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RESEARCH & KNOWLEDGE

Research Article

Above ground carbon biomass assessment using satellite remote sensing reflection values

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Abstract - This research focused on the estimation of above ground carbon biomass of orchards in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand using remote sensing with Modified Soil Adjusted Vegetation Index-2 (MSAVI2) and Fractional Vegetation Cover (FVC). The study methodology was conducted by bringing data from Landsat 8 OLI to adjust the reflection of the Top of Atmosphere (ToA) and classify the vegetation by using MSAVI2. Pixel values above 0-1 were determined to be vegetation and pixel values equal to or below 0 were determined not to be vegetation. Then, the pixel value was determined to classify the vegetation to be 0-100 by using FVC and the satellite data obtained from the previous process was applied to determine the correlation with the field data by statistical methods to get the correlation equation $y = 0.0874e^{0.064x}$ with a coefficient of determination $R^2 = 0.9123$. The calculation resulted in an above ground carbon content of 277.430 tCO_2/rai. In addition, the researchers also tested the statistical accuracy of the above ground carbon, which could be analyzed by Landsat 8 OLI and field data with a Paired Sample T-test. The result found no statistically significant difference at a confidence level of 95%.

Keywords: Above ground carbon biomass, remote sensing, FVC**,** MSAVI2

1. Introduction

The earth receives energy from the sun in the form of light energy. Some part of the energy is reflected back to space in the form of thermal energy. While some of this thermal energy will be absorbed by greenhouse gases, which are present in a small amount in the natural atmosphere. The thermal energy absorbed by greenhouse gases creates warmth and is required for living creatures in this world. If the amount of thermal energy is overloaded, it will be retained and the heat will be reflected back down to the earth and causes global warming. In fact, all greenhouse gases are caused by human activities. The gas that is most important is carbon dioxide (CO_2) (Teerawong *et al.*, 2012; Litynski *et al.*, 2006; Wasun *et al.*, 2010). At any rate, CO_2 is released into the atmosphere by various processes, such as fuel combustion and deforestation. Meanwhile, the growth of vegetation and the associated photosynthesis process helps vegetation to absorb CO_2 and transform it to biomass (stem, branches and leaves) and roots (Ogawa *et al.*, 1965; Senpaseuth *et al.*, 2009). As a result, CO_2 will be locked into the vegetation until it is cut from the area. This process is called "carbon biomass", which is regarded as the most effective process for reducing CO_2 with natural mechanisms (Teerawong and Pornchai, 2014; Teerawong and Yannawut, 2016). The assessment of carbon biomass of forests usually requires a high budget due to the difficulty of area exploration. Currently, remote sensing technology is used to assist the assessment of above ground carbon biomass due to satellite data that provides reflectivity at different wave lengths. Thus, the above ground carbon biomass obtained from satellites in forest areas can be determined quickly with less budget required (Liaghat and Alasundram, 2010; Laosuwan *et al.*, 2011; Odindi *et al.*, 2015). Remote sensing is considered to be a modern technology that is increasingly important. The data obtained from satellites has evolved rapidly in terms of recording and data analysis methods, especially data recording systems (sensor), which had been developed in terms of spatial resolution and spectral resolution. It resulted in a variety of applications in various fields (Campbell, 1996; Lu *et al.*, 2002; Laosuwan *et al.*, 2011; Teerawong and Yannawut, 2016; Laosuwan *et al.*, 2016; Yannawut and Teerawong, 2016; Teerawong *et al*, 2016; Teerawong *et al*, 2017; Yannawut and Teerawong, 2017).

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In addition, satellite data is currently accepted for use in monitoring changes in natural disasters and incidents caused by human actions in a timely manner.

In Thailand, related research papers could be found with the majority being assessments of carbon biomass in forests and plantations. There is no assessment of above ground carbon biomass in orchards. For this reason, this study aimed to assess the above ground carbon biomass of orchards in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand with the application of remote sensing data with MSAVI2 and FVC.

2. Study area and data collection

2.1Study area: The study area was in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand (Fig. 1) with 14 agriculturists participating and a total area of **72.20** rai selected to be a pilot project area for the study.

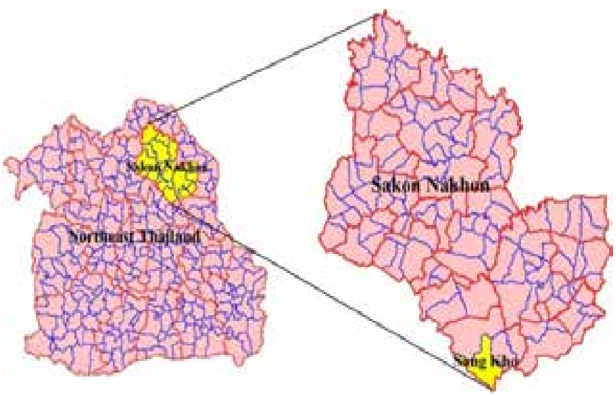


Figure 1. Study area.

2.2 Data collection: This study used the data from Landsat 8 OLI Path 126 Row 45 recorded on February 7, 2015 in the area of orchards in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand. The orchards in the pilot area were planted with 14 types of fruit trees including:

1) Maoberry (*Antidesma thwaitesianum* Mull. Arg.).
2) Sugar Apple (*Annona squamosal* L.).
3) Longan (*Dimocarpus longen* Lour.).
4) Pomelo (*Citrus maxima* Merr.).
5) Burmese Grape (*Baccaurea ramiflora* Lour.)
6) Marian Plum (*Bouea macrophylla* Griffith.)
7) Mulberry (*Morus alba* Linn.)
8) Jack Fruit (*Artocarpus heterophyllus* Lam.)
9) Mango (*Mangifera indica* L.).
10) Indian Gooseberry (*Phyllanthus emblica* L.)
11) Tamarind (*Tamarindus indica* L.)
12) Santol (*Sandoricum koetjape* Burm.)
13) Lychee (*Litchi chinensis*. Sonn.)
14) Lime (*Citrus aurantifolia Swing*.)

3. Research methodology

This study divided its methodology into two main processes as below:

1) The process of analyzing the data from the Landsat 8 OLI satellite.

2) The process of surveying field data to determine the carbon content in the plots in the study area.

The final process could be found from the statistical correlation between the data from the Landsat 8 OLI satellite and the field data to calculate the carbon content per area.

3.1 Analysis process of data from Landsat 8 OLI satellite

3.1.1 Electromagnetic waves from the sun hit the Top of Atmosphere (ToA) and its value is based on the distance between the earth and the sun, including the angle of incidence. Some of the electromagnetic waves cause phenomenon such as scattering. Air molecules, clouds and dust were partially absorbed by ozone, gas, dust and clouds. The rest was reflected by objects on the earth back to the data recorder on the satellite. This phenomenon may result in an error in the satellite data recording. To reduce the effects of the electromagnetic waves from the phenomenon, this research adjusted the ToA to ensure the accuracy of the data from the Landsat 8 OLI satellite in two steps: 1) converting digital numbers to radiance and 2) converting radiance to ToA reflectance by modeling in these two steps in the Spatial Modeler Language in the ERDAS program (Fig. 2), which was derived from Equation 1 and Equation 2 (Teerawong and Pornchai, 2014; Teerawong and Yannawut, 2016).

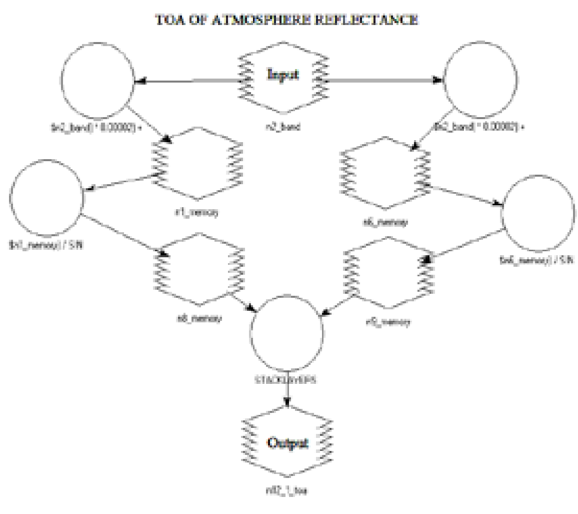


Figure 2. Top of Atmosphere model using spatial modeler.

$$L_\lambda = \left(\frac{(LMAX_\lambda - LMIN_\lambda)}{QCALMAX - QCALMIN} \right) \text{x} \left(QCAL - QCALMIN \right) + LMIN_\lambda$$

Where:

L_λ = Spectral Radiance at Sensor's Aperture (Wm^{-2} sr$^{-1}\mu$m^{-1})

$LMIN_\lambda$ = Minimum of Spectral Radiance (Wm^{-2} sr$^{-1}\mu$m^{-1})

$LMAX_\lambda$ = High of Spectral Radiance (Wm^{-2} sr$^{-1}\mu$m^{-1})

$QCAL$ = Quantized Calibrated Pixel Value in DN

$QCALMIN$ = Minimum Quantized Calibrated Pixel Value

$QCALMAX$ = Maximum Quantized Calibrated Pixel Value

2) Substitute the analyzed data from Equation 1 into the model as shown in Equation 2.

$$\rho_\lambda = \frac{\pi \text{ x } L_\lambda \text{ x } d^2}{E_{SUN_\lambda} \text{ x} \cos\theta_s}$$

(2)

Where:

ρ_λ = Unitless planetary reflectance

π = 3.14

L_λ = Spectral Radiance at Sensor's Aperture ($Wm^{-2} sr^{-1} \mu m^{-1}$)

d = Earth-Sun distance in astronomical units

E_{SUN_λ} = Mean solar exoatmospheric irradiances

θ_s = Solar zenith angle

3.1.2 The results of the data analyzed in 3.1.1 were used to determine the energy reflectance of the vegetation index with MSAVI2 (Fig. 3) by determining the pixels of the data from the Landsat 8 OLI satellite above 0-1 to be vegetation and when equal to or below 0 not to be vegetation. Then, the FVC (Fig. 4) could find the value as determined by the pixel value to classify the vegetation species to be 0-100. The researcher created the MSAVI2 and FVC in the Spatial Modeler Language in the ERDAS program (Fig. 4) according to Equation 3 and Equation 4 (Teerawong and Pornchai, 2014; Teerawong and Yannawut, 2016).

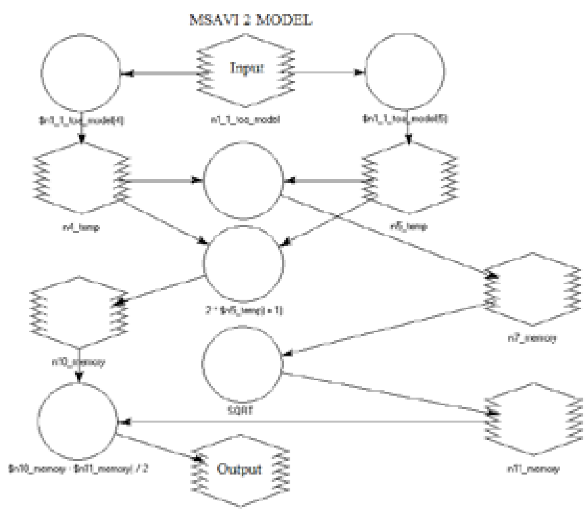


Figure 3. MSAVI2 model using Spatial Modeler Language.

$$MSAVI2 = \frac{(2NIR+1) - \sqrt{(2NIR+1)^2 - 8(NIR - Red)}}{2} \quad (3)$$

Where:

$MSAVI2$ = Vegetation Index

NIR = Near Infrared Band Reflectance

Red = Red Band Reflectance

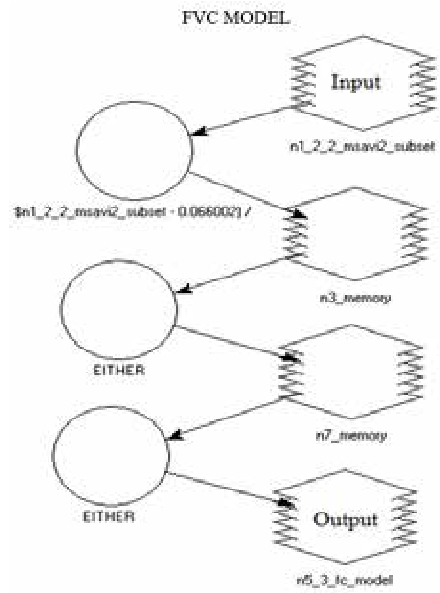


Figure 4. FVC model using Spatial Modeler Language.

$$FC = \frac{(VI - VI_{open})}{\left(VI_{canopy} - VI_{open}\right)} \times 100 \quad (4)$$

Where:

FC = Tree Canopy Fractional Cover

VI = Vegetation Index

VI_{open} = Vegetation Index of Open Areas

VI_{canopy} = Vegetation Index of Tree Canopy

3.2 Field data survey to determine carbon biomass in plots in study area

3.2.1 Area selection and making permanent plots

1) The areas were selected using stratified methods within the orchards belong to 14 agriculturists to be the pilot areas in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand. Then, stratified random methods were conducted to get the groups of areas. Then, the randomly selected areas were made into permanent plots according to the approximate species, groups of species of vegetation and growing time or properties.

2) This study made 12 permanent plots of 20×20 m in the orchards to be sampled in a total study area of 70.20 rai. Then, the data of types and amount of big vegetation with a Diameter at Breast Height (DBH) at 4.5 cm and above was measured using a clinometer. The data obtained from all the surveys in this study was recorded to be used in further analysis.

3.2.2 Assessment of carbon biomass

The researchers used the results of the data obtained from the field data survey to calculate the biomass of the vegetation in the permanent plots using the Allometric Equation (Equation 5 and Table 1) for the vegetation that is appropriate for Thailand (Ogawa *et al.,* 1965; Usa *et al.,* 2014), so it can be used in the assessment of carbon biomass in the study area.

$$\mathrm{ABG} = Ws + Wb + Wl \tag{5}$$

Where:
Ws = Weight of the stem (kg)
Wb = Weight of branches (kg)
Wl = Weight of leaves (kg)
Wt = Above ground total biomass

Table 1. Allometric equation.

Forest Type	Equation
- Agricultural plants (Ogawa *et al.*, 1965)	$Ws = 0.396\left(D^2H\right)^{0.933}$ $W_B = 0.00349\left(D^2H\right)^{1.030}$ $W_L = \left(28/\left(WS+WB+0.025\right)\right)^{-1}$ $Wt = Ws + Wb + Wl$
- Mango (Usa *et al.*, 2014)	$Ws = 1.525\left(D^2H\right)^{0.33604}$ $Wb = 0.954\left(D^2H\right)^{0.50995}$ $Wl = 0.913\left(D^2H\right)^{0.22404}$ $Wt = Ws + Wb + Wl$

The final step was to calculate the carbon content of vegetation in the permanent plots as presented in Equations 6, 7 and 8.

$$C\ sample = \sum \frac{C_{tree}}{sample} Area \tag{6}$$

$$\Delta C = C\ sample \times ForestArea \tag{7}$$

$$\Delta CO_{2e} = \Delta C \times \frac{44}{12} \tag{8}$$

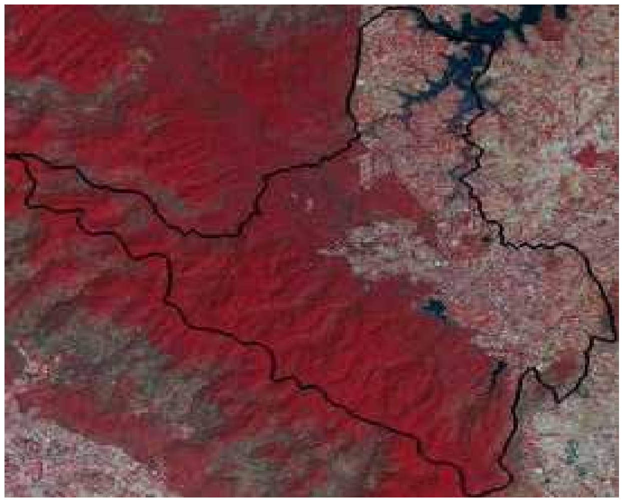
3.3 Analysis of biomass per area

This study brought FVC obtained from the correlation equation and presented in the model to develop the biomass per area. Then, the results of the biomass per area from the field data and the data analyzed from Landsat 8 OLI were brought to test the statistical accuracy.

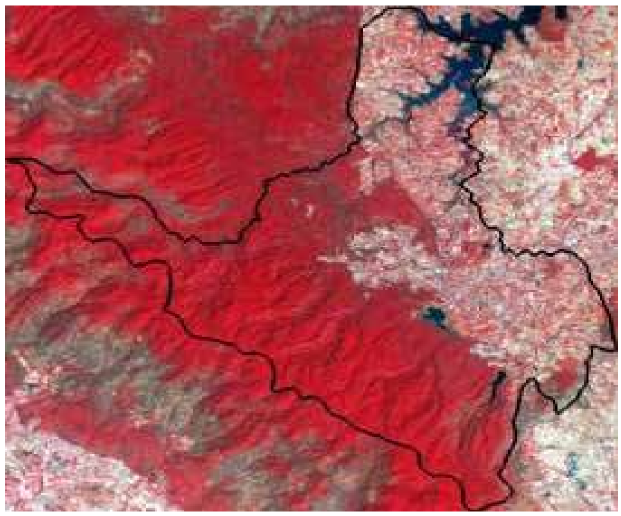
4. Result

4.1 Analysis results of data from Landsat 8 OLI satellite

4.1.1 The results of adjusting the ToA of the electromagnetic waves caused by the scattering phenomenon by air molecules, clouds and dust as well as absorption by ozone, gas, dust and clouds are presented in Fig. 5.
4.1.2 The result of the vegetation index with the MSAVI2 model and the result of the value adjustment by finding the FVC are shown with data from the Landsat 8 OLI satellite between 0-100, as presented in Fig. 6.



(a)



(b)

Figure 5. (a) Before ToA and (b) after ToA.

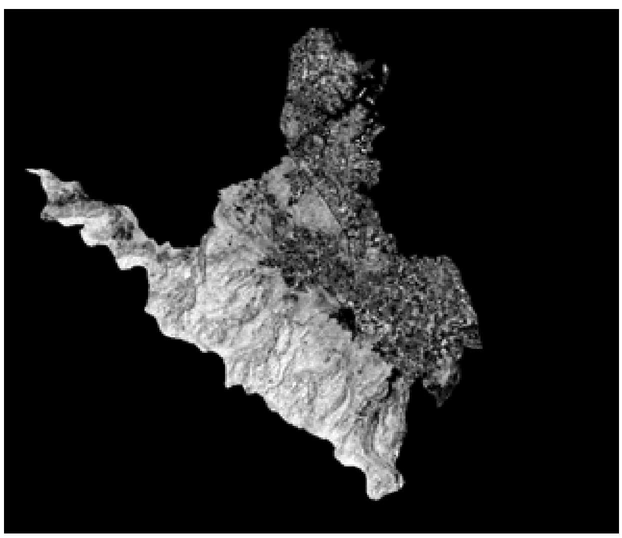


Figure 6. Result of FVC.

4.2 Results of fileld survey

All the 22 permanent plots in the study area had measurements of the heights of the vegetation at a size of greater than 4.5 cm DBH at a height of 130 cm. Then, the names and height of the vegetation were recorded to assess the above ground biomass. The correlation between the value of the FVC and the carbon content is shown in the model represented in Fig. 7 and obtained the correlation equation $y = 0.0874e^{0.0647x}$ with a coefficient of determination $R^2 = 0.9123$. A coefficient of determination (R^2) close to 1 indicates a high relationship. The graph of the correlation could be found if the value of FVC increases, and the carbon content will rise accordingly.

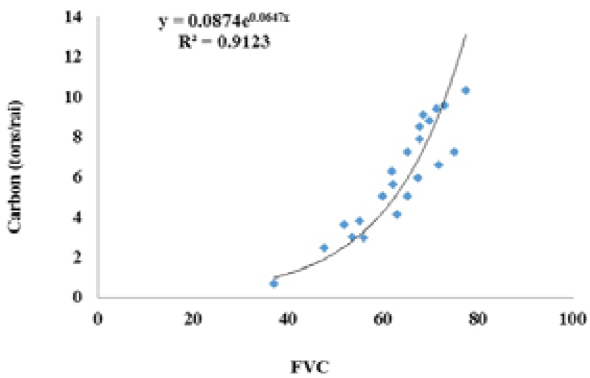


Figure 7. Correlation with FVC.

4.3 Analysis result of biomass perarea

In this study, the biomass in the area (tCO_2/rai) was estimated by using the FVC obtained from the equation to present the model developed. The result obtained from the estimate of tCO_2/rai from the data from the Landsat 8 OLI satellite (Fig. 8) showed that bright colors would give a high content of biomass, while on the other side, the dark colors will have less biomass content. Then, the results were brought to estimate the tco_2/pixel (Fig. 9). It could be found that the bright colors would give a high content of biomass, while on the other side, dark colors would give a lower content of biomass. As a result, the estimation of the carbon content in the orchards in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province has been conducted.

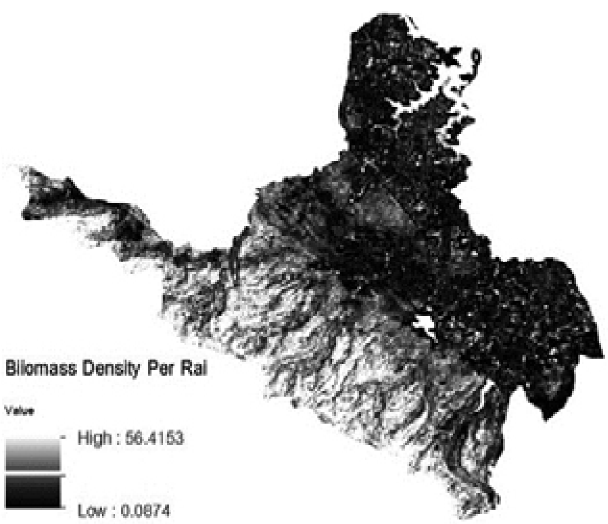


Figure 8. The tco_2/rai.

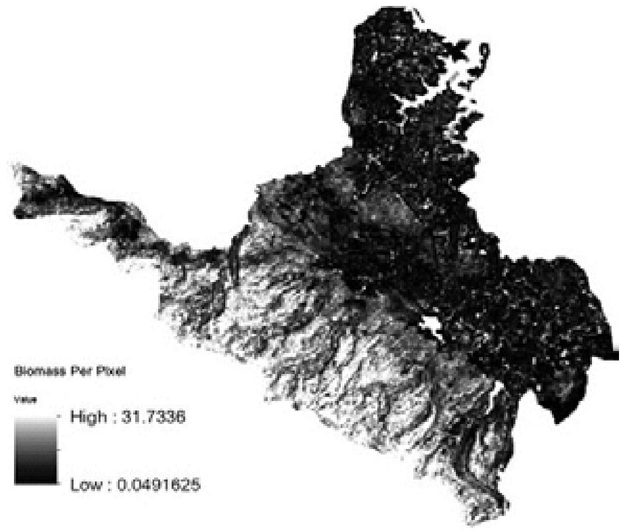


Figure 9. The tco_2/pixel.

5. Conclusions

This research aimed to assess the above ground carbon biomass in orchards in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand by applying remote sensing. The research determined the correlation between the above ground carbon biomass from the field survey with MSAVI2 and FVC to analyze the correlation in the form of a linear regression analysis to determine the correlation equation and coefficient of determination (R^2). As a result, the findings indicated the correlation equation $y = 0.0874e^{0.0647x}$ with a coefficient of determination of $R^2 = 0.9123$. Therefore, the calculation of the above ground carbon biomass indicated 277.430 tCO_2/rai in a total area of 70.10 rai. Moreover, the research also found that the results were in line with other research studies, namely the studies of Phutchard et al., 2014; Teerawong and Yannawut, 2016; Yannawut and Teerawong, 2016; Tianyu et al., 2016; and Yannawut and Teerawong, 2017, etc. In addition, a test of the statistical significance of the above ground carbon biomass of the data from the field survey was conducted. The analysis of the data from the Landsat 8 OLI satellite with a Pair Sample T-test showed statistical significance with a confidence level of 95%. When considering the results of the study, it is beneficial to apply the estimation of the above ground carbon biomass in the orchards in Sang Kho Sub-District, Phu Phan District, Sakon Nakhon Province in the northeast of Thailand with no requirement for surveying the entire field. This finding can reduce the costs and research timing as well as give up-to-date information to meet the demand for urgent information.

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