Assessment of natural recovery of mangrove from anthropogenic disturbance using neural network based classification of satellite images

学籍番号　47-186848
氏　　名　Win Sithu Maung
指導教員　佐々木淳

1. Introduction

Since mangrove forests around the world are declining due to human disturbances such as shrimp farming, agricultural expansion, urbanization, and over-harvesting for fuelwood, rehabilitation programs should be accelerated for mangrove conservation urgently. To compensate for mangrove loss, restoration programs have been implemented primarily by means of artificial plantation. Many studies pointed out that plantation projects may lead to unsatisfied results with low survival rates when a replanted mono-species is inappropriate to a selected site. Knowledge about natural recovery of mangrove is therefore needed for successful rehabilitation. Except for a few studies focusing on comparison of natural recovery and planted mangrove, there is limited information about spatial distribution and species diversity of naturally recovering mangrove at abandoned sites.

With the development of remote sensing and classification methodology, many studies have analyzed mangrove extent and species by applying different classifiers and satellite images. Freely availability of Sentinel-2 imageries since 2015 provided research opportunities in remote sensing field with the advantages of higher temporal and spectral resolution compared to other publicly accessible satellite imageries. Artificial Neural Network (ANN), the cutting-edge machine learning approach has become popular in various disciplines because of high accuracy and uncomplicated creation of a robust model. However, no information about ANN method using Sentinel-2 image is available for mangrove classification.

Wunbaik Mangrove Forest (WMF), which is located in Rakhine State, Myanmar, plays a vital role in providing ecological, environmental, and socio-economic goods and services to local community. However, due to aquaculture and agricultural expansions, WMF and its surrounding mangrove forest have been highly degraded since 1990s. Due to the fact that WMF possesses a high capacity of recovery due to abundant seed productivity and high germination rates of mangrove species [1], the study area is a suitable region to explore natural recovery of mangrove from human disturbances.

This study aims (1) to explore mangrove classification by using Sentinel-2 imagery and ANN classifier, (2) to fulfill information about mangrove changes of WMF between 2015 and 2020, and (3) to assess natural recovering mangrove from human disturbances in terms of spatial and species analysis.

2. Materials and Methods

2.1. Satellite image and topography

For mangrove classification, Sentinel-2 satellite images, which are freely provided by European Space Agency (ESA), were collected. Atmospheric correction and resampling were conducted using Semi-automatic Classification Plugin (SCP) in QGIS. Ground truth images were created manually in ArcGIS verifying with Google Earth Image. Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Combine Mangrove Recognition Index (CMRI) were calculated using satellite bands of Sentinel-2. For topographic information, NASA's Shuttle Radar Topography Mission (SRTM) and Multi-Error-Removed-Improved-Terrain (MERIT) were collected from USGS Earth explorer. Canopy height model (CHM) was derived from differentiation between SRTM and MERIT.

2.2. ANN classification and change detection

ANN classification was performed using mainly TensorFlow 2.5 on a supercomputer. A basic model was shaped by organizing multi perceptron layers of an input layer with different feature combinations, one hidden layer with 12 neurons, and an output layers with 2 neurons. The 10 bands of Sentinel-2 images acquired in January 2020, NDVI, NDWI, CMRI, SRTM, MERIT and CHM were used in different experiments of ANN classification. The most suitable combination of input features, which yielded the highest accuracy was selected for mangrove classification. The basic model was tuned with numbers of hidden layers and neurons. The tuned model was applied to predict a new dataset in 2015; its performance was evaluated using overall accuracy and kappa values by validating high-resolution Google Earth Imagery.

Spatial change in mangrove areas between 2015 and 2020 was identified with the aims of focusing on deforestation and recovery areas during the period. The main workflow of anlysis is described as Figure 1.

2.3. Field investigation

Field investigation was performed to acquire information about current status of mangrove forest and local livelihood situation in the study area by interview with township staff of Forest Department (FD) and local community as well as officials of two villages. Three abandoned sites were selected among disused shrimp ponds with the criteria of same abandonment year, no anthropogenic planting and accessibility. Mangrove tree species, diameter at the breast height (DBH), and tree height were identified at 50 plots at the three sites. Salinity and elevation data were collected to explore environmental preference of recovering mangrove species.

Dominant species compositions and species diversity were evaluated using the Important Value Index (IVI) formula [2] and the Shannon index (H)[3], respectively.

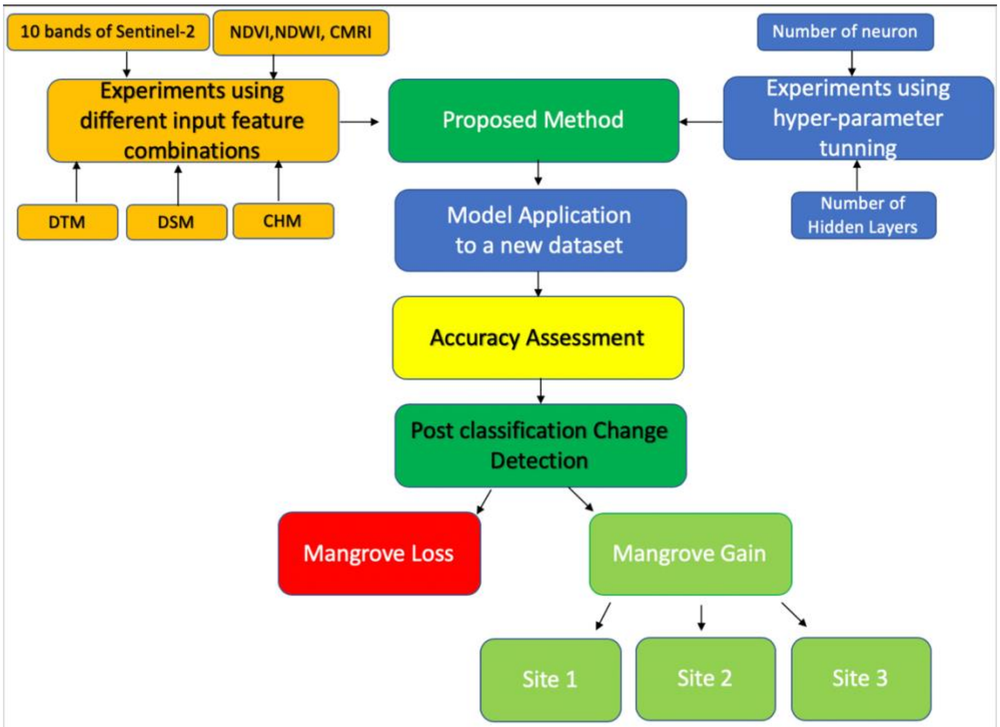

Figure 1 Workflow of ANN classification

3. Results

3.1. Classification Accuracy

Of the total 15 experiments after conducting input feature selection, experiment 6 using 10 bands of Sentinel-2 image, NDVI, NDWI, MERIT and CHM produced the highest accuracy of 95.85%(Figure *2*). After tuning numbers of hidden layers and neurons, overall accuracy and kappa values are 95.98% and 0.93 for 2020 and 94.5% and 0.88 for 2015. Through transfer learning approach, the performance of the model was improved into the overall accuracy of 97.2% and kappa values of 0.94.

3.2. Change Detection

Between 2015 and 2020, mangrove forests in the study area were found to decline from 254.3km2 to 249.83 km2. Using high resolution googleearth image, mangrove gain patches were found at FD plantations and natural recovered sites while shrimp pond and agricultural expansion are main drivers of mangrove loss in the study area.

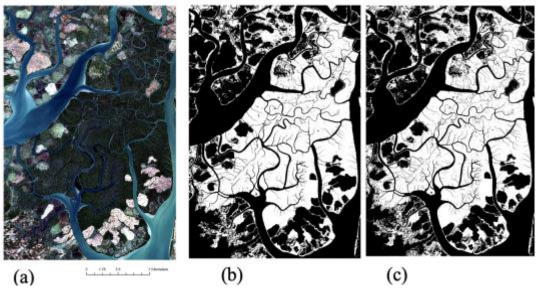

Figure 2 (a)True color image, (b) Ground truth image, and (c) Classified image

3.3. Characteristics of naturally recovering mangrove

Mangrove forests were found to naturally recover to 49..02 %, 55.93 %, and 50.00 % at sites 1, 2, and 3, respectively, between 2015 and

2020 without any restoration efforts (Figure *3*). The number of recovering species were found to be 11, 5, and 3 at sites 1, 2, and 3, respectively. Their dominant species identified from IVI were *Avicennia officinalis* at site 1 and *Avicennia marina* at sites 2 and 3. This study confirms that mangrove species are naturally recovering depending on their preferred environmental condition.

4. Discussion

Despite a number of studies using various classifiers and satellite images for mangrove classification[4], to my knowledge, the present study was the first attempt to explore neural network-based classification of Sentinel-2 images for mangrove distribution. The proposed method achieved a satisfactory accuracy for mangrove classification and the trained model in this study can be applied to any mangrove areas around the world.

In case of natural recovery of mangrove, a few studies compared planted and natural mangrove species at abandoned sites [5]. This study contributed not only species diversity but also spatial information about naturally recovering mangrove at different abandoned sites.

The finding of this study shows that mangroves are naturally recovering with diverse species at disused ponds during short period of abandonment. Due to the ongoing human pressures, protection for remnant mangrove should be more enhanced than restoration efforts. Moreover, the proposed classification of this study is a promising method that can be used for mangrove distribution in future researches.

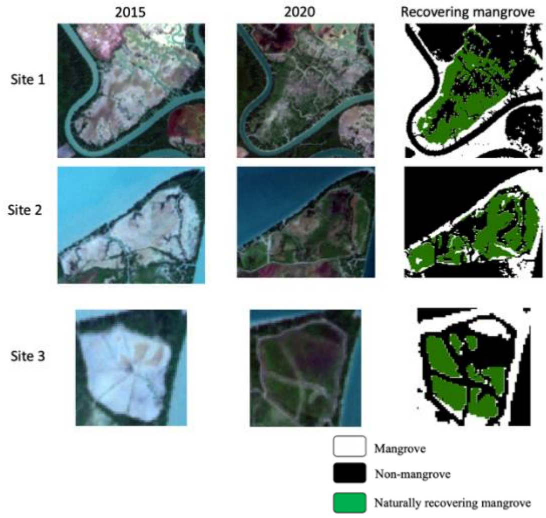

Figure 3 Identified natural recovering mangrove

References:

[1] D. O. Stanley, J. Broadhead, M. Aung Aung, Burma., "The atlas and guidelines for mangrove management in Wunbaik Reserved Forest," *FAO-UN, Myanmar Publ.*, no. 2011/04, pp. iii, 132 p., 2011.

[2] G. Cintrón and Y. Schaeffer-Novelli, "Methods for studying mangrove structure," in *The Mangrove Ecosystem: Research Methods*, 1984.

[3] C. E. SHANNON, "A Mathematical Theory of Communication," *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423., 1948.

[4] K. Yoshino *et al.*, "Remote sensing approaches for monitoring mangrove species, structure, and biomass: Opportunities and challenges," *RemoteSens.*, vol. 11, no. 3, pp. 1–24, 2019.

[5] A. C. Ferreira, G. Ganade, and J. Luiz de Attayde, "Restoration versus natural regeneration in a neotropical mangrove: Effects on plant biomass and crab communities," *Ocean Coast. Manag.*, vol. 110, pp. 38–45, 2015.