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Finding Threshold for NDVI to Classify Green Area: Case Study in the Central Thailand

Koltouch Annatakarn[1], Kritsada Annatakarn[1*], Rerkchai Fooprateepsiri[1*], Marwin Suwanprapab[2], Chisaphat Supunyachotsakul[2], Boonsap Witchayangkoon[3]

[1] Faculty of Engineering and Architecture, Uthenthawai Campus, Rajamangala University of Technology Tawan-Ok, Chon Buri, Thailand

[2] Engineering Program in Civil Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand

[3] Thammsat School of Engineering, Thammasat University, Pathumtani, Thailand

Abstract: Thailand and other countries worldwide are trying to increase green areas to fight against climate and deforestation issues and improve air quality. To observe a green area on a large-scale using satellite images are eligible. Free-of-charge satellite images such as Landsat 8 offer useful information to produce various outputs. Survey for a green area Normalized Different Vegetation Index (NDVI) is beneficial since satellite images are in charge. NDVI is an indicator that can analyze remote sensing measurements and Geographic Information System (GIS), assessing whether the target being observed contains live green vegetation. Although NDVI is a good indicator for observing a green area, NDVI still cannot classify a green area without thresholds. To find a proper threshold for NDVI classification, we have been through the three land-use types: urban, agricultural, and forest, with multi-temporal satellite images. We develop the software tool using Python code and remote sensing data for classification and accuracy assessment. Both experiments aim to observe a proper threshold that satisfies high prediction accuracy. Finding thresholds for NDVI is required ground truth which is trustable information of a green area and NDVI image. To provide ground truth, we used digitizing method to obtain the information. The type of area experiment uses a different type of area as a variant, and for a temporal area, we use time as a variant. A temporal area experiment observes the same is with different timing to compare the results. As a result, we found that a threshold around 0.325 to 0.367 is suited to observing a green area.

Keywords: normalized different vegetation index, remote sensing, geographic information system, Python.

寻找归一化不同植被指数的阈值以对绿地进行分类：泰国中部的案例研究

摘要：泰国和世界其他国家正在努力增加绿地以应对气候和森林砍伐问题并改善空气质量。使用卫星图像大规模观察绿色区域是有资格的。陆地卫星 8 等免费卫星图像提供了有用的信息来产生各种输出。由于卫星图像负责，因此对绿色区域归一化不同植被指数(NDVI)的调查是有益的。NDVI 是一种可以分析遥感测量和地理信息系统（地理信息系统）的指标，评估被观察的目标是否包含活的绿色植被。虽然 NDVI 是观察绿色区域的一个很好的指标，但 NDVI 仍然无法在没有阈值的情况下对绿色区域进行分类。为了找到合适的 NDVI 分类阈值，我们通过多时相卫星图像研究了三种土地利用类型：城市、农业和森林。我们使用 Python 代码和遥感数据开发软件工具，用于分类和准确性评估。这两个实验都旨在观察满足高预测精度的适当阈值。找到 NDVI 的阈值是必需的地面实况，它是绿色区域和 NDVI 图像的可信信息。为了提供基本事实，我们使用数字化方法来获取信息。区域实验的类型使用不同类型的区域作为变体，对于时间区域，我们使用时间作为变体。一个颞区实验观察相同是

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About the authors: Koltouch Annatakarn, Kritsada Annatakarn, Rerkchai Fooprateepsiri, Faculty of Engineering and Architecture, Uthenthawai Campus, Rajamangala University of Technology Tawan-Ok, Chon Buri, Thailand; Marwin Suwanprapab, Chisaphat Supunyachotsakul, Engineering Program in Civil Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand; Boonsap Witchayangkoon, Thammsat School of Engineering, Thammasat University, Pathumtani, Thailand

Corresponding authors Kritsada Annatakarn, Rerkchai Fooprateepsiri, singut51@gmail.com

用不同的时间来比较结果。结果，我们发现 0.325 到 0.367 左右的阈值适合观察绿色区域。

关键词：归一化不同植被指数、遥感、地理信息系统、Python。

1. Introduction

Climate change encompasses rising average temperatures and extreme weather events, shifting wildlife populations and habitats, rising seas, and a range of other impacts [1]. All of those changes are emerging as humans continue to add heat-trapping greenhouse gases to the atmosphere, changing the rhythms of climate that all living things have come to rely on.

In this study, we develop the software tool using Python code and remote sensing data with GIS to classify the green areas in central Thailand. We are concerned that deforestation is one of the main issues that make nature cannot absorb Greenhouse Gases (GHG) quickly enough to make the GHG go from the atmosphere. So, our study aims to write an algorithm to find the specific detail of a green area from the satellite image that cannot be known by using only eyes and make the program easily used widely.

The main objectives of the study are:

- To study the benefits of NDVI for finding a green area in a large-scale work.
- To find the proper threshold of NDVI to observe a green area.
- To find that our threshold is accurate enough to use for finding a green area.

2. Reviews

NDVI, also known as Normalized Difference Vegetation Index, is a vegetation quantifier that measures the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs).

The formula calculates NDVI:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Healthy vegetation reflects more NIR and green light (why we see vegetation as green). Furthermore, it absorbs more red and blue light, as displayed in Fig. 1.

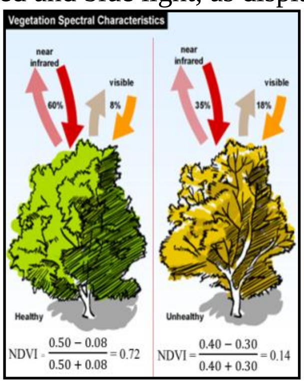


Fig. 1 Healthy vegetation reflects more in NIR than in RED

NDVI always ranges from -1 to 1, but there is no distinct boundary between vegetation and non-vegetation for each land cover type. For examples:

If NDVI is negative, it is non-vegetation and likely to be water.

If NDVI is around ≈0, it could be barren land or an urbanized area.

If NDVI is close to +1, it is vegetation and likely to be a dense forest.

Temporal optimization of image acquisition for land cover classification with Random Forest (RF) Classifier on Moderate Resolution Imaging Spectroradiometer (MODIS) time-series has been done in the last few years. The comparison of NDVI and MODIS Enhance Vegetation Index (EVI) that more accurately and can show sharper growing season peaks and greater sensitivity by time series (such as Hodrick-Prescott or Gaussian filters), different smoothing techniques, ranging from Fourier based filters [2]. The extracted NDVI and EVI values from Vegetation Indices (MOD13Q1) Version 6 data and arranged can create a time series stack. Then, as shown in Fig. 2, use the filters to eliminate the error values, and Random Forest cut out-of-bag error. The result shows that it would be great to use the EVI value to classify grassland and forest and use the NDVI value to classify Settlement and Peatland because it is less photosynthetically active classes.

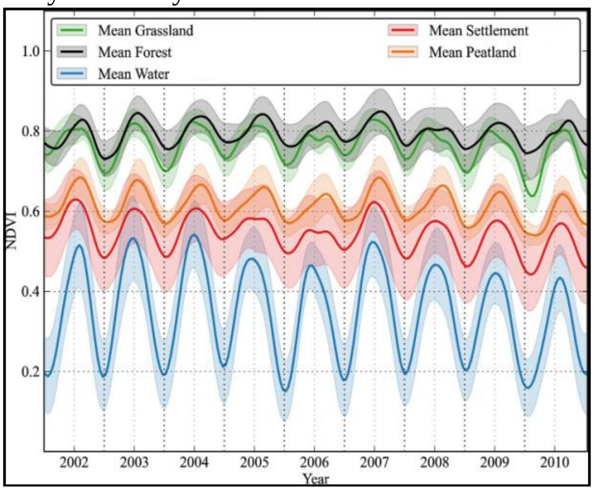


Fig. 2 Seasonal mean land cover class NDVI curves with one standard deviation above and below the mean shown in the shaded region [2]

Very High-Resolution (VHR) Object-Based Land Use–Land Cover Urban Classification Using Extreme Gradient Boosting (Xgb) has been widely reported for NDVI classification. The researchers want to compare a new invention, regularized implementation of

Gradient Boosting Machines (GBMs), called extreme gradient boosting, with the traditional boosting algorithms, Random Forest (RF) and Support Vector Machine (SVM), to find the most accurate and less time processing. Georganos et al. [3] showed some figures from 3 different places and segmented the data processed using Grass GIS. First and second place using random and stratified random sampling with strata defined using OpenStreetMap and making 3 training sets of 20, 40, and 60, as shown in Table 1. Lastly, they used the sensitivity to sample size in more depth (between 50 and 400 objects per class). At the same time, we also used ten randomly drawn distributions of training objects for each sample size category. After that, put the data from 3 different places to all boosting algorithms and record the result [3]. The result of Dakar, Senegal, is shown in Table 1. The author found that Xgboost performed very well in Overall Accuracy (OA) when using medium and large sample sizes, but it cost increased computational time. Feature Selection (FS) as Correlation-based Feature Selection (CFS) as a method for reducing dimensionality is more beneficial for small sample sizes.

Table 1 Comparison of the overall accuracy of classifiers in Darkar, Senegal [3]

Training sample	**SVM**	**SVM_{CFS}**	**RF**	**RF_{CFS}**	**Xgb**	**Xgb_{CFS}**
N_{20}	74.65	75.85	77.12	77.67	74.67	75.56
N_{40}	77.12	77.31	78.33	79.40	80.09	79.25
N_{60}	77.88	78.07	80.33	80.88	82.10	81.78
Times (sec)	0.25	0.18	1.51	1.01	3.62	2.21

This study is based on the experiences of the references mentioned above to apply for finding the NDVI threshold and evaluating the classification accuracy of mapping the green area in central Thailand.

3. Methodology

This study's methodology mainly focuses on analyzing NDVI values from Landsat8 images and evaluating the accuracy of mapping classification, as illustrated in Fig. 3.

3.1. Multi-Temporal Landsat 8 Data Collection

In our case, we calculate NDVI using imagery from Landsat 8 and the wavelength as described in Table 2 [4].

Table 2 Bands used for NDVI threshold from Landsat 8 collection 2 data

Path 129 Row 50 Filename	**Acquisition date**	**Cloud cover (%)**
LC08_L2SP_129050_20200219_20200822_02_T1	19 February 2020	0.58
LC08_L2SP_129050_20200829_20200906_02_T1	29 August 2020	3.02
LC08_L2SP_129050_20201117_20210315_02_T1	17 November 2020	5.32
Bands	**Wavelength (micrometers)**	**Resolution (meters)**
Band 4 - Red	0.64-0.67	30
Band 5 - Near Infrared (NIR)	0.85-0.88	30

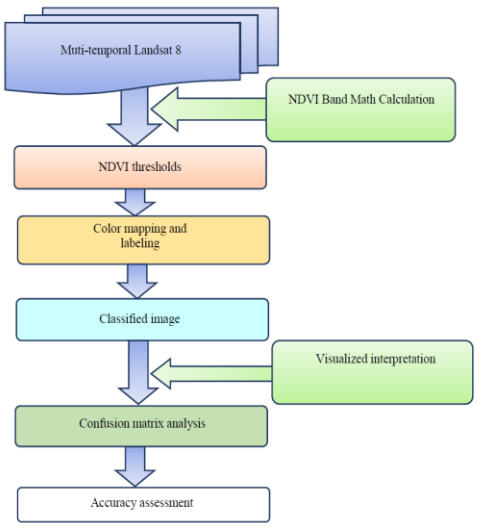


Fig. 3 Overview of research methodology

3.2. NDVI Band Math Calculation

Since our project aims to find a green area, in this process, we convert raw data from Landsat8 collection 2 into an NDVI raster.

Firstly, we have raster data from USGS in GeoTFF format. The output of this process is an NDVI imagery in tiff format. The NDVI value will vary around -1 to 1 in every pixel.

$$NDVI = \frac{Band5 - Band4}{Band5 + Band4}$$

3.3. NDVI Threshold

The software tool using Python Ver. 3.8 coding is applied. It follows the method of a Python-Based Open-Source System [5] for Geographic Object-Based Image Analysis (GEOBIA) utilizing Raster Attribute Tables (RAT). This guideline performs a formula system for GEOBIA, using entirely open-source software. The system is presented as raster clumps and storing attributes as a RAT [5]. The system is particularly suited to high-resolution multispectral imagery, but lower resolution data such as Landsat can also be used with fewer classes derived.

Table 3 NDVI color mapping and labeling

NDVI range	HTML color code	Color
NDVI < -0.2	#000000	
-0.2 < NDVI ≤ 0	#a50026	
0 < NDVI ≤ 0.1	#d73027	
0.1 < NDVI ≤ 0.2	#f46d43	
0.2 < NDVI ≤ 0.3	#fdae61	
0.3 < NDVI ≤ 0.4	#fee08b	
0.4 < NDVI ≤ 0.5	#ffffbf	
0.5 < NDVI ≤ 0.6	#d9ef8b	
0.6 < NDVI ≤ 0.7	#a6d96a	
0.7 < NDVI ≤ 0 .8	#66bd63	
0.8 < NDVI ≤ 0 .9	#1a9850	
0.9 < NDVI ≤ 1.0	#006837	

3.4. Color Mapping and Labeling

The NDVI value range is -1 to 1. NDVI Negative values (values near -1) are equal to water. Values near zero (-0.1 to 0.1) generally correspond to barren areas. Low, positive values represent shrub and grassland (approximately 0.2 to 0.4), as shown in Table 3, while high values indicate temperate and tropical rainforests (values approaching 1). It is a good proxy for live green vegetation [6].

3.5. Classified Image

The area type process studies compare the result of each image that comes with the different types of area [7]. The studies include forest areas, rural areas, and urban areas. We expected to see if the difference in the area affects the proper threshold and look for the threshold that satisfied high accuracy for all images.

The process started with raw imagery from Landsat 8 collection 2.

After that, we plot an accuracy graph for each type of area and compare the results. Finally, all specimens are clipped from the same satellite image. The properties of clipped images are the same with 30 meters cell size and 200 x 200 pixels.

3.6. Visualized Interpretation

Visualized interpretation is the process is to classifying the green area manually. The result is the representation of ground truth. We used the results of this process to compare with vegetation prediction from our algorithm.

Firstly, we clipped the RGB image into smaller and created a polygon to cover the green area. After that, we got a result of green area in area polygon format. We create polygon pixel by pixel to minimize any error in the digitizing process.

Secondly, we compare the ground truth to our prediction, and we need to convert it into a raster TIFF format because polygon format is just an area. However, raster formats contain an indicated value.

3.7. Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data in which the true values are known. In our case, the true value is called ground truth, as presented in Table 4.

Table 4 The confusion matrix

	Actually Positive (1)	**Actually Negative (0)**
Predicted Positive (1)	True Positive (TPs)	False Positive (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

The most basic terms of the matrix are true positives, true negatives, false positives, and false negatives; all these terms are whole numbers. *True positives (TP):* These are cases in which we predicted yes, and the answer is yes. *True negatives (TN):* We predicted no, and the answer is no. *False positives (FP):* We predicted yes, but the answer is no. *False negatives (FN):* We predicted no, but the answer is yes. We can compute accuracy, misclassification, precision, recall, and F-score with these data from the confusion matrix.

3.8. Accuracy Assessment

3.8.1. Accuracy

Accuracy is the number of correctly predicted results out of the total. Accuracy = (TP + TN) / (TP + TN + FP + FN). Accuracy should be considered when TP and TN are more important than the others.

3.8.2. Precision

Out of the total predicted positive values, how many were positive.

Precision = TP / (TP + FP)

3.8.3. Recall

Out of all the actual positive values, how many were correctly predicted as positive.

Recall = TP / (TP + FN)

3.8.4. F-1 Score (Beta = 1)

FP and FN are equally important, allowing the model to consider both precision and recall equally using a single score.

$$F1 = 2 \text{ x } \frac{Precision \text{ x } Recall}{Precision + Recall}$$

F-1 score is the Harmonic Mean of precision and recalls.

3.9. The Study Area

The study area is in Central Thailand and has a geographical coordinate range from Longitude 99°30'.0.0" E to 102°30'.0.0" E and Latitude 13°00'.0.0"N to 15°30'.0.0"N as displayed in Fig. 4. Multi-temporal Landsat8 data and land-use types such as urban, agriculture, and forest are also represented.

4. Result and Discussion

The study, analyzing areas of land use types, compares the result of each image that comes with the different types of area. The studies include forest areas, rural areas, and urban areas. We expected to see if the difference in the area affects the proper threshold and look for the threshold that satisfied high accuracy for all images. The process started with raw imagery from Landsat 8 Collection 2. After that, we plot an accuracy graph for each type of area and compare the results. Finally, all specimens are clipped from the same satellite image. The properties of clipped images are the same with 30 meters cell size and 200*200 pixels.

4.1. Results from Different Terrain

An urban area is a region surrounding a city. Urban areas are very developed, meaning dense human structures such as houses, commercial buildings, roads, bridges, and railways. Agriculture areas are areas that are not towns or cities. They are often farming or agricultural areas. Forest area is land under natural or planted stands of trees.

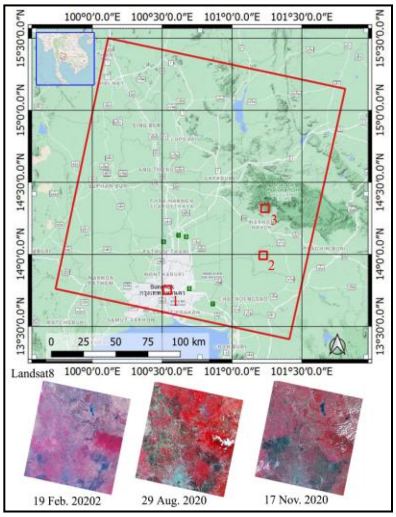
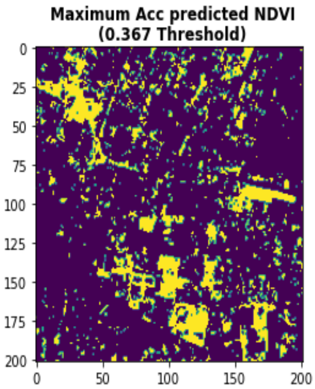
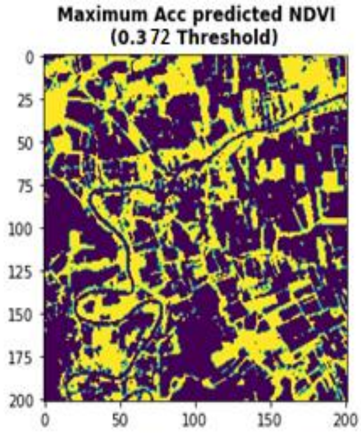


Fig. 4 The study area: (a) Urban type, (b) Agricultural type, and (c) Forest type

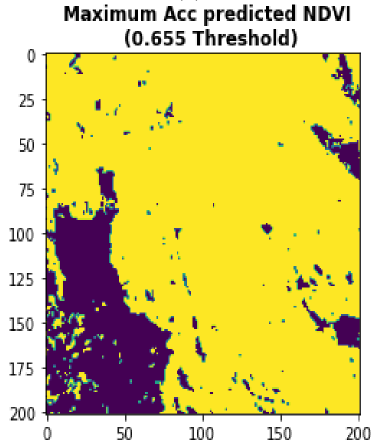
After we got all these areas representing different terrains, we applied the previous process to provide a proper threshold for each clipped area. We decided to apply the process to two satellite images; then, we compare the results. Fig. 5 shows the prediction of each area type as (a) urban, (b) agricultural, and (c) forest area in the scene dated 19/02/2020. For maximizing accuracy in the scene dated 19/02/2020, thresholds are 0.367,0.372,0.655 for urban, agricultural, and forest, respectively. Fig. 6 displays the prediction of each area type as (a) urban, (b) agricultural, and (c) forest area in the scene dated 17/11/2020. For maximizing accuracy in scene dated 19/02/2020, thresholds are 0.303, 0.274, 0.358 for urban, agricultural, and forest, respectively. Fig. 6 shows the graph plots from threshold and accuracy to observe thresholds that maximize accuracy.



(a)

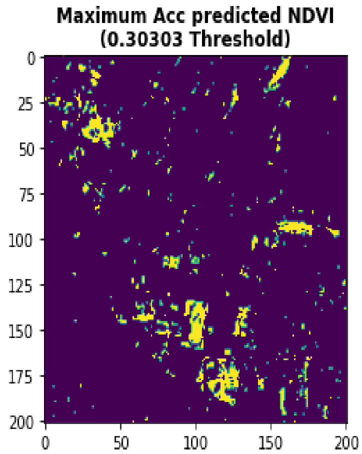


(b)

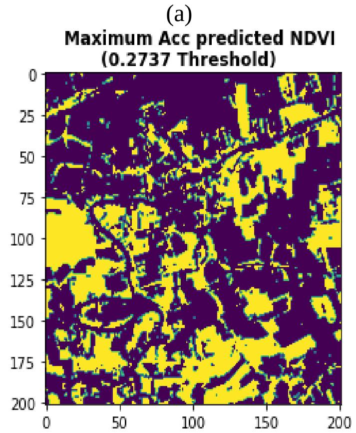


(c)

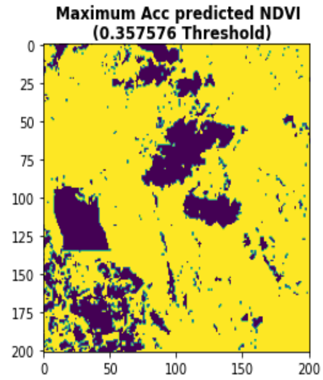
Fig. 4 Green area prediction in yellow color with maximum accuracy of (a) urban, (b) agricultural, and (c) forest area on the date 19/02/2020



(a)



(b)



(c)

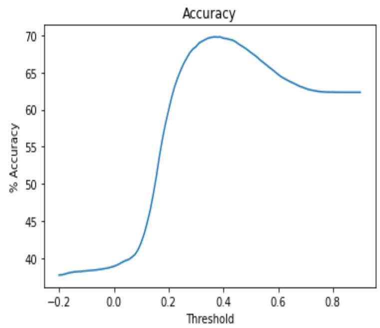
Fig. 5 Green area prediction in yellow color with maximum accuracy of (a) urban, (b) agricultural, and (c) forest area on the date 17/11/2020

After analyzing the statistics with plotting, we started to find the accuracy for each image, and the maximum threshold is shown in Table 5.

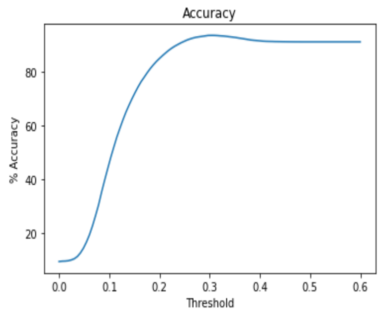
Table 5 Maximum accuracy and thresholds from the temporal experiment

Results	Landsat 8 Collection 2 acquisition date		
	19/02/2020	29/08/2020	17/11/2020
Maximum accuracy (%)	71.03	74.06	81.39
NDVI threshold	0.372	0.261	0.342

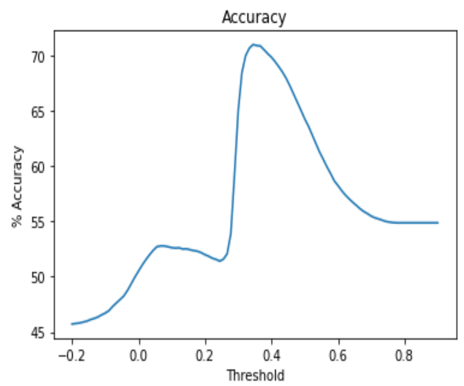
To classify a green area, we used NDVI (Normalized Difference Vegetation Indexes). However, NDVI can suggest a green area by using reflected light in the visible and near-infrared bands. However, NDVI cannot classify sharply without a proper threshold. Therefore, ground truths are relevant since we used them as a reference. The results provide a threshold from all 3 land-use types of area experiment and temporal area experiment and overlap area form comparing ground truth process.



(U1)



(U2)



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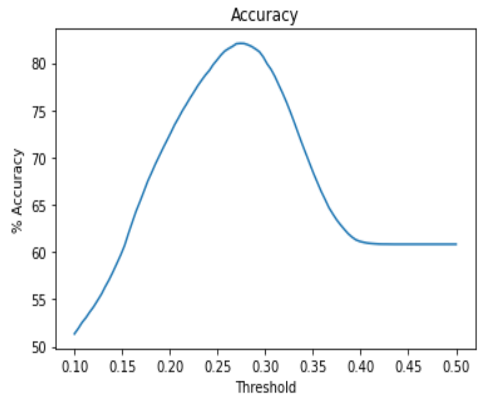
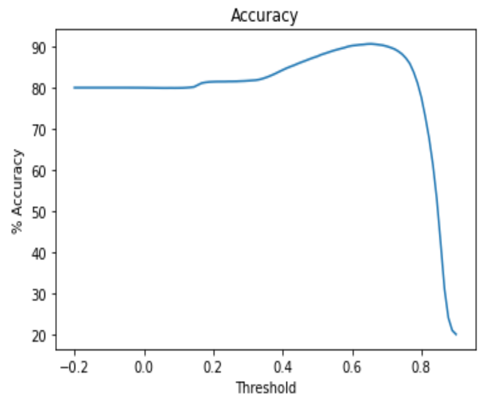
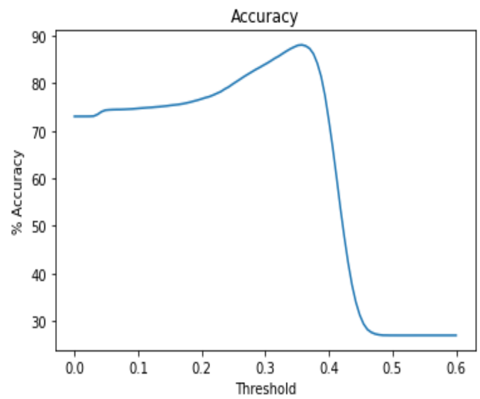


(A2)



(F1)



(F2)

Fig. 6 Plot of accuracy and thresholds of (U1) urban area scene date 19/2/2020 (U2) date 17/11/2020, (A1) agricultural area scene date 19/2/2020 (A2) date 17/11/2020, and (F1) forest area scene date 19/2/2020 (F2) date 17/11/2020

4.2. Results from Multi-Temporal Data Sets

The experiment results at a threshold equal to 0.372, 0.261, 0.342 with an accuracy of 70.372 %, 81.532%, 81.386% for an image taken on 19/02/2020, 29/08/2020, 17/11/2020 are shown in Table 6. To observe a threshold that works well for all timing, we use each threshold and mean of all three-timing scenes to find one proper threshold that satisfies overall high accuracy.

Table 6 Results of multi-temporal data sets

NDVI Threshold		**Accuracy %**			
		19/02/2020	**29/08/2020**	**17/11/2020**	**Mean**
19/02/2020	0.372	70.723	64.045	81.104	71.958
29/02/2020	0.261	51.766	81.533	75.810	69.703
17/11/2020	0.342	70.996	70.449	81.387	74.277
Mean	0.325	70.436	74.835	80.930	75.400

4.3. Comparing Ground Truth Results

The digitizing ground truth scene dated 19/02/2020 covers 84.381% of all areas, and the ground truth scene dated 17/11/2020 covers 80.022% of all areas. Ground truth scene dated 19/02/2020 and ground truth scene dated 17/11/2020 reach maximum accuracy of 90.648% and 95.490% at thresholds of 0.655 and 0.633. An overlap area contains 97% of the ground truth scene dated 17/11/2020 and 92% of the ground truth scene dated 17/11/2020.

5. Conclusion

In this study, a satellite image from Landsat 8 collection 2 was used as a data source. Different area types and temporal experiments were used to observe for a threshold that satisfied maximum accuracy. Form both experiments. The effective threshold for the area type experiment is 0.367 and 0.325 for the temporal experiment. Both can satisfy a high value of accuracy, which is 77.782% for area type and 75.4% for the temporal area. As a result, we found that even if we got an NDVI image of the same area, the prediction of a green area would change since vegetation is not permanent.

5.1. Recommendation for Future Work

Many experiments, tests, and samples have been left behind for the future due to the lack of time. Some processes, such as digitizing, take much time to provide a precise ground truth requires much time and effort. In the future, we aim to go deeper to observe for a threshold that can satisfy 90% of accuracy. More sample area and ground truth quality are relevant to develop further in terms of accuracy. Applying our work to find green areas is significantly beneficial for many associations such as the Forest Department and Ministry of Agriculture. More than that, these green area observations can increase awareness of deforestation and climate change issues.

Acknowledgement

Without the contribution of many people, this research would not have existed. It owes its existence to the support and inspiration of many people.

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