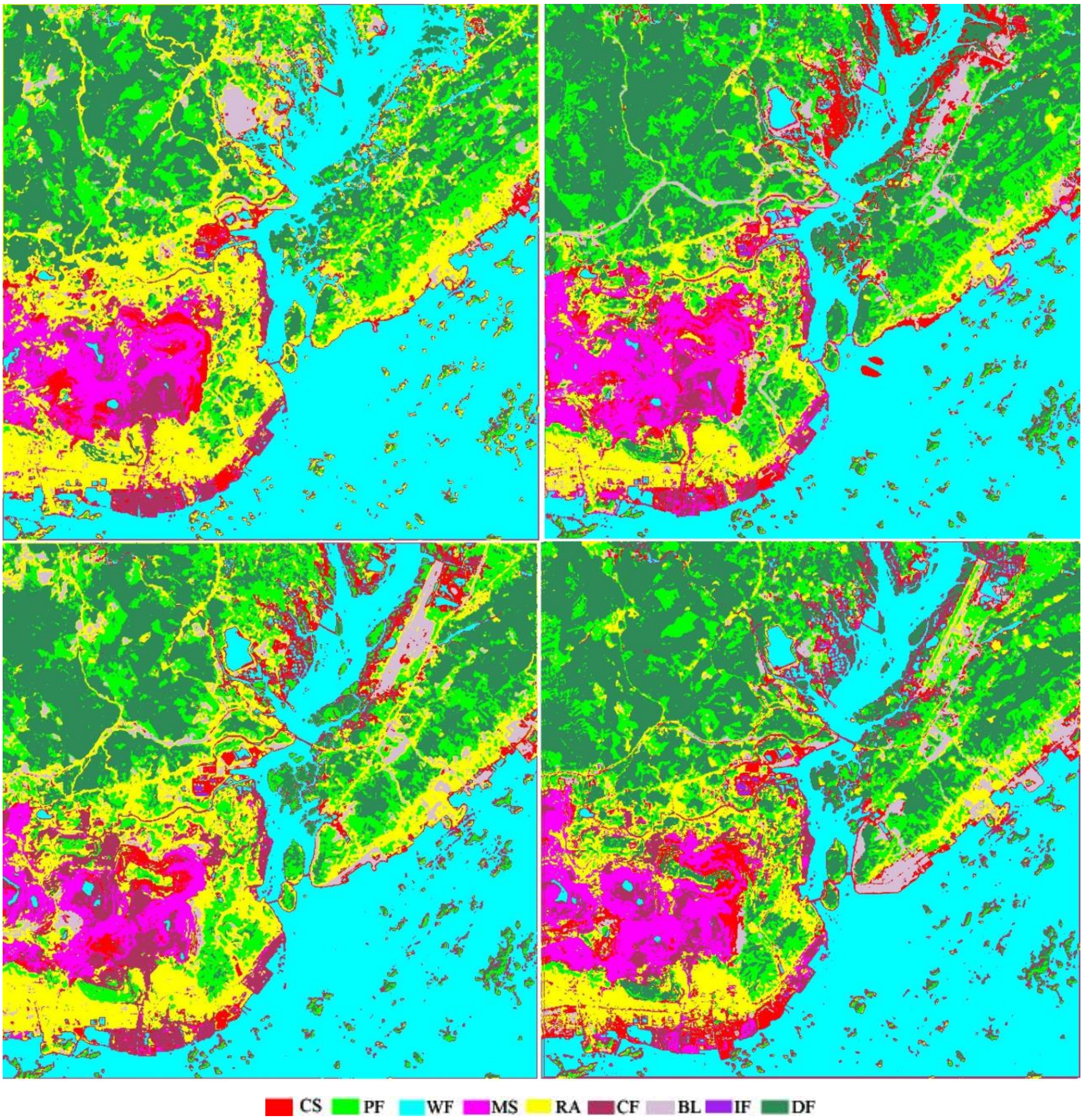


Figure 4. Results of SVM classification on 4 different dated Landsat 8 OLI + textured measures from 2014 to 2020; Upper left (11/10/2014), upper right (30/06/2016), lower left (06/10/2018), lower right (27/12/2020).

Table 3. Comparison of land cover classes in the study area from 2014 to 2020 (unit in hectares (ha))

| Classes | Areas in 2014 (ha) | Areas in 2020(ha) | Changes (ha) |
|---|---|---|---|
| Coal-ash dumped ground (CS) | 1490.36 | 1760.40 | 270.0450 |
| Water Surface (WF) | 10728.70 | 9595.40 | -1133.30 |
| Planted/Sparse Forest (PF) | 4380.82 | 4305.33 | -75.49 |
| Mining Sites (MS) | 1695.17 | 1753.69 | 58.52 |
| Residential Areas (RA) | 3695.24 | 3815.23 | 119.99 |
| Coal storage Field (CF) | 1252.31 | 2465.69 | 1213.3800 |
| Bare Land /Newly created Land (BL) | 2724.64 | 1134.47 | -1590.17 |
| Industrial-Factories (IF) | 23.85 | 38.32 | 14.47 |
| Dense Forest (DF) | 6408.92 | 7531.47 | 1122.55 |

While lands for industrial and factory, particularly coal-fired power plant increased by 14.47 ha, the areas for Coal-ash dumped ground had also increased noticeably by 270 ha from 1490,36 ha in 2014 to 1760.4 ha in 2020. This illustrates an increases of Coal-fired power plants operated in the area, which produced and released more coal-ash to environment as well as required more lands for dumping.

Although land for Mining sites were rather stable with slightly raised by only 58.52 ha, land for coal storage field had almost double with an increase of 1213.38 ha, from 1252.30 ha in 2014 to 2465.68 ha in 2020. This is because the mining industry has produced more coal products and coal-fired power plants consumes more fueled coal resulted in larger storage fields.

There was an increase of 119.99 ha of Residential areas from 3695.24 ha in 2014 to 3815.23 ha in 2020 because of urbanization with considerable numbers of new urban and residential areas had been settled.

Surprisingly, Bare lands/Newly created lands had remarkably reduced by 1590.16 ha from 2724.64 ha in 2014 to 1134. 47 ha in 2020, although there were considerable new land areas had been created. The main reason according to classification maps was this kind of land had been converted to forests, coal-ash dumped ground, coal storage field, residential areas and other classes.

There was a decrease by 1133.30 ha of water surface in the study area because of various social -economic activities, which filled water surface for generated new land, coal-ash dumped ground and residential areas.

The Planted/Sparse Forest has reduced slightly by 75.49 ha since many such areas has progressed to Dense Forest or cleared for other purposes. Consequently, Dense Forest has increased by 1122.55 ha, from 6408.92 ha in 2014 to 7531.47 ha in 2020.

## 4. CONCLUSION

In this study, Landsat 8 OLI image acquired at 4 different dates combined with 4 GLCM textured measures has been classified using traditional Maximum Likelihood and a Support Vector Machine classifiers to create land cover map and monitor changes over time of land cover classes over a typical area of coal mining sites and coal-fired power plants operations.

Results illustrated that using multi-dated satellite imagery, particularly Landsat 8 OLI data can effectively detect and monitor changes of land cover classes which closely linked to social-economic activities in the area. The SVM and ML classifier produced similar results when classified pure composed Landsat 8 OLI multispectral dataset. However, the SVM classifier outperform the ML classifier when classifying complex datasets consisted of Landsat 8 OLI multispectral bands + GLCM textured measures. Moreover, the integration of textured data can enhance classification results particularly when SVM classifier was applied.

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