Automatic Para-rubber Trees Classification in Thailand from LANDSAT-8 Imagery Using DCED Neural Network

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Abstract

Image classification has been one of the main processes performed on satellite imagery where there have been many studies attempt to developing an automatic approach since manual classification is known to be a time-consuming process. Automatic classifying specific types of vegetation in satellite imagery has been a challenging field of study. In this work, a neural network method, specifically deep convolutional encoder-decoder or known as DCED, is applied to the automatic classifying coverage area of Para-rubber trees in Thailand from LANDSAT-8 satellite imagery. The main procedure in this work comprises ground truth preparation, suitable model development with training and validation, and, finally, classification. As a result, the model developed in this work gives average accuracy of 86.9% in training datasets and 70.9% in validation datasets.

Keywords: Automatic classification, neural network, DCED, satellite imagery.

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1 Introduction

Nowadays, a vast number of products, such as machine parts, toys, merchandise, are made of rubber of which the source can be synthetic or natural. One of the main sources of natural rubber is from liquid sap (latex) of Para-rubber trees which is an important economic crop of Thailand. In practice, ground survey and satellite imagery classification for the coverage area of the Para-rubber trees, are regularly and periodically performed by a government entity, Rubber Authority of Thailand (RAOT), to keep track of supplies of the natural rubber and any possible diseases in the crops. At present, classifying Para-rubber trees from the satellite imagery has been the main approach manually performed by RAOT personnel since it requires less operating time, personnel, and costs. Nevertheless, this approach requires high experienced personnel and is also a very time-consuming process, especially when the extent of Para-rubber tree areas is widespread throughout the regions of Thailand with the majority being in the southern, northeastern, and eastern regions of Thailand. Therefore, routine monitoring of the Para-rubber tree areas requires an automated approach to help facilitate its process while maintaining reasonable accuracy.

The approaches of extracting information or features from the satellite imagery, so-called image classification, can be divided into three main categories: manual, semi-automatic, and automatic. Firstly, the manual classification method is an approach performed by humans by distinguishing and identifying the features or the information indicating the Para-rubber tree in the images using the experience of the operator. Secondly, semi-automatic classification is a process where automated computer algorithms are used together with the manual method. Finally, automatic classification is a process in which the computer algorithms automatically detect the features from the images without any human involvement. At present, machine learning, a branch in artificial intelligence (AI), has been a breakthrough technology for automatic processing of which the foundation is to develop algorithms that give the computer ability to recognize patterns without any predefined rules or models.

Automatic image classification on various satellite sensors and platforms has been one of the focused fields of study and the Para-rubber tree classification has been one of the applications in these fields [1–12]. In 2008, Li et al. [7] studied the influence of the carbon stocks of the ecosystems (carbon dynamics) on the changes in land use-land cover (LULC) in Xishuangbanna, the southwest region of China, over a 27-year period using LANDSAT imagery. In their study, the maximum likelihood classifier was used for LULC classification. Similarly, Hu et al. [5], who also employed the maximum likelihood classifier, analyzed LANDSAT-5 images over the Xishuangbanna region to classify 10 types of LULC with the accuracy assessment using high-resolution satellite imagery (Quickbird). In their studies [5, 7], the Para-rubber tree is a LULC class that was attempted to automatically classified. On the other hand, Li and Fox [2] performed automatic classification on satellite images taken from ASTER sensor onboard the TERRA platform in the region of Thai-Laos border and China-Laos border by using Mahalanobis classifier and multi-layer perceptron neural network. Such methods were also used on the non-thermal reflective bands, normalized difference vegetation index (NDVI), and the tasseled cap transformation data to automatically classify rubber trees over the northeastern region of Thailand [3]. In 2012, Li and Fox studied the Para-rubber tree classification over some regions of China and Southeast Asia countries by using data from MODIS of TERRA platform with statistical data by using Mahalanobis classifier. Their results indicated that such approach could eliminate the overestimation of Para-rubber tree areas found in their previous studies [2, 3]. In 2015, Badrinarayanan et al. [13] developed a deep convolutional encoder-decoder neural network or DCED which was shown to reduce the number of parameters in the network to 14.7×10^6 while the traditional deconvolution network method 134×10^6 parameters [14]. In addition, the DCED architecture was shown to have higher efficiency in comparison with the deconvolution network method [15].

In this work, an automatic classification model for classifying the areas of the Para-rubber tree from LANDSAT-8 imagery is developed by adopting the DCED neural network approach to help facilitate the routine process of extracting the Para-rubber tree areas in the region of Thailand. In the hidden layers within the DCED neural network in this study, the exponential linear unit (ELU) function is used as an activation function. The ELU was shown that it can yield convergence more efficiently and can give higher accuracy in comparison with other functions such as ReLU, leaky ReLU, and PReLU [16].

2 Data Preparation

The data required for developing an automatic Para-rubber tree classification from LANDSAT-8 imagery can be grouped into two main categories which are the satellite imagery and the ground truth, i.e., reference dataset of the areas known to be the Para-rubber tree. These datasets are then separated into two groups: training and validation datasets, which are used for developing the DCED model. The training dataset is used to designate the parameters within the model, the so-called trained model, while the validation dataset is used to assess the validity of the trained model. The information regarding the data preparation is as the followings:

2.1 Satellite Imagery Preparation

LANDSAT-8 satellite imagery courtesy of the U.S. Geological Survey are used as source images for classification. Two scenes of LANDSAT-8 imagery over the region of Thailand as shown in Figure 1 are chosen based on the conditions that they are cloudless and have the areas of the Para-rubber trees. The Scene-1 image is from (path, row)=(129, 48) with an acquisition date on February 13th, 2018, 03:36 am GMT in which most of the coverage is Para-rubber trees. The Scene-2 image is from (path, row)=(130, 50) with acquisition date on April 9th, 2018, 03:43 am GMT in which the area is

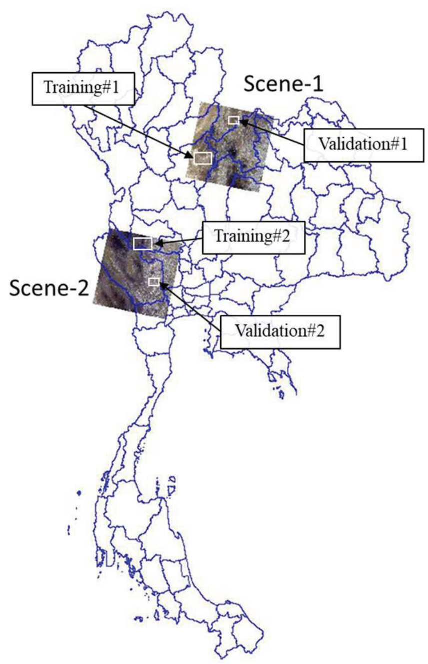


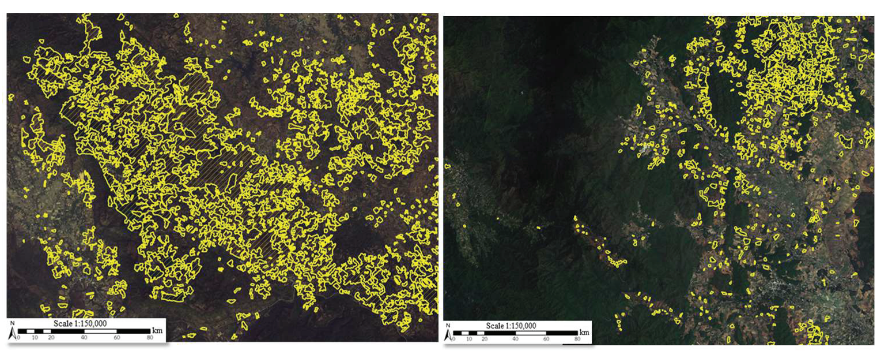
Figure 1 Two scenes of LANDSAT-8 satellite imagery used in this study: Scene-1 and Scene-2, and the extents of Training#1, Training#2, Validation#1, Validation#2 datasets.

mostly green forest that is not Para-rubber trees. The raw imagery downloaded from the U.S. Geological Survey (USGS) is a Collection 2 Level-2 Landsat 8 OLI/TIRS product which is a surface reflectance image. The raw images were then pre-processed into an analysis-ready dataset in GeoTIFF format by performing pan-sharpening to produce 15 m-resolution images and, subsequently, band-composition of red, green, blue bands.

Within each scene, two small patches, which are known to have both Para-rubber tree areas and non-Para-rubber tree areas, were selected for the training and validation datasets as shown in Figure 1. Therefore, there are two images for training purposes, called Training#1 (from Scene-1) and Training#2 (from Scene-2), and another two images for validation, called Validation#1 (from Scene-1) and Validation#2 (from Scene-2).

2.2 Ground Truth Preparation

The ground truth datasets were created in Training#1, Training#2, Validation#1, and Validation#2 images by performing manual classification using experienced analysts. The extents of the area classified as being Para-rubber trees are represented as polygons and are stored in a Shapefile format as a ground truth dataset. Therefore, the ground truth datasets contain the areas of both Para-rubber tree (inside the polygons) and non-Para-rubber tree (outside the polygons) which will be used for training and validation procedures. An example of the ground truth datasets over the Training#1 and Training#2 images are shown in Figure 2(a) and 2(b), respectively.



(a) (b)

Figure 2 Ground truth of Para-rubber tree areas (yellow polygons) over (a) Training#1 true-color image and (b) Training#2 true-color image.

3 Methodology

In this work, Python 3 with Tensor-flow, GDAL, and NumPy libraries are used to develop the DCED model for automatic Para-rubber tree classification from the satellite imagery. The procedures for developing the model have been divided into the training and the validation parts of which the explanations are as the followings:

First, the Training#1 and Training#2 datasets, including satellite images and their corresponding ground truths, are used for training the DCED model in the training procedure. In this work, the DCED is designed to have 13 encoder layers and 13 decoder layers with ELU function [16] as an activation function. The final layer of the model will provide a binary class over all pixels of the image indicating that each pixel is classified as Para-rubber tree or non-Para-rubber tree region. The output from the model can then be used to create a pixel-wise prediction map. Within the iteration, the model is designed to work with a small patch of an image with 224×224 pixels and a batch size of 24 and 100 batches per epoch. The training was performed until the output of the model meets the specified criteria when compared with the ground truth dataset.

Next, the trained parameters in the model obtained from the training procedure are assessed to check its validity by using the Validation datasets: Validation#1 and Validation#2. The validation procedure follows similar steps in the training procedure, except that there is no iteration. The DCED model with trained parameters is used to automatically classify the images to obtain the final output, pixel-wise prediction map. The output prediction map is then compared with the corresponding ground truth by using error matrix theory to measure precision (*P*), recall (*R*), F_1-score (F_1), and accuracy (*ACC*) which can be calculated as follows:

$$P = TP/(TP + FP) \tag{1}$$

$$R = TP/(TP + FN) \tag{2}$$

$$F_1 = 2PR/(P + R) \tag{3}$$

$$ACC = (TP + TN)/(TP + FP + TN + FN) \tag{4}$$

Where *TP* indicates True Positive which represents the cases when the model predicts Para-rubber tree correctly. *TN* indicates True Negative which represents the cases when the model predicts non-Para-rubber tree correctly. *FP* indicates False Positive which represents the cases when the model predicts the Para-rubber tree incorrectly. Finally, *FN* indicates False Negative which represents the cases when the model predicts non-Para-rubber tree incorrectly.

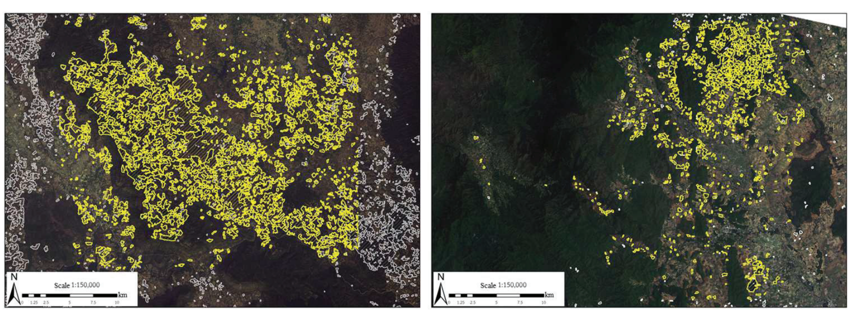
Finally, the trained and validated DCED model is used to classify Para-rubber tree areas to display the outcome in other regions.

4 Results and Discussions

Following the methodology explained previously, the results are to be separated into the results from the training and validation procedures. Noting that there are two sets of training and validation datasets from Scene#1 in which most of the areas are Para-rubber trees and Scene#2 in which most of the areas are green forest that is not Para-rubber trees.

In the training part, the DCED model with the trained parameters can yield the pixel-wise binary classification results showing Para-rubber tree and non-Para-rubber tree pixels which are subsequently digitized into polygons and stored as shapefile. Figure 3(a) and 3(b) show the predicted results from the model (gray) together with the ground truth (yellow) over their corresponding true-color images of Training#1 and Training#2, respectively.

The accuracy assessment on the trained DCED model in the training datasets is performed by pixel-wise comparison between the predicted results and the ground truth. As a result, error matrices of the Training#1 and Training#2 are established as shown in Tables 1 and 2, respectively, which yield $P = 89.49\%$, $R = 82.60\%$, $F_1 = 85.91\%$, $ACC = 86.45\%$ for Training#1 and $P = 90.82\%$, $R = 83.10\%$, $F_1 = 86.79\%$, $ACC = 87.35\%$ for Training#2 according to the calculation by using Equations (1)–(4). Therefore, the DCED model can provide the averages of $P = 90.16\%$,



(a) (b)

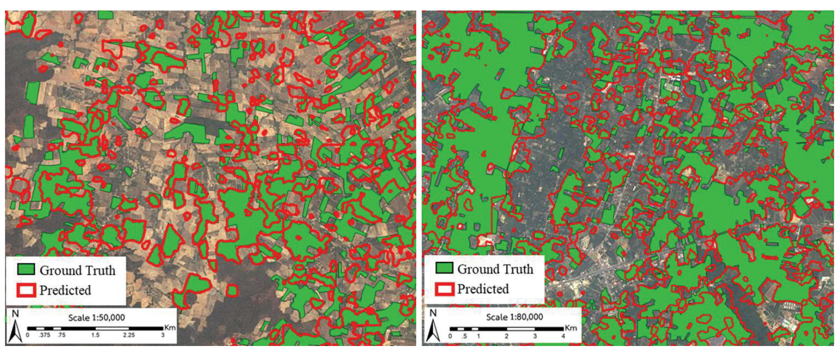
Figure 3 The predicted result using the DCED model (gray) and ground truth (yellow) of Para-rubber tree areas over the regions of (a) Training#1 and (b) Training#2.

Table 1 Error matrix calculated from the results using the DCED model on Training#1

Training#1		Actual	
		Pararubber	*Non-Pararubber*
Predicted	*Pararubber*	82.6% (True Positive)	9.7% (False Positive)
	Non-Pararubber	17.4% (False Negative)	90.3% (True Negative)

Table 2 Error matrix calculated from the results using the DCED model on Training#2

Training#2		Actual	
		Pararubber	*Non-Pararubber*
Predicted	*Pararubber*	83.1% (True Positive)	8.4% (False Positive)
	Non-Pararubber	16.9% (False Negative)	91.6% (True Negative)



(a) (b)

Figure 4 The predicted result using the DCED model (red) and ground truth (green) of Pararubber tree areas over the regions of (a) Validation#1 and (b) Validation#2.

$R = 82.85\%$, $F_1 = 86.35\%$, $ACC = 86.90\%$ based on all training datasets. It should be noted that the training datasets should not be used to assess how accurate the model is. However, the accuracy assessment of the training datasets is displayed here for showing how well the model does with the training datasets themselves based on the obtained trained parameters.

To validate the DCED model with the trained parameters, the validation datasets are used to assess the accuracy. The results from using the DCED model on the Validation#1 and Validation#2 are shown in Figure 4(a)

Table 3 Error matrix calculated from the results using the DCED model on Validation#1

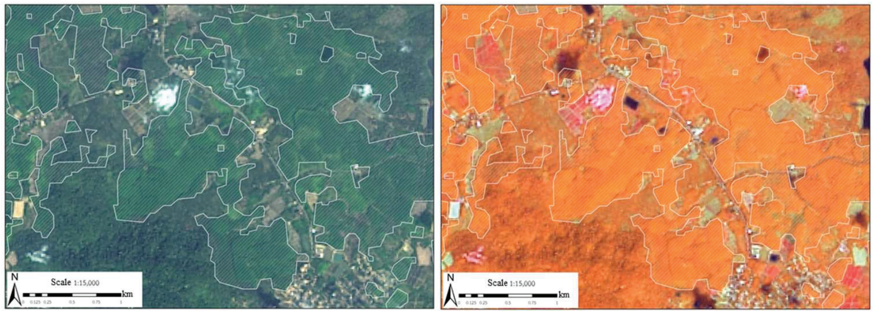
	Validation#1	Actual	
		Pararubber	*Non-Pararubber*
Predicted	*Pararubber*	80.4% (True Positive)	45.8% (False Positive)
	Non-Pararubber	19.6% (False Negative)	54.2% (True Negative)

Table 4 Error matrix calculated from the results using the DCED model on Validation#2

	Validation#2	Actual	
		Pararubber	*Non-Pararubber*
Predicted	*Pararubber*	81.2% (True Positive)	32.2% (False Positive)
	Non-Pararubber	18.8% (False Negative)	67.8% (True Negative)

and 4(b), respectively, where the red polygons designate the predicted results while the green polygons represent the ground truth. From the results, the error matrices from the Validation#1 and Validation#2 datasets are shown in Tables 3 and 4, respectively, which give $P = 63.71\%$, $R = 80.40\%$, $F_1 = 71.09\%$, and $ACC = 67.30\%$ for Validation#1 and $P = 71.60\%$, $R = 81.20\%$, $F_1 = 76.10\%$, and $ACC = 74.50\%$ for Validation#2. Therefore, the accuracy of the DCED model for automatic Para-rubber tree classification from LANDSAT-8 imagery developed in this work can provide $P = 67.66\%$, $R = 80.80\%$, $F_1 = 73.595\%$, $ACC = 70.90\%$ based on all validation datasets.

The validated DCED model is then used to predict the areas of the Para-rubber trees in other regions within Scene#1 to visually verify the results. The predicted Para-rubber tree areas using the DCED model (polygons) are shown in Figure 5(a) over LANDSAT-8 true-color image using RGB-band while Figure 5(b) shows the predicted results over a false-color image using band-564. Noting that the false-color image is normally used for manual Para-rubber tree classification where light orange regions are most likely Para-rubber tree areas. From observing the result as shown in Figure 5(b), the DCED model developed in this work can detect the areas with light orange color relatively well which indicates an accurate prediction of Para-rubber tree areas on LANDSAT-8 imagery.



(a) (b)

Figure 5 Prediction of Para-rubber tree areas using the DCED model developed in this work on LANDSAT-8 imagery displaying (a) RGB colors and (b) false colors from band-564.

5 Concluding Remarks

The DCED neural network approach is used to develop an automatic Para-rubber tree classification process from LANDSAT-8 imagery. The predicted results from the DCED model in this work are shown to be valid based on the validation datasets which were created by the manual method. However, the amount of training and validation datasets are still considered to be relatively small. Therefore, further analysis and assessment are still required to fully validate the model, as well as improving the accuracy of the model. In addition, there are much different deep learning and neural network approaches that are yet to study and could lead to a better classification model which would be the next steps of this work.

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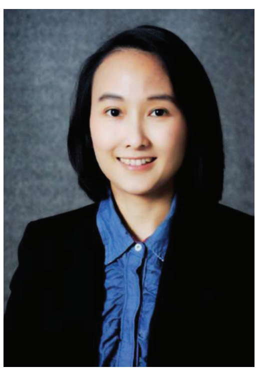
Biographies



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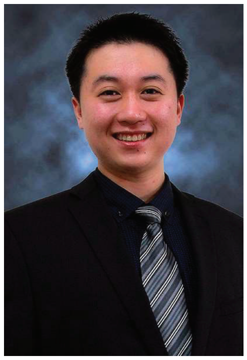

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