An Evaluation of EO-1 Hyperion Data for Estimating Leaf Area Index of Rubber Plantations

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Abstract
The leaf area index (LAI) is one of the most important parameters for quantifying the physical conditions of rubber plantations. Modern remote sensing tools such as hyperspectral sensors can be effectively used for estimating the LAI of crops. Unfortunately, only few examples are found in the literature on the application of hyperspectral data for estimating rubber LAI and the understanding of the underlying mechanisms remain unclear. Thus, the aim of this study is to explore one step beyond the existing research. The current study is the first time that the capability of hyperspectral data for estimating the LAI of rubber plantations has been investigated. Four popular vegetation indices (i.e., Simple Ratio index (SR_{705}), Modified Simple Ratio Index (MSR_{705}), Normalized Difference Vegetation Index ($NDVI_{705}$), and Modified Soil Adjusted Vegetation Index ($MSAVI_{705}$)) and the EO-1 Hyperion image of the rubber plantations in Pak Chom District, Loei Province, Thailand were the chosen for the investigation. Despite additional fine-tuning need to be done on the statistical model parameters, the proposed models reveal significant high statistical correlations. The best-fitted model was determined to be the $MSAVI_{705}$ model (R^2 = 0.775), which possesses the lowest RMSE values (=0.160). It is anticipated that the methodology presented in this study can be used as a guideline for estimating the LAI of rubber plantations in other areas.

1. Introduction

The leaf Area Index (LAI) plays an important role in quantifying the energy and mass exchange of terrestrial ecosystems. It is evident that the field LAI has been used for modeling photosynthesis processes (Duchemin et al.,2006), evapotranspiration rates (Chen et al.,2006), carbon dioxide productions (Chen et al., 2007), water and energy exchanges (Baldocchi and Harley, 1995, Leuning et al., 1995 and Chase et al., 1996), climate changes (Borchers et al., 1995), rainfall interceptions, canopy density dynamics (Granier et al., 2000 and Thomas and Winner, 2000) and forest stand yields (Gholz, 1982, Waring, 1983, Bolstad and Gower, 1990 and Bolstad et al., 2001). On the rubber plantations, field-measured LAI is one of the most important factors used for calculating biomass growth (Boithias et al., 2012) and latex production (Rodrigo et al., 2005, Righi and Bernardes, 2008 and Boithias et al., 2012). Measuring LAI in the field is generally a time-consuming task due to the very large spatial extent of the study area (Jonckheere et al., 2004). Such efforts have been considerably improved by using several kinds of remote sensing sensors. The evidence of this can be found in the following literature including the use of multispectral sensors (Chen and Cihlar, 1996, Turner et al., 1999, Eklundh et al., 2001, Cohen et al., 2003, Soudani et al., 2006, Ganguly et al., 2008a, Ganguly et al., 2008b and Tong and He, 2013), high spatial resolution sensors (Colombo et al., 2003, Chen et al., 2004, Soudani et al., 2006, Laongmanee et al., 2013 and Tong and He, 2013) and light detection and ranging (LiDAR) sensors(Chen et al., 2004, Riaño et al., 2004, Morsdorf et al., 2006 and Zhao and Popescu,2009). The application of spaceborne hyperspectral remote sensing technology for LAI estimation is also popular and has been exhaustively tested with forest stands (Gong et al., 2003, Pu et al., 2003, Pu and Gong, 2004, Pu et al., 2005, Le Maire et al., 2008, Pu et al., 2008 and Heiskanen et al., 2013). This application is now being extended to the estimation of crop LAI, but few examples are found in the literature (Rao et al., 2006, Wu et al., 2010, Thenkabail et al., 2013 and Vyas et al., 2013). These studies examined the relationship between hyperspectral indices and the crop LAI for different kinds of crops (e.g., flax, chestnuts, corn, potato, cotton, rice and sugarcane etc.) (Rao et al., 2006, Wu et al., 2010 and Vyas et al., 2013).

However, it is surprising that much studies on the application of hyperspectral data for estimating rubber LAI have not yet been carried out and there remains poor understanding of the underlying mechanism. Consequently, this study is a pioneering effort to investigate whether hyperspectral data can be used for estimating LAI 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 objective of this work is not intended to be an exhaustive statistical analysis but rather to be the first study to report simple linear correlations between popular vegetation indices derived from the hyperspectral data and the LAI values collected in the field. The results of the correlation models are to be compared against independent testing data so as to reveal the root mean square errors of the models. The outcome of this study is expected to be of use as the basis for further fine-tuning of the statistical parameters in the near future.

2. Materials and Methods

2.1 Study Area

The study site (Figure 1) is located within Pak Chom District, Loei Province, Thailand (18°01′12.70″N, 101°53′15.53″E). The study area is covered with numerous high hills and mountains, and has a cool, foggy climate. The temperatures in the hot season (April–May) can rise above 40 degrees Celsius, and it is the only province in Thailand which regularly drops below 0 degrees in the evenings in the cold season (December–January). Most of the land in the study area (approximately 490 km^2) comprises 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. Two rubber clones were reported to be found in study area including RRIM600 and RRIT251. RRIM600 is the dominant species and covers 90% of the rubber plantation areas.

2.2 Image Acquisition and Processing

EO-1 Hyperion image from path 129 row 48 was captured on 20 December 2009 covering the lower side of the Mekong River (the dark blue line at the top of Figure 1). The Hyperion image has 242 wavebands ranging from 400 nm to 2500 nm with 10 nm spectral resolution and 30 m spatial resolution (Beck, 2003). The image was provided as Hyperion level 1R data that was radiometrically corrected and calibrated into 196 wavebands. Only 155 stable bands (Datt et al., 2003) were selected for this study. A de-streaking algorithm was also required to minimize the effect of systematic noise. Then, the image was atmospherically corrected and transformed to reflectance using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm under the environment of commercial software (ENVI version 4.7). 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 (Thenkabail et al., 2013). Tropical atmospheric input parameters are chosen in this study (i.e., Aerosol Model = Rural, Initial Visibility = 10 km, Water Retrieval = Yes, Aerosol Retrieval = None, and Water Absorption Feature = 940 nm).The locations of easily recognizable landscape features (e.g., canals, roads and houses) were recorded and used for rectifying the image. The ground control points were recorded by hand-held GPS receivers (Garmin 60CSX), and the differential global positioning system (DGPS) technique (Kaplan and Hegarty, 2006) 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 winterbetween10and 15 January 2010. A stratified random sampling method was used for locating the sample plots. The species names, crown cover areas, and DGPS coordinates in the UTM system were recorded from each 15x15 m^2 sampling station. In this study, the field-measured LAI was based on crown cover areas per unit ground area. Each sampling station was of an age between 5 and 25 years. There were 80 sampling stations in total (see Figure 1).

2.4 Data Modeling and Regression Analyses

Following the regression-based methodology (Wu et al., 2010), 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($MSAVI_{705}$)were chosen for constructing the LAI models (Table 1). Half of the rubber plots were randomly selected for developing the linear regression models between the vegetation indices and the LAI. The remaining field data were then 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.

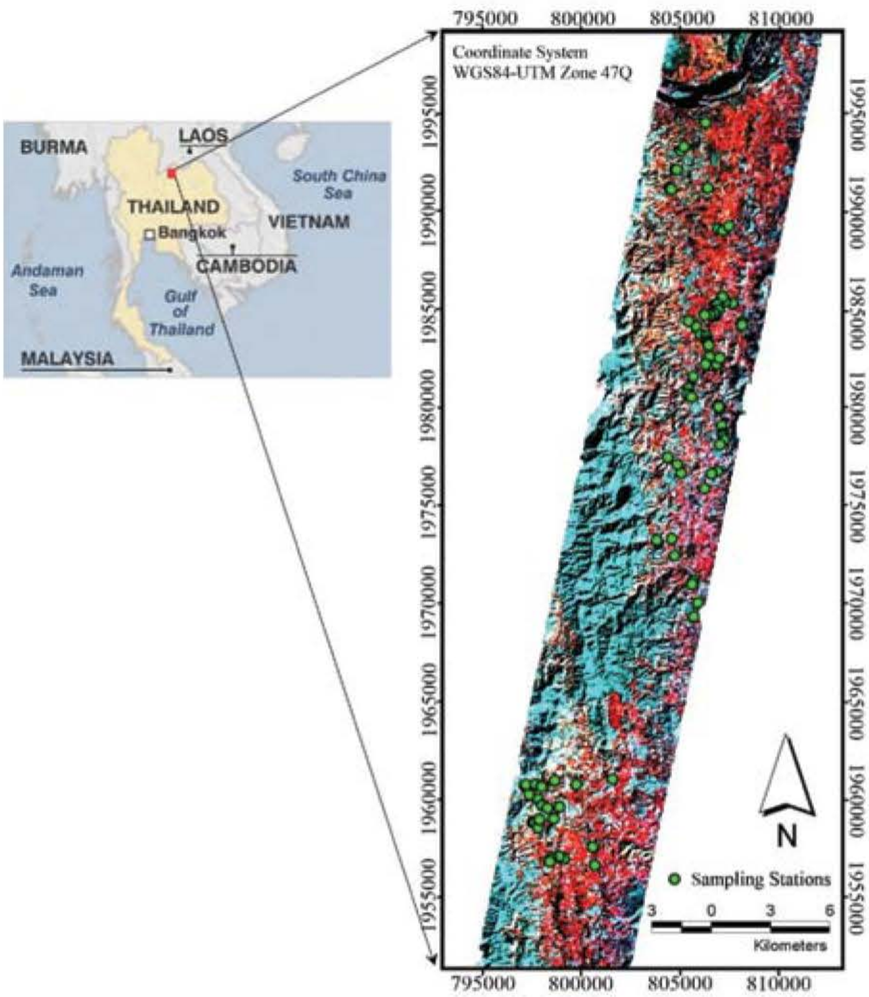


Figure 1: The location of the rubber plantation in Pak Chom District, Loei Province, Thailand shown against an enlarged satellite image of the study (right) captured by the EO-1 Hyperion sensor on 20 December 2009 and the positions of the 80 sampling stations throughout the study area

Table 1: Four selected vegetation indices

Vegetation Index	Author
$SR_{705} = R_{750}/R_{705}$	Gitelson and Merzlyak, 1996
$NDVI_{705} = (R_{750} - R_{705})/(R_{750} + R_{705})$	Rouse et al., 1974
$MSR_{705} = (R_{750}/R_{705} - 1)/\sqrt{(\frac{R_{750}}{R_{705}} + 1)}$	Sims and Gamon, 2002
$MSAVI_{705} = 0.5\left[2R_{750} + 1 - \sqrt{(2R_{750} + 1)^2 - 8(R_{750} - R_{705})}\right]$	Huete, 1988

3. Results

The average field LAI value measured in the field was 0.949 m^2/m^2 (N = 80, SD = 0.186). The adjusted R^2 values of the linear regression models are reported in Table 2 and the highest value is underlined. The maximum R^2 value belonged to the SR_{705} model (R^2=0.820). However, the lowest RMSE value belonged to the $MSAVI_{705}$ model (RMSE=0.160). The plots of the all models are illustrated in Figure 2. For brevity, only the final LAI map of the SR_{705} model and the $MSAVI_{705}$ model are shown in Figure 3. A one-way ANOVA test was also used for testing the similarity between the regression models when four different vegetation indices were used. It turned out that the four models are statistically not different (i.e., p-value<0.01, N = 80).

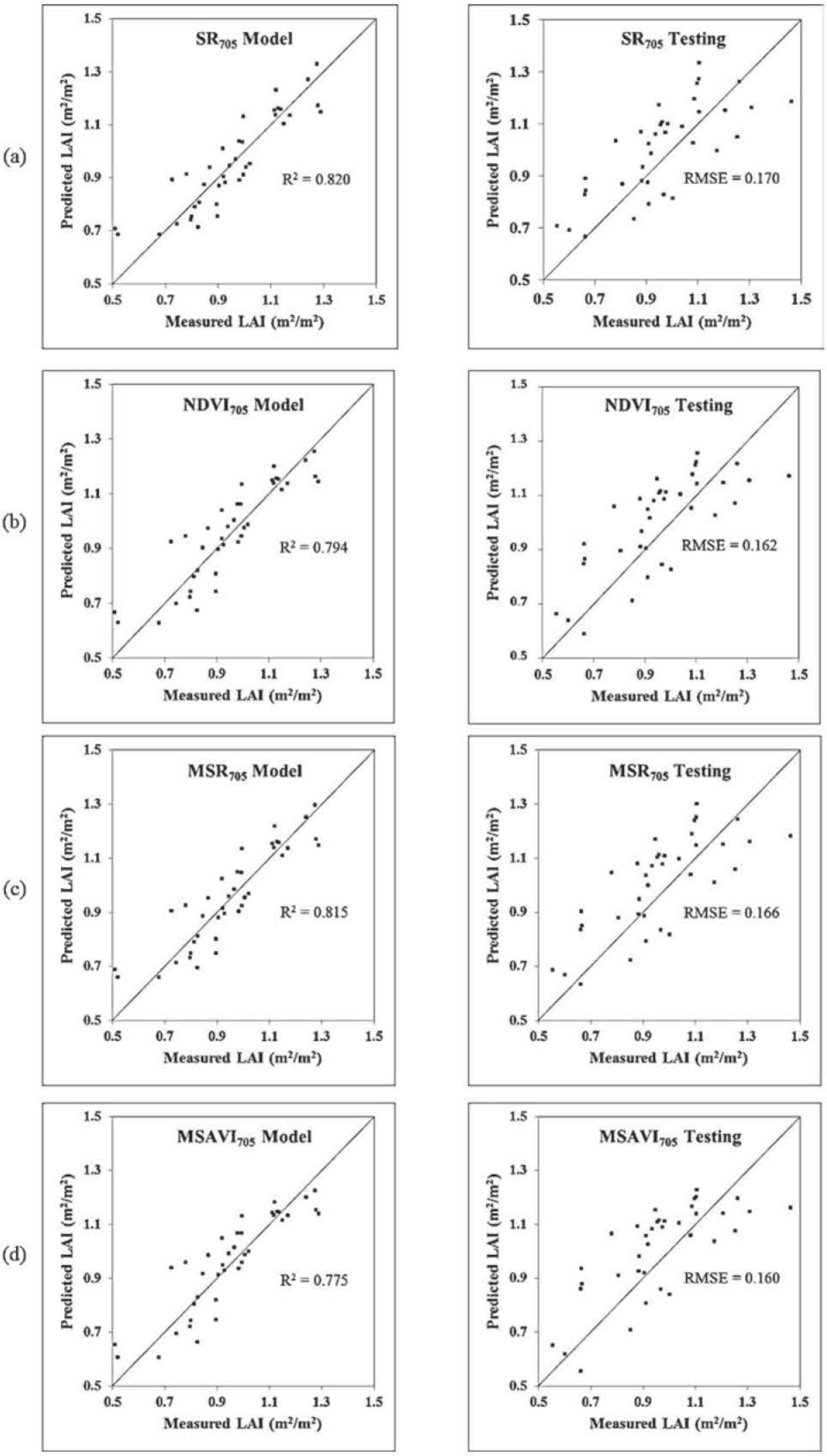
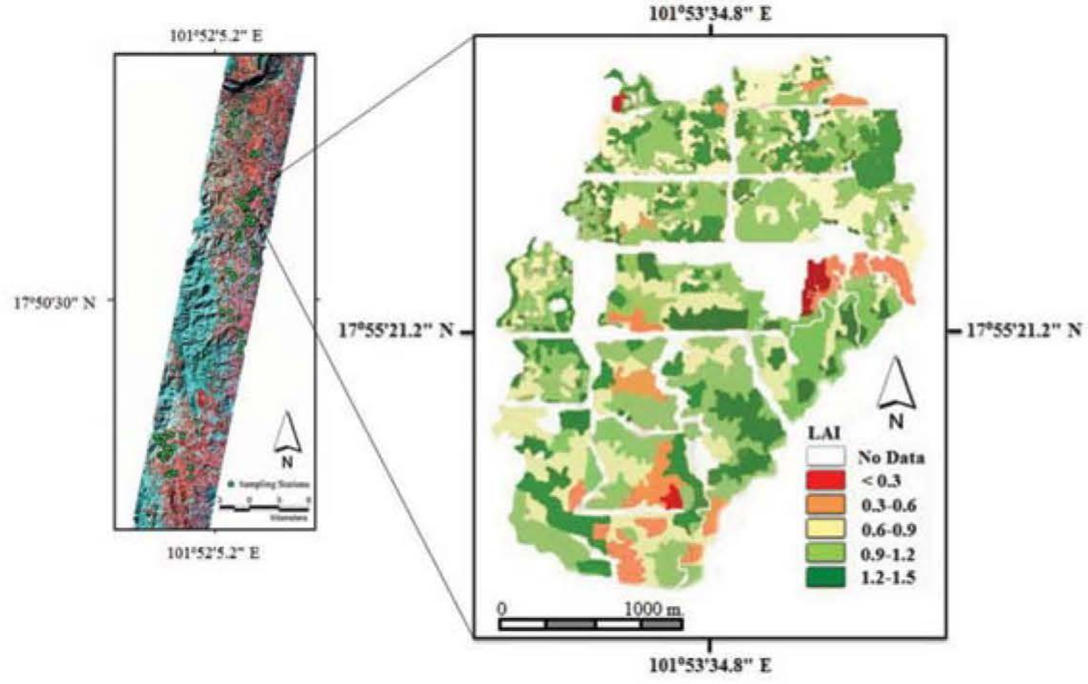
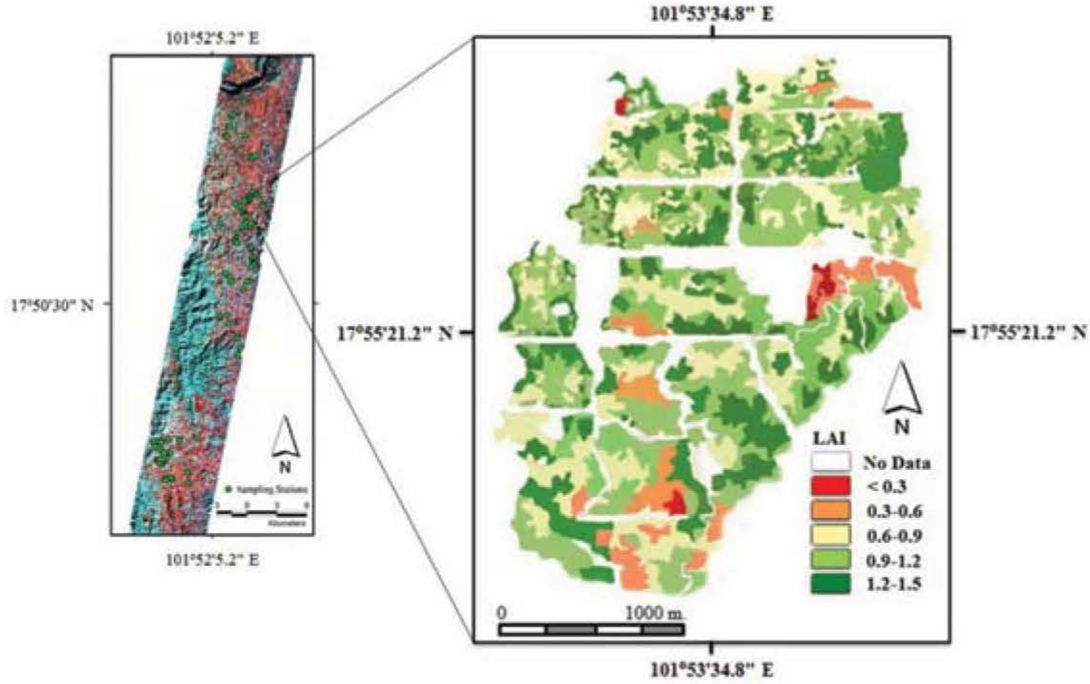


Figure 2: The scattering plots with the RMSE values of all models: (a) SR_{705}, (b) $NDVI_{705}$, (c) MSR_{705} and (d) $MSAVI_{705}$



(a)



(b)

Figure 3: LAI map estimated using (a) SR_{705} and (b) $MSAVI_{705}$ (objects outside the study areas are masked out)

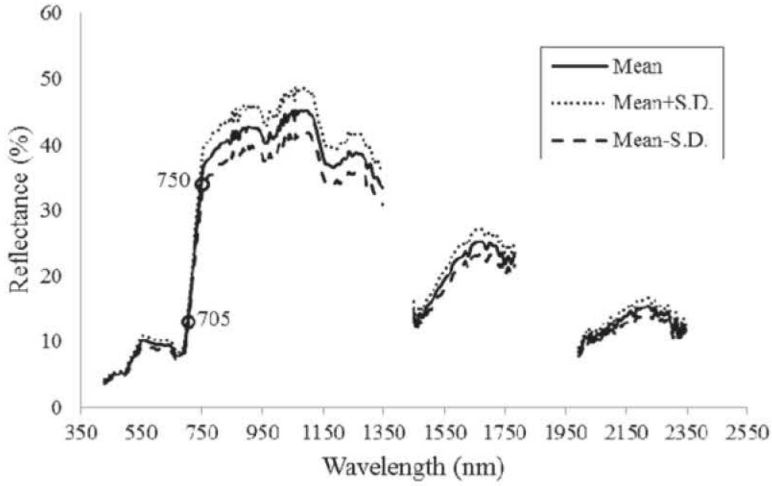


Figure 4: The mean Hyperion spectra (the solid line) and the standard deviation curves (the two dashed lines) of rubber plantations calculated from 80 sampling stations

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

VIs	**R^2**	**RMSE**
SR_{705}	0.820	0.170
$NDVI_{705}$	0.794	0.162
MSR_{705}	0.815	0.166
$MSAVI_{705}$	0.775	0.160

Additionally, the mean spectral signature and the standard deviation curves of 80 sampling stations are plotted in Figure 4 for the purpose of visualization. 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 13 ± 0.07 % and 34 ± 0.07 %, respectively.

4. Discussion and Conclusion

The outcome of this study confirms that hyperspectral data can be used for estimating the LAI of rubber plantations as a first step in conducting more in-depth studies (please see Table 2 and Figure 2). The relationship is shown between the field LAI and the model derived from SR_{705}, $NDVI_{705}$, MSR_{705} and $MSAVI_{705}$ yielding R^2 = 0.820, 0.794, 0.815, and 0.775 respectively. The $MSAVI_{705}$ model produced the lowest error rate when compared against the independent field data (RMSE= 0.160). Although the four indices are not statistically different (one-way ANOVA test p-value<0.01, N=80), the slight superiority of the $MSAVI_{705}$ model may be explained by the low foliar density of the study area (i.e, the LAI values < 2.5) as the MSAVI index performs well under this condition (Broge and Leblanc, 2001). Strong statistical correlations of the proposed four rubber LAI models agree with prior studies that were conducted with different types of plants (Rao et al., 2006, Wu et al., 2010 and Vyas et al., 2013). Although none of the published works has directly examined the statistical correlations between rubber LAI and remote sensing derived vegetation indices, the closest study (Wu et al., 2010) reported the relationships between hyperspectral vegetation indices and eight different kinds of crops (e.g., flax, chestnut, corn, bamboo, potato, pine, saccharose and tea). In comparison, the selected spectral locations that had high statistical correlations with this related work (the best R^2 = 0.67 and RMSE = 0.55) are the same as spectral locations used in the proposed models of this study, but their best-fitted vegetation index was $MCARI2_{705}$. Next, the study on teak and bamboo (Vyas et al., 2013) are also noted. The authors used the EO-1 Hyperion image to calculate the LAI models using the partial least-square regression techniques (PLS).The best results belonged to their tailor-made normalized difference model (R^2 = 0.87, RMSE = 0.425). In addition, it was also found that the narrowband NDVI derived from EO-1 Hyperion had high statistical connections for the case of LAI estimation of cotton, rice, and sugar cane (Rao et al., 2006). Since the aim of this report is not to provide a thorough analysis and the choice of statistical techniques are admittedly primitive, the final results may be further improved upon by applying band selection/transformation algorithm (Gong et al., 2003, Pu et al., 2003, Pu and Gong, 2004, Pu et al., 2005 and Pu et al., 2008) and using enhanced math models (Rao et al., 2006, Le Maire et al., 2008, Wu et al., 2010, Heiskanen et al., 2013 and Vyas et al., 2013). A guideline on how to fine-tune the crop models can be found in a recently published paper (Thenkabail et al., 2013). This study thoroughly examined the relationships between different vegetation indices derived from EO-1 Hyperion and the biophysical characteristics of crops. The authors concluded that different types of crops required specific spectral treatments (i.e., best-fitted vegetation indices). The reader should note that the rubber plantations in the study area are dominated by the most commercialized rubber species RRIM600. This might have some implications when applying the proposed models to rubber plantations of different species. Further studies on different rubber species are therefore required before conclusions can be made on this issue. In summary, this study explores one step beyond the existing research. It is the first time that the capability of hyperspectral data for estimating the LAI of rubber plantations has been investigated. Despite the remaining fine-tuning to be done on the model parameters, the proposed statistical models reveal high statistical correlations (i.e., the best $R^2 = 0.820$) with low RMSE values (i.e., the lowest RMSE = 0.160). Therefore, we anticipate that the methodology presented in this study can serve as a useful guideline for estimating the LAI of rubber plantations.

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