Aboveground Biomass Estimation in an Upland Tropical Evergreen Forest Environment from Landsat 7 ETM+

Suwanprasit, C.[1*] and Strobl, J.[2]
[1]Department of Geography, Faculty of Social Sciences, Chiang Mai University, 239 Huay Keaw Road Mueang, Chiang Mai, 50200, Thailand, E-mail: Chanida.suwanprasit@gmail.com
[2]Interfaculty Department of Geoinformatics – Z_GIS, University of Salzburg, Hellbrunnerstrasse 34, Salzburg 5020, Austria, E-mail: Josef.Strobl@sbg.ac.at
Correspondance Author

Abstract
The study area is an evergreen forest in Phu Hin Rong Kla National Park, Thailand.Tropical evergreen forests are important as they possess the highest biomass amongst tropical forests. Remote sensing has been used in many studies to estimate the volume of aboveground biomass. The gap filled Landsat 7 ETM+ data and the forest observed parameters have been analyzed to find out the quantity of aboveground biomass and carbon sequestration. The forest parameters were measured in 30 randomly selected sample plots measuring 30 m x 30 m. The measurements were then used for computing the aboveground biomass using two allometric equations (TM51 and ND71). The analysis showed the best model for aboveground biomass estimation was a combination of TM51 and ND71 (R^2 = 0.658) and the total of aboveground biomass and carbon sequestration were 112,062,010 ton and 5,603,100 ton carbon respectively. The application of the study would be useful for understanding the terrestrial carbon dynamics and global climate change.

1. Introduction

Estimation of Aboveground Biomass (AGB) is an essential aspect of studies of carbon stocks and the effects of deforestation and carbon sequestration on the global carbon balance (Alban et al., 1978). It is also valuable information for many other global issues such as forecasting ecosystem productivity, carbon budget, carbon cycles, nutrient allocation, and fuel accumulation in terrestrial ecosystems (Amichev et al., 2008, Zhao et al., 2012, Moser et al., 2011, Stape et al., 2008 and Zhang et al., 2007). Moreover, for tropical forests, regional change in biomass is associated with important components of climate change (Brown, 1997). Spatial estimates of the biomass and volume of trees are becoming more and more important to forest management and planning. Unfortunately, studies in tropical forests are more demanding and time-consuming than in temperate forests because of high plant species diversity, poorly known plant taxonomy and many of the remaining tropical forests are in remote areas with difficult access. Therefore, it is rarely practicable to collect sufficient field data that covers the area of interest. Hence, interpolation is often made between widely scattered field sampled points. In order to estimate the AGB, forest stand parameters such as tree height, basal area, stand structure, bole diameter at breast height (DBH) are required as independent variables for the models. There are a number of commonly used variables for estimating biomass including, tree height, basal area, and stand structure, bole diameter at breast height (DBH) (Brown, 1997). A strong relation of biomass with basal area has been found in many studies (Rai and Proctor, 1986). There are 3 main approaches to estimating AGB based on (1) Field measurement, (2) GIS-based and (3) Remote sensing data (Lu, 2006).

Remote sensing is increasingly used as a source of data for the efficient and sustainable use of natural resources and it is considered to be the most reliable means for spatial biomass estimation for tropical regions (Roy and Ravan, 1996). Remote sensing data is often used as the dependent variable and therefore there is need to have ground based field surveys as the independent variable (Hahn, 1984 and Smith, 1986). A number of studies have demonstrated the potential of remote sensing for biomass studies (Gao et al., 2013, Main-Knorn et al., 2011, Tian et al., 2012, Miettinen and Liew, 2009 and Xu et al., 2010). Past studies have shown varying degrees of success in estimating forest biomass from remote sensing data in temperate and tropical forests worldwide (Drake et al., 2003, Benie et al., 2005, Anaya et al., 2009, Dubayah et al., 2010, Gleason and Im, 2011, Zheng et al., 2012, Riegel et al., 2013). Remote sensing data is becoming the primary source for biomass estimation (Lu, 2006). Research on remote sensing based biomass estimation approaches and discussion of existing issues influencing biomass estimation are valuable for further improving biomass estimation performance.

The potential of remote sensing for estimating biomass was reviewed in (Lu, 2006 and Koch, 2010). New remote sensing technology such as LiDAR (light detection and ranging), polarimetric radar interferometry and hyperspectral data can better estimate forest biomass than optical remote sensed data however methodologies and operational cost should be concerned (Koch, 2010). Therefore optical sensor data would be an alternative source which can directly estimate using several approaches such as multiple regression analysis, K nearest - neighbor, and neural network and indirectly estimated from canopy parameters using multiple regression analysis or various canopy reflectance models. Vegetation indices have been successfully used for aboveground biomass estimation (Lu, 2006).

Overall, spectral indices of vegetation derived from the near-infrared and visible (usually red) bands of the remote sensing data are widely employed as measures of green vegetation density (Steven et al., 2003). Many vegetation indices have been developed and applied to biophysical parameter studies but not all vegetation indices are significantly correlated with aboveground biomass (Lu, 2006). For example, Sader et al., (1989) found that Normalized Difference Vegetation Index (NDVI) is not a good predictor of stand structure variables (e.g. height, diameter of main stem) or total biomass in uneven age, mixed broadleaf forest. Despite the application of vegetation indices for biomass studies, the accuracy of these biomass models has been questioned because in reality, optical remote sensing provides information on canopy leaf density rather than on biomass (Zhang and Fu, 1999).

Several studies have already been carried out to predict forest attributes using remote sensing imagery. Sader et al., (1989) assessed the feasibility of detecting tropical forest successional age class and total biomass differences using Landsat TM in the mountain forest of Puerto Rico. National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) data for estimating of tropical forest biophysical properties in south - west Ghana was used in (Foody et al., 2003). Steininger (2000) also tested estimation of aboveground biomass of tropical secondary forest from canopy spectral reflectance using satellite optical data. (Foody et al., 2003) compared the estimation of tropical forest biomass from Landsat TM data for sites in Brazil, Malaysia and Thailand using regression and neural networks and discussed the transferability of the estimates among the regions. Thenkabail et al., (2004) compared narrowband hyperspectral Hypersion data with broadband hyperspatial IKONOS data, multispectral Advanced Land Imager (ALI) and Landsat 7 ETM+ data by using classification of complex rainforest vegetation in southern Cameroon.

Thus, there is great interest in estimating the biomass of forests and their role in regulating the cycling of carbon and nutrients. The objective of this study was to estimate the AGB and carbon sequestration in an Indo-Malay tropical evergreen forest using field measured parameters and vegetation indices derived from Landsat 7 ETM+ Gap-filled spectral reflectance of Phukin Rong Kla National Park in Central Thailand.

2. Study Area

The study area was tropical evergreen forest in Phu Hin Rong Kla National Park. The park is located in northeast part of Thailand, in Phitsanulok and Loei Provinces. It lies between 16° 53′ to 17° 07′ E and 101° 56′ to 101° 06′ N (Figure 1) and covers an area of 307 km^2. The general topography of the park is steeply mountainous. The northern part of the park in Chaiburi district borders Laos while the southern part runs into Phetchabun Province. The mountain range includes the peaks of Phu Phangma, Phu Lomlo, Phu Hin Rong Kla and Phu Man Khao which is the tallest peak with an altitude of 1,820 m above sea level. The second tallest is Phu Lomlo with an altitude of 1,664 m. The park is the source of many streams, including Huai Mueat Don, and Huai Luang Yai (Division, 2002).

Phu Hin Rong Kla’s climate is cool the year around, especially in the cool season, when temperature can occasionally drop to freezing point. Mist cover is frequent and the maximum temperature is below 25 oC (Division, 2002). The park is covered by mixed deciduous, dry evergreen and hill evergreen forests. The most important tree species found in the park are Lagerstroemia calyculata, Pterocarpus macrocarpus, Shorea siamensis, and S. obtuse, Afzelia xylocarpa (Division, 2002).

3. Methods

In this study, forest parameters namely diameter at breast height (DBH), tree height, species and number of trees in each sample plot were measured. These parameters were used to estimate the AGB. Remotely sensed data on the other hand was used to provide vegetation indices for correlation analysis with the estimated AGB.

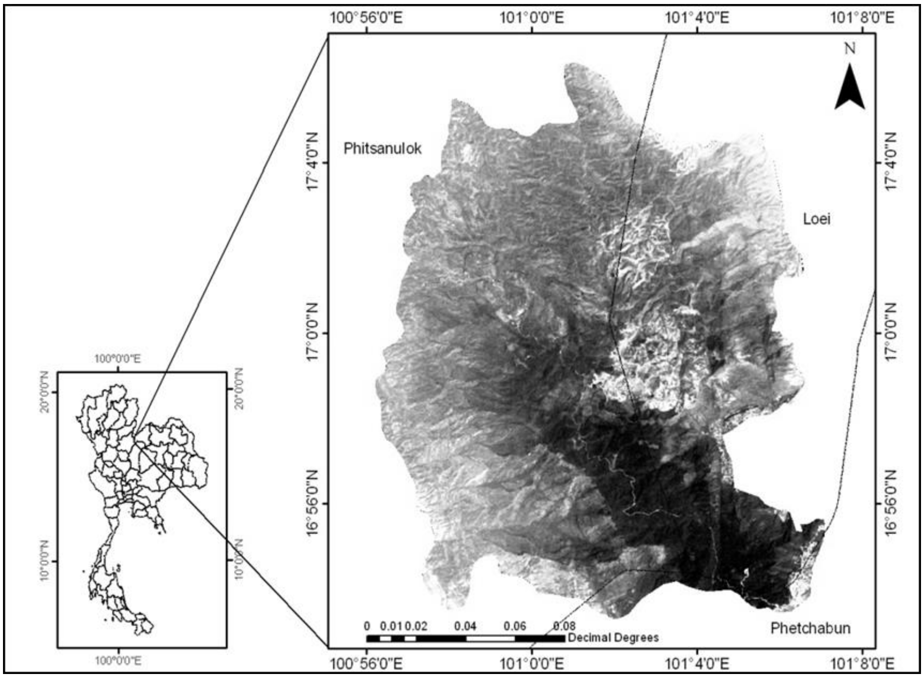


Figure 1: Location of study area, Phu Hin Rong Kla National Park, Thailand

3.1 Field Data Collection and Allometric Equations

In April 2009, 30 sample plots were randomly selected and forest parameters were measured (Thompson, 1990). Each plot was composed of an area of 30 m x 30 m which is the same as the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) pixel size. All trees more than 4.5 cm in DBH (Viriyabuncha et al., 2002) were measured. The locations of each plot were determined by the global positioning system (GPS). The measured parameters were used for estimating the AGB based on allometric relationships. The biomass of individual trees was estimated using two regression equations 1 and 2-5 developed by (Brown,1997) and (Tsutsumi et al., 1983) respectively.

$$Br\_TB = 42.69 - 12.800D + 1.242D^2 \quad \text{Equation 1}$$

Where, Br_TB is the Brown allometric equation and D is the DBH (cm),

$$Ws = 0.0509D^2H^{0.919} \quad \text{Equation 2}$$

$$Wb = 0.00893D^2H^{0.977} \quad \text{Equation 3}$$

$$Wl = 0.0140D^2H^{0.669} \quad \text{Eqaution 4}$$

$$Ts\_TB = Ws + Wb + Wl \quad \text{Equation 5}$$

Where, Ts_TB is the Tsutsumi allometric equation, Ws is the stem biomass (kg), Wb is the branch biomass (kg), Wl is the leaf biomass (kg) and H is the tree height (cm).

3.2 Data and Image Processing

Two Landsat ETM+ images, covering the study areas and located on path 129 and row 48 were used for analysis. These Landsat scenes were acquired on February 09, 2002 and February 12, 2009. Band 1-5 and 7 of both Landsat 7 ETM+ were used in this study. The 30 m pixel resolution images were geo-referenced to UTM coordinates using existing Landsat 7 ETM+ gap-filled image, atmospheric and topographic corrections (by ASTER GDEM 30m resolution) were also made. Missing data resulting from the failure of the Scan Line Corrector (SLC) on the Landsat 7 ETM+ sensor, was filled using the Landsat Gap Fill function (Scaramuzza et al., 2004). The boundary of Phu Hin Rong Kla National Park was then overlaid to exclude pixels outside the study area.

The radiance and reflectance of Landsat 7 ETM+ bands were used for calculating the RVI, NDVI, SAVI, ARVI, MSAVI, ND41, ND51, ND53, TM41, TM51, TM53, VIS123 and MVIS vegetation indices and band ratios (Table 1). These vegetation indices and band ratios have been shown to be indicators of overall green biomass, canopy closure, tree density, and tree species diversity (Kaufman and Tanré, 1992, Schultz and Halpert, 1995, Lawrence and Ripple, 1998 and Gong et al., 2003).

Table 1: Vegetation indices and band ratios used in this study

Vegetation Index	Equation	Source
Ratio Vegetation Index (RVI)	$RVI = \frac{NIR}{Red}$	(Jordan, 1969)
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - Red}{NIR + Red}$	(Rouse et al., 1973)
Soil-Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(NIR - R)(1 + L)}{(NIR + R + L)}$	(Huete, 1988)
Modified Soil Adjusted Vegetation Index (MSAVI)	$MSAVI = 2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - Red)}$	(Qi et al., 1994)
Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = \frac{(NIR - 2R + B)}{(NIR + 2R - B)}$	(Kaufman and Tanré, 1992)
VIS123	$VIS123 = B1 + B2 + B3$	(Lu et al., 2004)
MVIS	$MVIS = \frac{MID57}{VIS123}$	This study
ND41	$ND41 = \frac{(B4 - B1)}{(B4 + B1)}$	
ND51	$ND51 = \frac{(B5 - B1)}{(B5 + B1)}$	
ND53	$ND53 = \frac{(B5 - B3)}{(B5 + B3)}$	
ND71	$ND71 = \frac{(B7 - B1)}{(B7 + B1)}$	
TM41	$TM41 = \frac{B4}{B1}$	
TM51	$TM51 = \frac{B5}{B1}$	
TM53	$TM53 = \frac{B5}{B3}$	
TM71	$TM71 = \frac{B7}{B1}$	

Remark: Where, VIS123 is the linear combination of Landsat 7 ETM+ Band 1, 2 and 3

MVIS is the ratio of Landsat 7 ETM+ between linear transform of middle infrared region bands (Band 5 and 7) and VIS123

NDab (ND41, ND51 and ND71) is the normalized ratio between Band a and b (where, a and b are the number of Landsat 7 ETM+ bands)

TMab (TM41, TM51, TM53 and TM71) is the simple ratio between Band a and b (where, a and b are the number of Landsat 7 ETM+ bands)

The best vegetation indices were used in this study to estimate the amount of AGB in the whole study area by using regression analysis. A correlation with $p < 0.05$ is taken as significant. Landsat 7 ETM+ for the study area was classified into 2 groups (evergreen forest and non-evergreen forest) by comparing three image classifiers that included Maximum Likelihood (ML), Artificial Neural Networks (ANNs) and Support Vector Machine (SVM). The best accuracy to classify evergreen forest was found using SVM in agreement with many publications (Brown et al., 1999, Heikkinen et al., 2011 and Koetz et al., 2008).

4. Results

4.1 Forest Stand Parameters

Within the 30 randomly selected sample plots whose locations were determined using a Handheld GPS, a total of 2,200 trees were measured. The major tree species identified were Lithocarpus calthiformis Rehd. Et Wils. and Syzygium cumini Druce. The highest tree and biggest girth measured was for a Lithocarpus calathiformis Rehd. et Wils., with a height of 50 m and a girth of 4.33 m. The tree height and DBH ranged from 3 m to 50 m and 3.39 cm to 137.77 cm respectively, which represented a full range of stand structures that occurred in the study area (Table 2). The average tree height and DBH were 13.71 m (standard deviation (S.D.) = 7.84 m) and 18.90 cm (standard deviation (S.D.) = 15.48 cm) respectively. The biomass was estimated using allometric equations from Brown (1997) and Tsutsumi et al. (1983). The averages of AGB from Brown and Tsutsumi allometric equations per 30 x 30 m plot were 567.53 kg and 996.97 kg respectively.

Table 2: Descriptive statistics of the validation samples for DBH, tree height and biomass

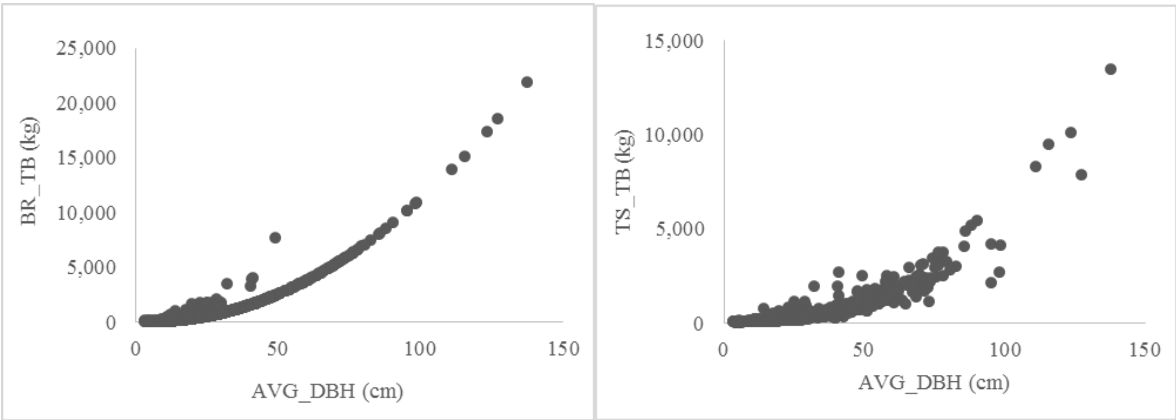
		Statistics		
		Mean	**Min**	**Max**
Forest parameters	DBH (cm)	18.90	3.39	137.77
	Tree Height (m)	13.71	3.00	50.00
AGB (kg)	Br_TB*	567.53	9.71	21,854.00
	Ts_TB**	996.97	7.20	58,282.40

Remark: * Brown and ** Tsutsumi allometric equations

Table 3: Pearson's correlation coefficients for tree height, average DBH and AGB volume using Brown and Tsutsumi allometric equations

	Forest Parameters		**AGB Volume**	
	Average DBH	**Tree Height**	**Br_TB**	**Ts_TB**
Average DBH	1.000	0.711**	0.888**	0.807**
Tree Height	0.711**	1.000	0.564**	0.594**
Br_TB	0.888**	0.564**	1.000	0.957**
Ts_TB	0.807**	0.594**	0.957**	1.000

Remark: ** Correlation is significant at the 0.01 level (2-tailed)



(a) (b)

Figure 2: Scatter plot describing the correlation between AGB and average with (a) Brown allometric equation and (b) Tsutsumi allometric equation

4.2 Correlation between AGB and Forest Stand Parameters

In this study, AGB is defined as the biomass of live trees greater than 4.5 cm in DBH. The AGB volume calculated from both equations has a good relationship with forest stand parameters (Table 3 and Figure 2). In addition, the correlation coefficient (*r*) between average DBH and AGB from Brown allometric equation (r = 0.888) is higher than AGB calculated using the Tsutsumi allometric equation (*r* = 0.807) and tree height also has a high correlation with average DBH. The correlation coefficient of the Brown allometric equation (*r* = 0.564) is similar to the correlation derived from the Tsutsumi allometric equation (*r* = 0.594), even though the Brown allometric equation has no tree height parameter included in it.

4.3 Aboveground Biomass and Landsat 7 ETM+ Spectral Reflectance

All selected AGB stand volumes from Tsutsumi and Brown allometric equations have significant ($p < 0.05$) but negative correlations with Landsat 7 ETM+ reflectance. Moreover, Band 1 to 3 are significantly correlated with AGB using both equations but such relationships vary depending upon the characteristics of the study areas such as forest stand density, vegetation age and species composition (Lu et al., 2004). The highest correlation coefficient is found using Band 1 (-0.715) for the Tsutsumi allometric equation. Table 4 summarizes the correlation coefficients between the selected AGB stand volumes and Landsat 7 ETM+ spectral reflectance in the study area using both the Tsutsumi and Brown allometric equations.

4.4 AGB and Vegetation Indices and Band Ratios

Not all vegetation indices are significantly ($p < 0.05$) related to forest stand parameters (Lu et al., 2004). Table 5 and Table 6 summarize the correlation coefficients between AGB volume estimated from Brown and Tsutsumi allometric equations with vegetation indices in the study area. The results show that all indices were significantly correlated with AGB in the sample plots using both equations except MSAVI. The highest correlation coefficient was found using the TM51 with the Tsutsumi allometric equation. Moreover, the correlation coefficients for AGB volume that were calculated from the Brown allometric equation are higher than AGB values that were calculated from the Tsutsumi allometric equation for all indices except RVI. However, most vegetation indices are not better related to forest stand parameters than ETM+ spectral reflectance except TM51 (Table 6).

Table 4: Pearson's correlation coefficient from two AGB volumes by using Brown equation and Tsutsumi allometric equations and six Landsat 7 ETM+ spectral bands

AGB	**Landsat 7 ETM+ spectral bands**					
	Band1	**Band2**	**Band3**	**Band4**	**Band5**	**Band7**
BR_TB	-0.638**	-0.589**	-0.593**	-0.114^{ns}	-0.213^{ns}	-0.226^{ns}
TS_TB	-0.715**	-0.673**	-0.606**	-0.185^{ns}	-0.188^{ns}	-0.186^{ns}

Remark: ** Correlation is significant at the 0.01 level (2-tailed). ^{ns} is not significant.

Table 5: Pearson's correlation coefficient from two AGB volumes by using Brown and Tsutsumi allometric equations and vegetation indices

Index	RVI	NDVI	SAVI	ARVI	MSAVI	VIS123	MVIS
Br_TB	0.527**	0.569**	0.569**	0.626**	0.11^{ns}	-0.645**	0.635**
Ts_TB	0.496**	0.572**	0.572**	0.646**	0.047^{ns}	-0.706**	0.710**

Remark: ** Correlation is significant at the 0.01 level (2-tailed). ^{ns} is not significant.

Table 6: Pearson's correlation coefficient from two AGB volumes by using Brown and Tsutsumi allometric equations and band ratios.

Index	ND41	ND51	ND53	ND71	TM41	TM51	TM71	TM53
Br_TB	0.627**	0.517**	0.628**	0.399*	0.680**	0.659**	0.522**	0.630**
Ts_TB	0.698**	0.603**	0.663**	0.487**	0.703**	0.721**	0.599**	0.620*

Remark: ** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

4.5 Biomass and Carbon Sequestration Estimation

4.5.1 Model selection

The top five models with the highest coefficient determination are showed in Table 7. Cubic model which added TM51 in the model was the highest coefficient of determination (R^2 = 0.501) among models using Brown allometric equation. For the Tsutsumi allometric equation, the highest coefficient of determination was a multiple regression model which included TM51 and ND71 in the model (R^2 = 0.658).

4.5.2 Aboveground Biomass and Carbon Sequestration in the Evergreen Forest Area

The Tsusumi allometric equation had the highest correlation coefficient (R^2 = 0.658). The model was fitted using multiple linear regression (including TM51 and ND71 as variables in the model). The estimated AGB in evergreen forest is shown in Figure 3(a) and Table 8 presents descriptive statistic. The total of AGB in the whole study area was 112,062,010 ton. The average of AGB in evergreen forest areas was 872 ton/ha. The result was similar to that found by (Viriyabuncha et al., 2002) at Doi Suthep - Pui National Park, Chiang Mai, evergreen forest mixed deciduous forest where AGB was in the range 32-903 ton/ha. The carbon content estimation would be about 50% of the amount of total aboveground biomass (Dixon et al., 1996). Therefore, the carbon sequestration of evergreen forest was calculated and the total carbon in the whole area was stored as 5,603,100 ton carbon/whole area (307 km^2). The average of carbon storage of hill evergreen forest was 497 ton carbon/ha. Figure 3(b) and Table 8 showed the carbon sequestration in evergreen forest area in the study area.

5. Discussion

The study found an inverse relationship of spectral reflectance with AGB information except Band 4 where almost no relationship was apparent. Similar conclusions were drawn in many of the previous studies (Horler et al., 1983, Spanner et al., 1990, Roy and Ravan, 1996). The inverse relationship between the biomass and spectral reflectance could be the result of increased canopy shadowing within larger stands and the decreased understory brightness (soil brightness) due to increased density of biomass (Spanner et al., 1990). There was an inverse relationship between amount of shadow and reflectance in all bands (Ahlcrona, 1988). Results from the study by (Horler et al., 1983) specified this phenomenon for particular spectral regions, for example band 5 or 7 of Landsat TM and stated that shadowing is a factor at least as important as leaf moisture content influencing the spectral reflectance of forests in the shortwave infrared spectral region. Thus, the higher spectral reflectance of the sample plots with less biomass can be explained partially by a lower amount of shadow, which results in a higher contribution to the spectral radiance from the background soil.

Table 7: Top five of the highest coefficient determination between two allometric equations and spectral reflectance

Models		R^2
Brown allometric equation		
1	$AGB = 4.024 – 0.010(TM51) + 0.0000226(TM51)^2 – 0.000000008(TM51)^3$	0.501
2	$AGB = 3.151 – 0.004(TM51) + 0.00000958(TM51)^2$	0.499
3	$AGB = 7.822 – 0.017(TM41) + 0.000056(TM41)^2 – 0.000000027(TM41)^3$	0.480
4	$AGB = 4.904 + 0.003(TM41) + 0.0000126(TM41)^2$	0.477
5	$AGB = 843.853e^{-0.002(B1)}$	0.468
Tsutsumi allometric equation		
1	$AGB = 421.905(TM51) – 1,823.46(ND71) – 204.4$	0.658
2	$AGB = 126.233(TM51) – 0.364(VIS123) + 880.342$	0.602
3	$AGB = 730.67e^{-0.087(B1)}$	0.573
4	$AGB = 3.124 – 0.002(TM51)+ 0.000004 (TM51)^2 – 0.000000001(TM51)^3$	0.547
5	$AGB = 2,179.93 – 0.7(VIS123) – 0.01(VIS123)^2 + 0.000000277(VIS123)^3$	0.546

Table 8: Descriptive statistic of AGB estimated and carbon sequestration from Tsutsumi allometric equation, TM51 and ND71 for study area (307 km^2)

Descriptive Statistic	Minimum (ton/ha)	Maximum (ton/ha)	Mean (ton/ha)	Range	Summary (ton/whole area)
AGB	0	34,216	872	34,216	112,062,010
Carbon sequestration	0	17,108	467	17,108	5,603,100

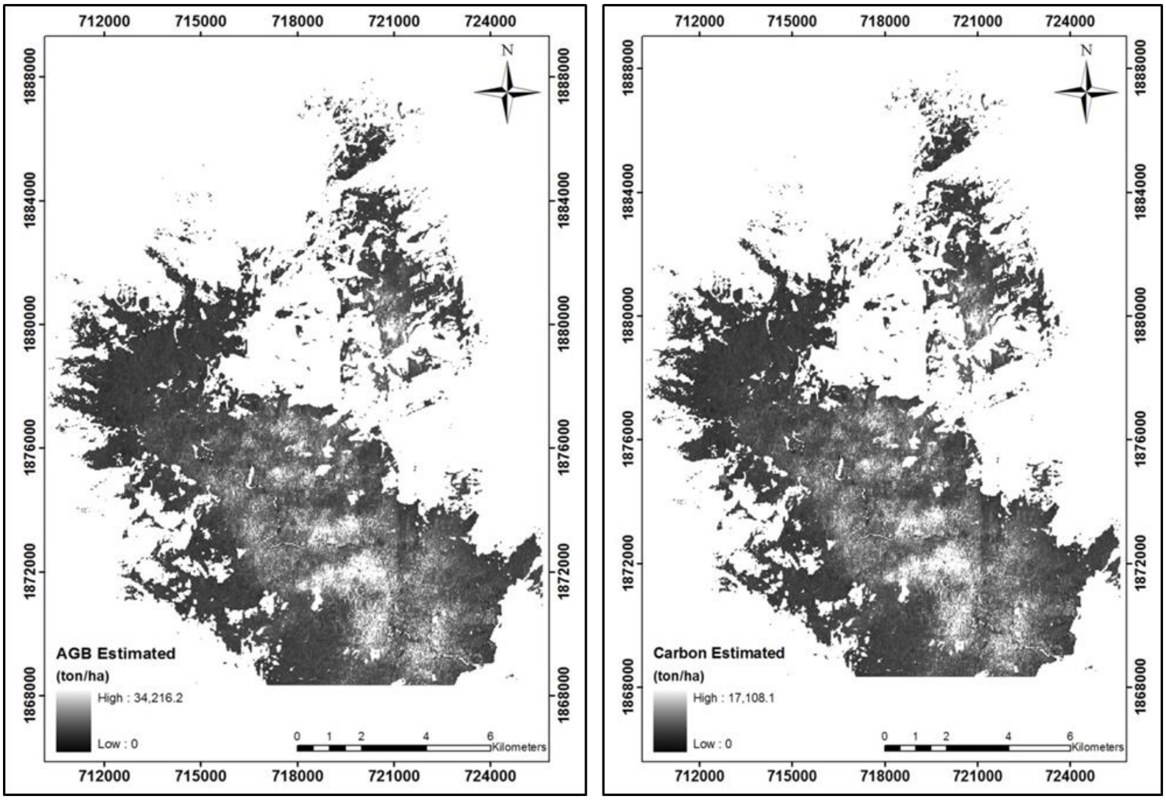


Figure 3: (a) Aboveground biomass and (b) Carbon sequestration estimated in evergreen forest area

Previous studies have shown that there is a high correlation between AGB and vegetation indices (Sader et al., 1989, Huete et a., 1997, Yemefack et al., 2006, Zheng et al., 2004, Anaya et al., 2009 and Helmer et al., 2009). Conversely, there are some studies that have found low or weak correlation between AGB and vegetation indices (Foody et al., 2003, Lu et al., 2004 and De La Cueva, 2008). In this study, the correlations between some vegetation indices derived from Landsat 7 ETM+ spectral bands such as Band 4, Band 5 and Band 7 are not significantly correlated with the AGB in the study area. The inverse relationship typically (as shown in Table 4) can be found between spectral band data and ABG (Roy and Ravan, 1996). They proposed that the underlying causes were; (i) increased canopy shadowing within larger stands (ii) decreased soil brightness due to increased density with which biomass increases.

The low correlation was attributed to the inability of limited data set with such spectral resolution to account for the variability of forest biophysical features that relate to biomass. Therefore, the disadvantage of Landsat data is a limitation of resolution. Canopy discontinuities are sometimes lost in the 30 m x 30 m resolution (Feldpausch et al., 2006) because of mixing of pixels. Moreover (Okuda et al., 2004) concluded that Landsat data is probably insufficient to detect local difference in AGB by using only visible, near-infrared and shortwave infrared wavelengths (0.4 – 2.5 mm). In addition, the study area was upland tropical evergreen forest, therefore, there are difficulties in measuring these variables accurately and inter-species differences should ideally be accounted for throughout. The species composition, forest stands structure and associated canopy shadows, and vegetation vigor, are considered to be important factors affecting vegetation reflectance (Lu et al., 2004). Furthermore, Landsat 7 ETM+ data primarily captures canopy information instead of individual tree information due to its limited spatial resolution. For these reasons, future research may focus on the integration of multi - source data, particularly RADAR or LIDAR with higher penetrating power (Saatchi et al., 2011, Solberg et al., 2014, Montesano et al., 2015), which involves the effective integration of remote sensing, GIS and modeling techniques.

6. Conclusion

This study attempted to provide specifically adapted methods to extract aboveground biomass/carbon information from optical remote sensed data from

Indo-Malay tropical forest. The multiple regression models were developed based on integration of Landsat 7 ETM+ images and forest stand parameters. The Tsutsumi allometric equation was found to be the best predictor of AGB from Landsat 7 ETM+ data using TM51 and ND71 (R^2 = 0.658) in this study. Usually, the Band 1 (Blue region) shows a very poor relationship between forest variables and spectral reflectance satellite image data. However, the relationship can be significantly improved using a correlation of Band 1 with Band from the infrared region (Band 4, 5 and 7) to formulate a band ratio that is better correlated with AGB. Moreover, this study also found that NDVI was not the best vegetation index for estimating AGB in this area.

Although optical remote sensed data still produce lower accuracy for AGB estimation than active remote sensed data such as LiDAR and Radar, the data sources availability and longer archive are the advantages of optical remote sensed data. Therefore AGB estimation methods development in tropical forest using optical images is still very important due to the difficulty in gathering ground-truth data representative of a large area. However the results can be used to guide the selection of suitable Landsat 7 ETM+ band(s) and vegetation indices for AGB estimation in Indo-Malay tropical forest in the future, the integration of multisource data for better AGB estimation should be more explored and concerned.

7. Acknowledgments

Authors wish to gratefully acknowledge support from Dr.Raymond J. Ritchie for his helpful comments on the paper. This research was supported by the Austrian agency for international mobility and cooperation in education, science and research (OeAD-GmbH) for field data collecting.

References

Ahlcrona, E., 1988, *The Impact of Climate and Man on Land Transformation in Central Sudan: Applications of Remote Sensing*, Lund University Press.

Alban, D. H., Perala, D. A. and Schlaegel, B. E., 1978, Biomass and Nutrient Distribution in Aspen, Pine, and Spruce Stands on the Same Soil Type in Minnesota. *Canadian Journal of Forest Research*, Vol. 8(3).

Amichev, B. Y., Burger, J. A. and Rodrigue, J. A., 2008, Carbon Sequestration by Forests and Soils on Mined Land in the Midwestern and Appalachian Coalfields of the US. *Forest Ecology and Management*, Vol. 256(11), 1949-1959. doi: DOI 10.1016/j.foreco.2008.07.020.

Anaya, J. A., Chuvieco, E. and Palacios-Orueta, A., 2009, Aboveground Biomass Assessment in Colombia: A Remote Sensing Approach. *Forest Ecology and Management*, Vol. 257(4), 1237-1246. doi:DOI10.1016/j.foreco.2008.11.016.

Benie, G. B., Kabore, S. S., Goita, K. and Courel, M. F., 2005, Remote Sensing-Based Spatio-Temporal Modeling to Predict Biomass in Sahelian Grazing Ecosystem. *Ecological Modelling*, Vol. 184(2-4), 341-354. doi: DOI 10.1016/j.ecolmodel.2004.10.012.

Brown, S., 1997, Estimating Biomass and Biomass Change of Tropical Forests: A Primer. *FAO Forestry Paper-134*. Rom, Italy: Food and Agriculture Organization of the United Nations.

Brown, S. L., Schroeder, P. and Kern, J. S., 1999, Spatial Distribution of Biomass in Forests of the Eastern USA. *Forest Ecology and Management*, Vol. 123(1), 81-90.

De La Cueva, A. V., 2008, Structural Attributes of Three Forest Types in Central Spain and Landsat ETM Plus Information Evaluated with Redundancy Analysis. *International Journal of Remote Sensing*. Vol. 29(19), 5657-5676. doi: Doi 10.1080/01431160801891853.

Division, Forest Land Resources, 2002, *Master Plan Database of Phu Hin Rongla National Park Management, Phitsanulok and Loei Provinces*. In Forest Land Resources Division. Bangkok: Forest Land Resources Division.

Dixon, R. K., Krankina, O. N. and Kobak, K. I., 1996, Global Climate Change Adaptation: Examples from Russian Boreal Forests. *Adapting to Climate Change: An International Perspective*, 359-373.

Drake, J. B., Knox, R. G., Dubayah, R. O., Clark, D. B., Condit, R., Blair, J. B. and Hofton, M., 2003, Above-Ground Biomass Estimation in Closed Canopy Neotropical Forests Using Lidar Remote Sensing: Factors Affecting the Generality of Relationships. *Global Ecology and Biogeography*, Vol. 12(2), 147-159. doi: DOI 10.1046/j.1466-822X.2003.00010.x.

Dubayah, R. O., Sheldon, S. L., Clark, D. B., Hofton, M. A., Blair, J. B., Hurtt, G. C. and Chazdon, R. L., 2010, Estimation of Tropical Forest Height and Biomass Dynamics Using Lidar Remote Sensing at La Selva, Costa Rica. *Journal of Geophysical Research-Biogeosciences*, Vol. 115(G2). DOI: 10.1029-/2009JG000933.

Feldpausch, T. R., McDonald, A. J., Passos, C. A. M., Lehmann, J. and Riha, S. J., 2006, Biomass, Harvestable Area, and Forest Structure

Estimated from Commercial Timber Inventories and Remotely Sensed Imagery in Southern Amazonia. *Forest Ecology and Management*, Vol. 233(1), 121-132.

Foody, G. M., Boyd, D. S. and Cutler, M. E. J., 2003, Predictive Relations of Tropical Forest Biomass from Landsat TM Data and their Transferability between Regions. *Remote Sensing of Environment*. Vol. 85(4), 463-474. doi: Doi 10.1016/S0034-4257(03)00039-7.

Gao, Y. H., Liu, X. X. Min, C. C., He, H. L., Yu, G. R., Liu, M., Zhu, X. D. and Wang, Q., 2013, Estimation of the NorthSouth Transect of Eastern China Forest Biomass Using Remote Sensing and Forest Inventory Data. *International Journal of Remote Sensing*, Vol. 34(15), 5598-5610. Doi 10.1080/01431161.2013.794985.

Gleason, C. J. and Im, J., 2011. A Review of Remote Sensing of Forest Biomass and Biofuel: Options for Small-Area Applications. *Giscience & Remote Sensing*, Vol. 48(2):141-170. Doi 10.2747/1548-1603.48.2.141.

Gong, P., Pu, R., Biging, G. S. and Larrieu, M. R., 2003, Estimation of Forest Leaf Area Index Using Vegetation Indices Derived from Hyperion Hyperspectral Data. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 41(6), 1355 -1362, DOI: 10.1109/TGRS.2003.812910.

Hahn, J. T., 1984, *Tree Volume and Biomass Equations for the Lake States*. Research Paper NC-250. St. Paul, MN: U.S. Dept. of Agriculture, Forest Service, North Central Forest Experiment Station.

Heikkinen, V., Korpela, I., Tokola, T., Honkavaara, E. and Parkkinen, J., 2011, An SVM Classification of Tree Species Radiometric Signatures Based on the Leica ADS40 Sensor. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 49(11), 4539-4551. doi: Doi 10.1109/Tgrs.2011.2141143.

Helmer, E. H., Lefsky, M. A. and Roberts, D. A., 2009, Biomass Accumulation Rates of Amazonian Secondary Forest and Biomass of Old-Growth Forests from Landsat Time Series and the Geoscience Laser Altimeter System. Journal of Applied Remote Sensing, Vol. 3(1). Doi 10.1117/1.3082116.

Horler, D. N. H., Dockray, M. and Barber., J., 1983, The Red Edge of Plant Leaf Reflectance. *International Journal of Remote Sensing*, Vol.4 (2), 273-288.

Huete, A. R., 1988, A Soil-Adjusted Vegetation Index (Savi). *Remote Sensing of Environment*, Vol. 25(3), 295-309.

Huete, A. R., Liu, H. Q. and vanLeeuwen, W. J. D., 1997.,The Use of Vegetation Indices in Forested Regions: Issues of Linearity and Saturation. *IGARSS'97. 1997 IEEE International Geoscience and Remote Sensing Symposium Proceedings. Remote Sensing - A Scientific Vision for Sustainable Development*. Vols I-Iv:1966-1968. DOI: 10.1109/IGARSS.1997.60-9169.

Jordan, C. F., 1969, Derivation of Leaf-Area Index from Quality of Light on Forest Floor. *Ecology*, Vol. 50(4), 663-666.

Kaufman, Y. J. and Tanré, D., 1992, Atmospherically Resistant Previous Termvegetation Indexnext Term (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 30(10). DOI: 10.110-9/36.134076

Koch, B., 2010, Status and Future of Laser Scanning, Synthetic Aperture Radar and Hyperspectral Remote Sensing Data For Forest Biomass Assessment. *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 65(6), 581-590. doi: DOI 10.1016/j.isprsjprs-.2010.09.001.

Koetz, B., Morsdorf, F., van der Linden, S., Curt, T. and Allgower, B., 2008, Multi-Source Land Cover Classification for Forest Fire Management Based on Imaging Spectrometry and LiDAR Data. *Forest Ecology and Management*, Vol. 256(3), 263-271. doi: DOI 10.1016/j.forec-o.2008.04.025.

Lawrence, R. L. and Ripple, W. J., 1998, Comparisons among Previous Termvegetation Indicesnext Term and Bandwise Regression in a Highly Disturbed, Heterogeneous Landscape: Mount St. Helens, Washington. *Remote Sensing of Environment* , Vol. 64(1), 91-102. https://doi.org/10.1016/S0034-4257(97)00171-5.

Lu, D. S., 2006, The Potential and Challenge of Remote Sensing-Based Biomass Estimation. *International Journal of Remote Sensing*, Vol. 27(7), 1297-1328. doi: Doi 10.1080/014311-60500486732.

Lu, D. S., Mausel, P., Brondizio, E. and Moran, E., 2004, Relationships between Forest Stand Parameters and Landsat TM Spectral Responses in the Brazilian Amazon Basin. *Forest Ecology and Management*, Vol. 198(1-3),149-167. doi: DOI 10.1016/j.foreco.2004.03.048.

Main-Knorn, M., Moisen, G. G., Healey, S. P., Keeton, W. S., Freeman, E. A. and Hostert, P., 2011, Evaluating the Remote Sensing and Inventory-Based Estimation of Biomass in the Western Carpathians. *Remote Sensing*, Vol. 3(7), 1427-1446. doi: Doi 10.3390/Rs3071427.

Miettinen, J. and Liew, S. C., 2009, Estimation of Biomass Distribution in Peninsular Malaysia and in the Islands of Sumatra, Java and Borneo Based on Multi-Resolution Remote Sensing Land Cover Analysis. *Mitigation and Adaptation Strategies for Global Change*, Vol. 14(4), 357-373. doi: DOI 10.1007/s11027-009-9169-6.

Montesano, P. M., Rosette, J., Sun, G., North, P., Nelson, R. F., Dubayah, R. O, Ranson, K. J. and Kharuk, V., 2015, The Uncertainty of Biomass Estimates from Modeled ICESat-2 Returns Across a Boreal Forest Gradient. *Remote Sensing of Environment*, Vol. 158, 95-109. doi: DOI 10.1016/j.rse.2014.10.029.

Moser, G., Leuschner, C., Hertel, D., Graefe, S., Soethe, N. and Iost, S., 2011, Elevation Effects on the Carbon Budget of Tropical Mountain Forests (S Ecuador): The Role of the Belowground Compartment. *Global Change Biology*, Vol. 17(6), 2211-2226. doi: DOI 10.1111/j.1365-2486.2010.02367.x.

Okuda, T., Suzuki, M., Numata, S., Yoshida, K., Nishimura, S., Adachi, N., Niiyama, K., Manokaran, N. and Hashim, M., 2004, Estimation of Aboveground Biomass in Logged and Primary Lowland Rainforests Using 3-D Photogrammetric Analysis. *Forest Ecology and Management*, Vol. 203(1-3), 63-75. DOI 10.1016/j.foreco.2004.07.056.

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H. and Sorooshian, S., 1994, A Modified Soil Adjusted Vegetation Index. *Remote Sensing of Environment*, Vol. 48(2), 119-126.

Rai, S. N. and Proctor, J., 1986, Ecological Studies on Four Rainforests in Karnataka, India: II. Litterfall. *Journal of Ecology*, Vol. 74(2), 455-463.

Riegel, J. B., Bernhardt, E. and Swenson, J., 2013, Estimating Above-Ground Carbon Biomass in a Newly Restored Coastal Plain Wetland Using Remote Sensing. *Plos One*, Vol. 8(6). DOI 10.1371/journal.pone.0068251.

Rouse, J. W., Hass, R. H., Schell, J. A. and Deering, D. W., 1973, Monitoring Vegetation Systems in the Great Plains with ERTS. *Paper Read at Proceedings of the third ERTS Symposium. NASA SP-351*, 301–317.

Roy, P. S. and Ravan, S. A., 1996, Biomass Estimation Using Satellite Remote Sensing Data-An Investigation On Possible Approaches For Natural Forest. *Journal of Biosciences*, Vol. 21(4), 535-561.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T. A., Salas, W., Zutta, B. R., Buermann, W., Lewis, S. L., Hagen, S., Petrova, S., White, L., Silman, M. and Morel, A., 2011, Benchmark Map of Forest Carbon Stocks in Tropical Regions Across Three Continents. *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 108(24), 9899-9904. DOI 10.1073/pnas.1019576108.

Sader, S. A., Waide, R. B., Lawrence, W. T. and Joyce, A. T., 1989, Tropical Forest Biomass and Successional Age Class Relationships to a Vegetation Index Derived from Landsat Tm Data. *Remote Sensing of Environment*, Vol. 28, 159-198.

Scaramuzza, P., Micijevic, E. and Chander, G., 2009, *SLC Gap-Filled Products Phase One Methodology 20042009*. Available from http://landsat.usgs.gov/.

Schultz, P. A. and Halpert, M. S., 1995, Global Analysis of the Relationships among a Previous Termvegetation Index, Next Term Precipitation, and Land Surface Temperature. *International Journal of Remote Sensing*, Vol. 16(15), https://doi.org/10.1080/01431169508954590.

Smith, W. B., 1986, Factors and Equations to Estimate Forest Biomass in the North-Central Region. *USDA Forest Service North Central Forest Experiment Station Research Paper*, Vol. 268,1-6.

Solberg, S., Næsset, E., Gobakken, T. and Bollandsås, O. M., 2014, Forest Biomass Change Estimated from Height Change in Interferometric SAR Height Models. *Carbon Balance and Management*, Vol. 9(1), 5. doi: 10.1186/s13021-014-0005-2.

Spanner, M. A., Pierce, L. L., Peterson, D. L. and Running, S. W., 1990, Remote-Sensing of Temperate Coniferous Forest Leaf-Area Index-the Influence of Canopy Closure, Understory Vegetation and Background Reflectance. *International Journal of Remote Sensing*, Vol. 11(1), 95-111.

Stape, J. L., Binkley, D. and Ryan, M. G., 2008, Production and Carbon Allocation in a Clonal Eucalyptus Plantation with Water And Nutrient Manipulations. *Forest Ecology and Management*, Vol. 255(3-4), 920-930. doi: DOI 10.1016/j.foreco.2007.09.085.

Steininger, M. K., 2000, Satellite Estimation of Tropical Secondary Forest Above-Ground Biomass: Data from Brazil and Bolivia. *International Journal of Remote Sensing*, Vol. 21(6-7), 1139-1157.

Steven, M. D., Malthus, T. J., Baret, F., Xu, H. and Chopping, M. J., 2003, Intercalibration of Vegetation Indices from Different Sensor Systems. *Remote Sensing of Environment*, Vol. 88(4), 412-422. DOI 10.1016/j.rse.2003.08.010.

Thenkabail, P. S., Enclona, E. A., Ashton, M. S., Legg, C. and De Dieu, M. J., 2004, Hyperion, IKONOS, ALI and ETM Plus Sensors in the Study of African Rainforests. *Remote Sensing of Environment*, Vol. 90(1), 23-43. doi: DOI 10.1016/j.rse.2003.11.018.

Thompson, S. K.,1990, Adaptive Cluster Sampling. *Journal of the American Statistical Association*, Vol. 85 (412):1050-1059.

Tian, X., Su, Z. B., Chen, E. X., Li, Z. Y., van der Tol, C., Guo, J. P. and He, Q. S., 2012, Estimation of Forest Above-Ground Biomass Using Multi-Parameter Remote Sensing Data Over a Cold and Arid Area. International Journal of Applied Earth Observation and Geoinformation, Vol. 14(1), 160-168. DOI 10.1016/j.jag.2011.09.010.

Tsutsumi, T., Yoda, K., Sahunalu, P., Dhanmanonda, P. and Prachaiyo, B., 1983, Forest: Felling, Burning and Regeneration. *In Shifting Cultivation*, 13-62. Tokyo.

Viriyabuncha, C., Vacharangkura, T., Petmak, P. and Ishizuka, M., 2002, *The Evaluation System for Carbon Storage in Forest Ecosystem in Thailand (I. above ground biomass).* edited by Sivilculture Research Division: Royal Forest Department.

Xu, M., Cao, C. X., Tong, Q. X., Li, Z. Y., Zhang, H., He, Q. S., Gao, M. X., Zhao, J. A., Zheng, S., Chen, W. and Zheng, L. F., 2010, Remote Sensing Based Shrub Above-Ground Biomass and Carbon Storage Mapping in Mu US Desert, China. *Science China-Technological Sciences*, Vol. 53,176-183. DOI 10.1007/s11431-010-3231-1.

Yemefack, M., Bijker, W. and De Jong, S. M., 2006, Investigating Relationships between Landsat-7 ETM+ Data and Spatial Segregation of LULC Types Under Shifting Agriculture in Southern Cameroon. International Journal of Applied Earth Observation and Geoinformation, Vol. 8(2), 96-112. DOI 10.1016/j.jag-.2005.08.003.

Zhang, J. and Fu, C., 1999, A Study on Relationships between Remote Sensing Information and Plant Photo-Synthetic Parameters in Estimating Biomass Model. *Acta Geodaetica et Cartographica Sinica*, Vol. 28(5).

Zhang, J., Ge, Y., Chang, J., Jiang, B., Jiang, H., Peng, C. H., Zhu, J. R., Yuan, W. G., Qi, L. Z. and Yu, S. Q., 2007, Carbon Storage by Ecological Service Forests in Zhejiang Province, Subtropical China. *Forest Ecology and Management*, Vol. 245(1-3), 64-75. DOI 10.1016/j.foreco.2007.03.042.

Zhao, J. F., Yan, X. D. and Jia, G. S., 2012, Simulating Net Carbon Budget of Forest Ecosystems and its Response to Climate Change in Northeastern China Using Improved FORCCHN. *Chinese Geographical Science*, Vol. 22(1), 29-41. DOI: 10.1007/s11769-012-0512-6.

Zheng, D. L., Rademacher, J., Chen, J. Q., Crow, T., Bresee, M., le Moine, J. and Ryu, S. R., 2004, Estimating Aboveground Biomass Using Landsat 7 ETM+ Data Across a Managed Landscape in Northern Wisconsin, USA. Remote Sensing of Environment, Vol. 93(3), 402-411. DOI 10.1016/j.rse.2004.08.008.

Zheng, X. Q., Shen, F. J., Zheng, S. N., Argaman, E., Blumberg, D., Ben-Asher, J. and Amir, S., 2012, Estimation of Regional Evapotranspiration and Biomass Production from Remote Sensing Data by Artificial Neural Network (ANN) Method. *Journal of Food Agriculture & Environment*, Vol 10(3-4), 1558-1561.