An Evaluation of EO-1 Hyperion Data for Estimating Age of Rubber Plantation

Siwa Kaewplang[1,*] and Neti Srihanu[2]
[1,*] Faculty of Engineering, Mahasarakham University, Tumbol Khamriang, Ampher Kantarawichai, Mahasarakham, 44150 Thailand
[2] Department of Electronic Engineering, Northeastern University, Ampher Muang, Khon Kaen 40000, Thailand

siwakaewplang@yahoo.com* and neti.sri@neu.ac.th

Abstract. *In this paper, the ability to estimate the rubber plantation's age of hyperspectral remote sensing with Hyperion satellite is proposed. Age of rubber plantation was estimated by four popular vegetation indices (i.e., Simple Ratio index, Modified Simple Ratio Index, Normalized Difference Vegetation Index, and Modified Soil Adjusted Vegetation Index). Despite additional fine-tuning needing to be done on the statistical model parameters, the proposed models reveal significantly high statistical correlations. The best-fitted model was determined to be the* $MSAVI_{705}$ *model (*R^2 *= 0.624), which possesses the lowest RMSE values (=2.625). It is anticipated that the methodology presented in this study can be used as a guideline for estimating the rubber plantation's age in other areas.*

Keywords:

Hyperspectral remote sensing, age of rubber plantation, vegetation indices

1. Introduction

Rubber plantation plays an important role in natural rubber and is a most important for contribution the Timber supply [1-3]. Rubber plantation stand age is very important variable in determining the distribution of carbon pools and fluxes in Rubber tree ecosystems [4-6]. Data of stand age parameters will help researchers to studies on the rubber plantation such as energy and mass exchanges and carbon cycle as well as for rubber plantation management [4-7].

Inventory information in the field is generally a time-consuming task due to the large spatial of the field study area. Such efforts have been improved by using remote sensing sensors.

A previous studies claim the advantage of remote sensing data for the rubber stand age with regression and classification [2, 8-10]. The previous study [1] showed near-infrared and middle-infrared bands of TM data could provide use for modeling the rubber stand age in Malaysia. Furthermore, [11] found that linear regression of NDVI, ETM4/ETM3 and the brightness component of the tasseled cap transformation [12] can use to evaluate of rubber stand age.

The application of spaceborne hyperspectral remote sensing technology has been use for tested with plant and forest stands [17-18, 20-21]. Vegetation indices are often used as independent variables in developing for stand age prediction models [1, 5-7, 9, 11]. However, the studies on the application of hyperspectral data for estimating rubber's age have not yet been carried out and there remains unclear about the underlying principle of mechanism.

Consequently, this study is a pilot project to investigate hyperspectral data that could be used for estimating age in regard to rubber plantations. The EO-1 Hyperion image of the rubber plantations in Pak Chom District, Loei Province, Thailand was chosen for the investigation. The aim of this study to be the first study to report simple linear correlations between popular vegetation indices derived from the hyperspectral data and age of rubber plantation values collected from the field. The outcome of the correlation models are to be compared independent variable testing data with the root mean square errors of the models. The results of this study are subjected to be used for the further fine-tuning of the statistical parameters for researcher in the near future.

2. Materials and Methods

2.1 Study Area

The study area (Fig. 1) is located in Pak Chom District, Loei Province, Thailand (18°01'12.70"N, 101°53'15.53"E). Study areas are in the hills and mountains. The temperatures in the summer season (April-May) above 40 degrees Celsius, and below 0 degrees in the evenings in the cold season (December-January). The most of the study area (approximately 490 km^2) includes degraded forest land, paddy fields, orchards and rubber plantations. The total land area of the rubber plantations in this project is approximately 55 km^2.

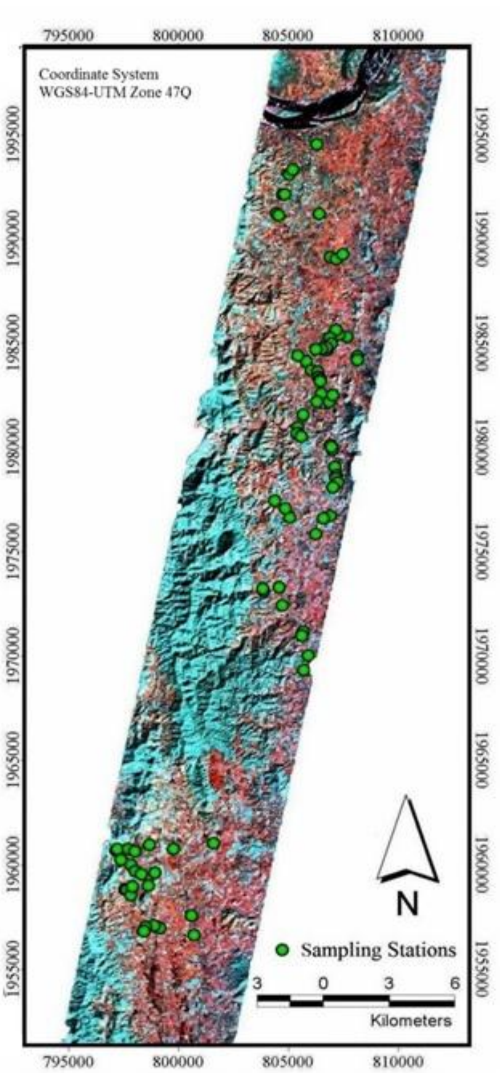


Fig. 1: The location of the rubber plantation in Pak Chom District, Loei Province, Thailand shown against an enlargedsatellite image of the study (right) captured by the EO-1 Hyperion sensor on 20 December 2009 and the positions of the 150 sampling stations throughout the study area.

2.2 Image acquisition and processing

EO-1 Hyperion Satellite image from path 129 row 48 was created on 20 December 2009 on the lower side of the Mekong River (the dark blue line at the top of Fig. 1). The Hyperion Satellite image has 242 wavebands ranging from 400 nm to 2500 nm with 10 nm spectral resolution and 30 m spatial resolution [19]. The image was provided as Hyperion level 1R data that was radiometrically corrected and calibrated into 196 wavebands. Only 155 stable bands [20] were selected for this study. EO-1 Hyperion Satellite image was atmospherically corrected and transformed to reflectance using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm. It provides well-adjusted input for the atmospheric correction through derivation of atmospheric properties such as surface albedo, surface altitude, water vapor column and aerosol from the image [21]. Tropical atmospheric input parameters are chosen in this study. The ground control points were recorded by hand-held GPS receivers (Garmin 60CSX), and the differential global positioning system (DGPS) technique [21] was used for post-processing the GPS data. The final positional accuracy of the image after resampling is less than the size of one pixel (i.e., < 0.5 pixels). The selected interpolation method is a nearest neighbor algorithm.

2.3 Field Data Collection

The field data was collected during the winter between 6 and 18 December 2015. A stratified random sampling method was used for locating the sample plots. The species names, rubber plantation stand age, and DGPS coordinates in the UTM system were recorded from each 15x15 m2 sampling station. In this stud. Each sampling station was of an age between 5 and 25 years. There were 150 sampling stations in total (see Fig. 1).

2.4 Data Modeling and Regression Analyses

This study were chosen four popular vegetation indices including Simple Ratio index (SR_{705}), Normalized Difference Vegetation Index ($NDVI_{705}$), Modified Simple Ratio Index (MSR_{705}) and Modified Soil-Adjusted Vegetation Index ($MSAVI_{705}$) for constructing rubber plantation Age models (Table 1). Random a half of number the rubber plantation plots were selected for developing the linear regression models between the four vegetation indices and the age. The remaining field rubber plantation data were used for calculating the root mean square errors of the regression models (RMSE). This process was carried out repeatedly 30 times under a data rotation scheme.

Table 1: Four selected vegetation indices

Vegetation Index	
$SR_{705} = R_{750} / R_{705}$	*[23]*
$NDVI_{705} = (R_{750} - R_{705}) / (R_{750} + R_{705})$	*[24]*
$MSR_{705} = (R_{750}/R_{705} - 1) / \sqrt{(\frac{R_{750}}{R_{705}} + 1)}$	*[25]*
$MSAVI_{705} = 0.5[2R_{705} + 1 - \sqrt{(2R_{750}+1)^2 - 8(R_{750} - R_{705})}]$	*[26]*

3. Results

The average field rubber plantation stand age value measured in the field was 15.34 years (N = 150, SD =

2.356). The adjusted R^2 values of the linear regression models are showed in Table 2. The maximum R2 value was the $MSAVI_{705}$ model (R^2=0.624 and RMSE=2.625). The plots of the age map estimated using $MSAVI_{705}$ (objects outside the study areas are masked out) are showed in Fig. 2 and Scatter plots of observed age versus predicted age for validation data are shown in Fig. 3. This study used A one-way ANOVA test was also used for testing between the regression models with four popular different vegetation indices. The result of the four models are statistically not different (i.e., p-value<0.01, N = 150).

In addition, the mean spectral signature and the standard deviation curves of 150 sampling stations are plotted in Fig. 4. The two red-edge positions (705 nm and 750 nm) are circled in the plot. The mean reflectance and its standard deviation values of the two locations are 12 ± 0.08 % and 35 ± 0.06 %, respectively.

Table 2: The adjusted R^2 values and the RMSE values of four linear regression models indicating P <0.01

VIs	R^2	RMSE (year)
SR_{705}	0.581	2.725
$NDVI_{705}$	0.524	3.115
MSR_{705}	0.519	3.228
$MSAVI_{705}$	0.624	2.625

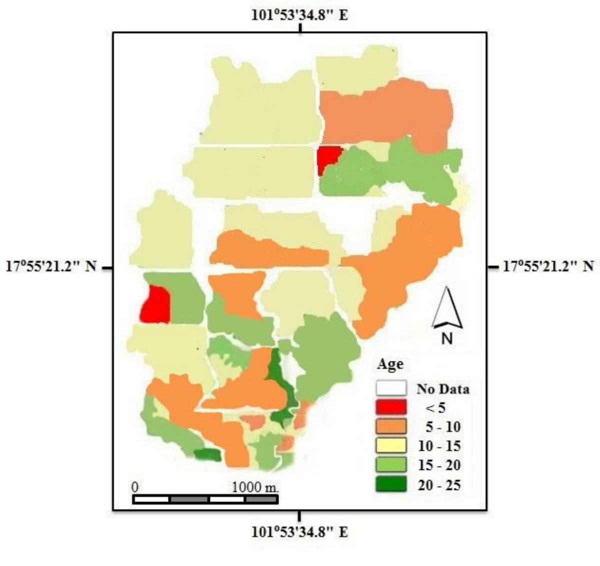
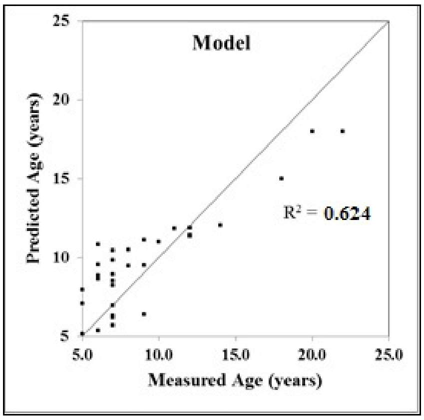
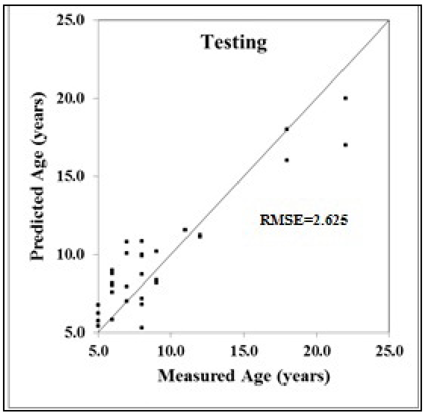


Fig. 2: Age map estimated using $MSAVI_{705}$ (objects outside the study areas are masked out)



(a)



(b)

Fig. 3: Scatter plots of observed age versus predicted age for validation data: (a) for the investigated model and (b) for the testing results

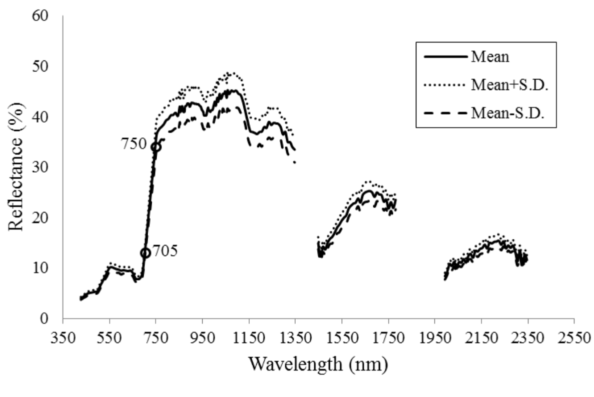


Fig. 4: The mean Hyperion spectra (the solid line) and the standard deviation curves (the two dashed lines) of rubber plantations calculated from 150 sampling stations.

4. Discussion and Conclusion

The result of this study from the recorded hyperspectral data can be used for estimating age of rubber plantations (please see Table 2 and Fig. 3). Regression model between age of field rubber plantations and the model derived from SR_{705}, $NDVI_{705}$, MSR_{705} and $MSAVI_{705}$ yielding R^2 = 0.581, 0.524, 0.519, and 0.624 respectively. The $MSAVI_{705}$ model give the lowest error rate when compared against the independent field data (RMSE= 2.625). While the four Vegetation indices are not statistically different (one-way ANOVA test p-value<0.01, N=150).

Strong statistical correlations of the rubber plantation age models agree with early studies with different types of plants [2, 8-10, 27-28]. Although none of the previous published paper has directly examined statistical correlations between rubber plantation's age and hyperspectral remote sensing derived vegetation indices

The aim of this study to report simple linear correlations between popular vegetation indices derived from the hyperspectral data and age of rubber plantation values collected from the field. This report is not to provide a thorough analysis. The results could be improved by using enhanced math models [20-21] and applying band selection/transformation algorithm [16-17].

In summary, this study is the first time that shown the efficacy of hyperspectral data for estimating age of rubber plantations. The proposed statistical models show statistical correlations (i.e., the best R^2 = 0.624) with low RMSE values (i.e., the lowest RMSE = 2.625). Consequently, we expect the methodology in this study can useful guideline for estimating age of rubber plantations.

Acknowledgements

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Biography

Siwa Kaewplang was born in Thailand. He received his Phd. from Chulalongkorn University in 2014. He is a lecturers of civil engineering at Mahasarakham University, Thailand. His research interests include Digital Photogrammetry; Climate Change; Environmental management; Environmental modeling; Geographic Information System; Geostatistics; GIS; Global warming; Remote sensing; Hyperspectral remote sensing; Image classification; Image processing; Information technology; Precision agriculture; Natural resource management; Tropical forest; Tropical vegetation; Water resource management

Neti Srihanu received the B.Eng. and M.Eng. degrees in electrical and electronic system engineering from Nagaoka University of Technology, Japan, in 1994 and 1996, respectively. He is a lecturers of electronic engineering at North Eastern University, Thailand. His current research interests include neural networks, pattern recognition, and image processing, Remote sensing; Hyperspectral remote sensing; Image classification; Image processing; Information technology; Precision agriculture.