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Orchard Classification from Satellite Image Data using Fuzzy K-mean to Estimate of Carbon Sequestration

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ABSTRACT

The aim of the study is to estimate carbon sequestration in terms of above-ground biomass (AGB) within the orchard or perennial tree from the high resolution image. The objective of this study is to classify the land use from the Sentinel-2 image data for estimating the AGB by using the vegetation indices consists: normalization difference vegetation index (NDVI) and ratio vegetation index (RVI). The fuzzy k-mean was applied to classify the land use divide into 6 classes. The orchard or perennial (OP) from the classified was to estimated the AGB value by using the spatial analysis based on regression model. The results of land use classified show that the overall accuracy and the kappa coefficient was 88%, and 0.65, respectively. The regression equation for estimated of the AGB value using vegetation indices, the regression equation was the y=(27.23*NDVI)+(-3.21*RVI) with coefficient of determination R^2 = 0.71. The calculate of the AGB in the orchard or perennial tree from the classified was 14769.93 tCO2e.

Key words : *Spatial regression model, Above-ground biomass, Image classification*

Introduction

In recent year, the application of remote sensing to estimate of carbon sequestration is increasingly applied such as (Myeong *et al*., (2016), Vischarnakorn *et al*., (2014), Laosuwan an Uttaruk, (2016) and Uttaruk and Laosuwan, (2016). They used Landsat satellite image to estimate spatial biomass in the large areas by using the spectral reflection of the vegetation. The normalization difference vegetation index (NDVI) and ratio vegetation index (RVI) the used wildly to calculate the biomass density (Kinyanjui *et al.,* 2014, Cohen and Goward, 2004). The summaries of techniques for estimate biomass using NDVI and RVI indices of Landsat data include linear or nonlinear regression models, K nearest-neighbour, and neural network (Lu, 2006, Konda *et al.,* 2017). The summaries of techniques found that used Landsat data to data analysis in large areas focused on the estimated biomass in the forest area mostly. The techniques for estimate AGB can be grouped into two broad categories: parametric and nonparametric algorithms (Lu, 2006, Lu *et al*., 2016). Parametric algorithms refer to common statistical regression, which the expression relating the dependent variable (AGB) and the independent variable (derived from remote sensing data) is explicit and easy to calculate (Lu *et al.,* 2016). The key is to identify suitable remote sensing variables that have strong relationships with biomass (Lu *et al*., 2012, Liu *et al.*, 2017).

Presently, the study of carbon sequestration in the agricultural area is caused by carbon storage in plants and soils that is similar to carbon storage in forest areas (Laosuwan and Uttaruk, 2016). Nair (2010) offers that agroforestry has a high potential for carbon sequestration because of their perceived ability for greater capture and utilization of growth resources than in single crop or pasture systems. The use of agricultural areas for reduction of greenhouse gas (GHG) emissions is highly potential and very interesting, especially in Thailand which has more than 243,730.814 km^2 of agricultural areas (Uttaruk and Laosuwan, 2019). This article, focus on carbon sequestration in terms of agricultural area base on the high resolution image from Sentinel-2 image data of Thailand. However, the estimate of carbon sequestration on small scales such as agroforest or agricultural area is related to the land cover types. The estimate of carbon sequestration in the orchard or perennial plantation area which requires a classification of land cover from Sentinel-2 image data.

Materials and Methods

Data collection and study area

This study used the data from Sentinel-2 images in Path 127 Row 49, for an area of the orchards belonging to eleven farmers at Sang Kho sub district, Phu Phan district, Sakon Nakhon province in northeast Thailand lies between 16.54° to 16.58° N Latitude and 103.54° to 103.56° E Longitude. These areas were a pilot area of carbon credit project through the agricultural sector for carbon sequestration assessment of the orchards or perennial tree. The study area was variety type of land cover; it is difficult to classify the land cover as shown in Fig 1.

Methods

Vegetation indices

The normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) was used to improve the ability to separate healthy vegetation from other land cover types. In their original equations, they provide normalized values in the interval from "1 to 1. The NDVI is a normalized ratio of NIR (near infrared) and Red (red band) defined as (Tucker, 1979):

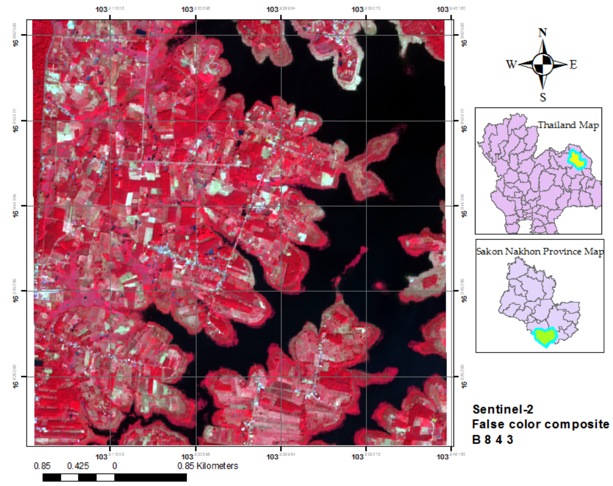

Fig. 1. The location of the study area

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad .. (1)$$

The ratio vegetation index (RVI) is calculated by simply dividing the reflectance values of the near infrared band by those of the red band defined as Birth and Mcvey, (1968):

$$RVI = \frac{NIR}{Red} \quad .. (2)$$

The result clearly captures the contrast between the red and infrared bands for vegetated pixels, with high index values being produced by combinations of low red and high infrared reflectance (Silleos *et al.,* 2006).

Image clustering using fuzzy k-mean technique

Fuzzy k-mean clustering is an unsupervised clustering algorithm by divide the partition of data into k cluster. Fuzzy k-means is a generalization from the k-means algorithm based on the conceptual of fuzzy logic (Dunn, 1973). The algorithm is performed with an iterative optimization of minimizing a fuzzy objective function (Bezdex, 1981).

$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^{m}, d_{ij} \quad .. (3)$$

Where:
J = minimized the objective function,
c = number of clusters,
n = total number of pixels,
u_{ij} = degree of membership of pixel x_j in the cluster i,
d_{ij} = the Euclidean distance between pixel x_j and cluster center v_i.

m = an exponential weight (or fuzziness) for each fuzzy membership, degree of fuzziness of each cluster increases along with the *m*.

The matrix of u_{ij} to transition from "hard" to "fuzzy" clustering should satisfy the following constraint:

$\sum_{j=1}^{n} u_i$, for *i=1* to *c*

$\sum_{i=1}^{c} u_i$, for *j=1* to *n* .. (4)

The process of image clustering is performed using fuzzy k-means is now presented as follows.

(1) Initial number of clusters *c* and randomly to select cluster center.

(2) Calculate the membership u_{ij} using the following equation:

$$u_{ij} = \left((d_{ij})^{1/m-1} \sum_{j=1}^{n} \left(\frac{1}{d_{ij}} \right)^{1/m-1} \right)^{-1} \quad .. (5)$$

(3) Calculate the cluster center v_i as following equation:

$$v_i = \frac{\sum_{j=1}^{n} (u_{ij})^m x_j}{\sum_{j=1}^{n} (u_{ij})^m} \quad .. (6)$$

(4) Compare the minimum the objective function of *J* value.

(5) Repeat step 2) and 3) until the minimum *J* value is achieved.

Accuracy Assessment of land cover classification

The accuracy assessment of this paper to a comparison of the proposed method with fuzzy k-mean clustering by using confusion matrices. The matrices were performed on 349 samples of the reference points to evaluate the classification procedure. The overall accuracy and the kappa coefficient (Congalton and Green, 2013), (Jensen, 1996) were used to evaluate classified.

Field survey to determine the carbon content in the plot areas

The study site is located in Sang Kho sub district, Phu Phan district, Sakon Nakhon province which is containing various forest types. The sampling plot area selection from farmers who were members of the community, and then stratified random method was used to be a group study case. Then randomly select permanent plot according to the species or group of species cultivated plants or by age of transplant or agroforestry management system whose property is similar (Uttaruk and Laosuwan, 2016). The number of permanent sampling plots in the orchard or perennial tree is a total of 23 plots, by each plot has a dimension of 20m × 20 m. and all of the trees in the plot are measuring heights of trees at 1.30 meters and recording names, sizes, and heights of trees (Uttaruk and Laosuwan, 2019).

Spatial analysis of AGB base on statistical regression model

The basic of spatial analysis is the technique for predict or estimate the values of a geographic variable that have known at the location to predict or estimate which are unknown at these locations or other locations. The statistical regression model is one of the paramedic algorithms which produce good results for an estimate of the AGB and remote sensing data. In general, the parametric algorithms to predict new data that requires the parameters of the model. The common type of statistical regression model used to archive that aim estimate in which relationship from one or more independence variable and a single dependent variable . In this study, the NDVI, and RVI were defined as independent variables, and ABG was defined as the dependent variable. The multi-linear regression model equation defines as:

$Y = a + bX_1 + cX_2 + dX_3 + \ldots$

Where

Y defines the dependent variable;

X_1, X_2 and X_3 define independent variables;

a, b, c, d define constants.

Proposed methods

This study was proposed methods based on vegetation indices and clustering methods to classify the orchard or perennial tree from the Sentinel-2 image data. Furthermore, the assessment of carbon sequestration using spatial analysis base on the statistical regression model. The first step calculating vegetation indices of NDVI and RVI from Sentinel-2 satellite image. The second step classifies land use using the fuzzy k-mean methods. The accuracy assessment using the kappa coefficient and overall accuracy to compare the results of fuzzy k-mean methods. Furthermore, the assessment of carbon sequestration using spatial analysis based on the statistical regression model combination with the vegetation indices of NDVI and RVI from Sentinel-2 satellite image. The field survey to determine the carbon content in the plot areas and calculate the ABG using the allometric equation.

Results

The results of fuzzy k-mean classified and accuracy assessment.

The results of land use classified of the Setinel-2 image data using fuzzy k-mean have been applied. The land use was classified into 6 classes are the forest (F), water bodies (W), field crop (FC), urban (U), orchard or perennial (OP), and cultivation plant (CP). The results of confusion matrices were used compared to the accuracy assessment of land use classified as following:

The results of land use classification is shown in Fig 2. and the area of the land use classifications from the fuzzy k-mean techniques shown as percentage values of an area in Table 1. Table 1 shows that the percentage of an orchard or perennial tree from combinations of bands 1, 2, 3, and 4.

Table 1. Percentage values of an area from land use classified.

Lu Class	Area	
	sq.km	percentage
Forest (F)	3.89	13
Water bodies (W)	6.51	22
field crop (FC)	11.60	39
Urban (U)	1.20	4
Orchard or perennial (OP)	5.63	19
cultivation plant (CP)	0.87	3
Total	29.70	100

The accuracy assessment of land use classification using the confusion matrices show that the overall accuracy was 88 % and the kappa coefficient was 0.65 as shown in Table 2.

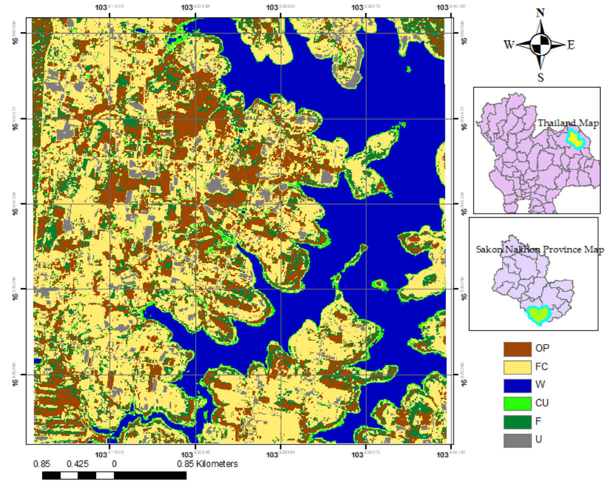

Fig 2. The land use classification using fuzzy k-mean

The results of spatial analysis of AGB base on statistical regression model

The results regression coefficient between the AGB values form surveying with the independent variable NDVI and RVI from the data measurement with 23 sampling plots. The regression equation for estimated of the AGB value using vegetation indices, the regression equation is:

$$y = (27.23 \times NDVI) + (-3.21 * RVI)$$

The value indicates that $R^2 = 0.71$ of the coefficients of determine. The results of the analysis of the variance in the model is shown in Table 3.

The results of estimated the AGB using regression model and remote sensing data.

The regression model applied to estimate the spatial mapping of carbon sequestration in the orchard or

Table 2. Confusion matrices and kappa coefficient of land use classified from Band 1,2,3 and 4

LU class	Reference data						Total
	OP	FC	W	CP	F	U	
OP	79	10	2	1	1	0	93
FC	15	89	0	1	0	1	106
W	0	0	77	0	0	0	77
CP	0	0	2	20	0	0	22
F	3	2	0	0	27	0	32
U	0	1	1	0	0	16	18
Total	97	102	82	22	28	17	348

Overall accuracy: 88
Kappa coefficient: 0.65

Table 3. ANOVA Table of the regression model.

	df	SS	MS	F	Significance F
Regression	2	445.31	222.66	25.01	3.61E-06
Residual	21	186.93	8.906		
T Total	23	632.25			

perennial tree area. The results of spatial mapping of AGB is shown in Fig 3 and the results of estimated the AGB in the orchard or perennial tree area was 14769.93 tCO2e.

Discussion and Conclusion

The experimental results of land use classification by using the fuzzy k-mean technique show the percentage of the orchard or perennial tree from the Sentinel-2 imagery as shown in Table 2. The accuracy assessment of land use classified show that the overall accuracy was 88 % and kappa coefficient was 0.65, from the reference data. In the Table 3 we show the land use classified comparison with the reference data found that the results of classified was 81 %. Also, the statistic is the producer's accuracy of the orchard or perennial tree was 85 % classification is interested in how well a certain area can be classified. Accordingly from both statistics it was shown that the fuzzy k-mean can be classify the orchard or perennial tree it well.

The results of spatial analysis of AGB using regression model and remote sensing data. The R2 values of the regression model showed the performance of regression model. The spatial analysis of the AGB map shows the high value was 7.18 tCO2e in the plot of 40 meters × 40 meters. The AGB volume was high as well as the NDVI value was low and the RVI value was high. Consequently, the regression model has better performance for the estimation of the spatial analysis of AGB in the orchard and perennial tree.

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Conflict of Interest

All the authors declare no conflict of interest.

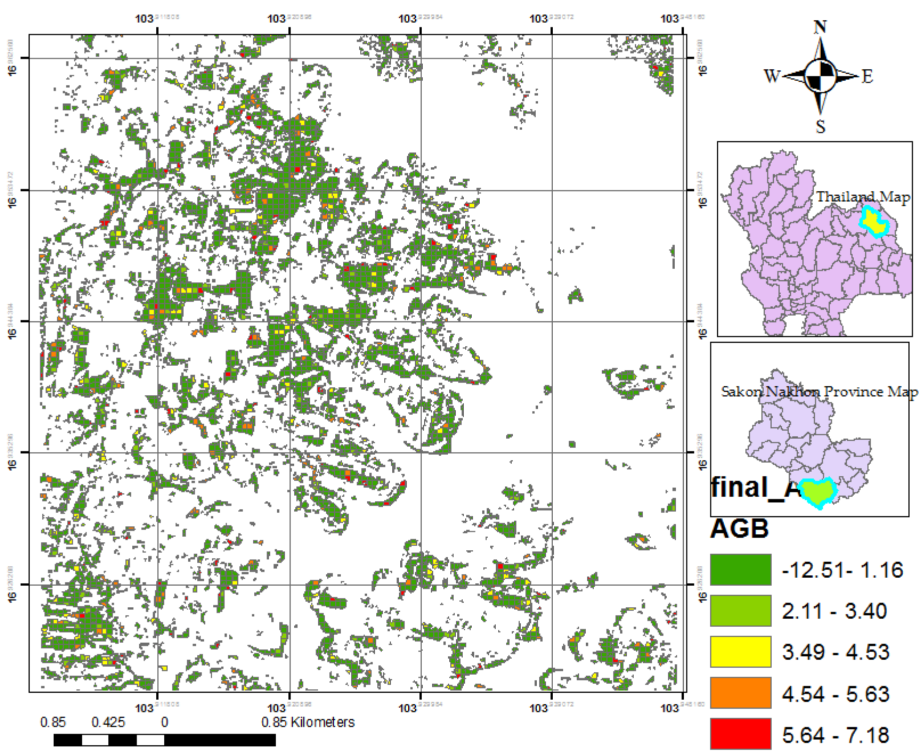

Fig 3. The AGB mapping

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