DERIVATION OF BIOCHEMICAL INDICATOR OF TROPICAL RAINFOREST USING ASTER DATA

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ABSTRACT: This paper highlights the study undertaken on extraction of biochemical parameters, namely the pigment chlorophyll, carbon, nitrogen and moisture of *noebalanocarpus heimii sp*. derived from ASTER data. These biochemical information are important elements in understanding plant physiological status. The vegetation biochemical parameters also directly proportional to the stage of vigourness, and hence identifying those biochemical constituents are very crucial in understanding the biotic ecology, spatially and temporally. In this study, tree census data, in-situ spectro-radiometric and foliar samples of selected important marker species were modeled semi-empirically with the corresponding ASTER data. Vegetation indices were used as main input in the modeling. Results indicated that Green NDVI and RDVI correlated with pigment chlorophyll ($R^2 < 0.7$, $p < 0.05$, n=56) and moisture within canopies are moderately correlated with MSI ($R^2 < 0.5$, $p < 0.05$, n=56) when modeled respective foliar's nutrients for neobalanocarpus heimii sp. Hence, we concluded that ultra-fine spectral resolution of <5 nm is required for biochemical indicators in this studies.

1 Introduction

Plant biochemical is an important parameter for testing plant physiological status. The biochemical involving activities of nutrient cycle, the distribution of biomass, carbon storage and decomposition of leaves (Matson et al, 1994 and Serrano et al, 2002). The main reaction of biochemical plant usually occurs in chloroplasts. Through this component, pigment chlorophyll act as a medium for biochemical processes involving element such as carbon (C), hydrogen (H) oxygen (O_2) to react with light to produce carbohydrates. This biochemical activities however began to change when across spatially and temporally. The variation of biochemical seems to be complex however this information is very useful for better understanding of forest ecosystems.

Remote sensing technique offers a reliable and a fastest way for leaf biochemical estimation across spatially and temporally (Stagakis el al, 2010). Yet, the intentions are not well given for biochemical studies on neobalanocarpus heimii sp. These species was also known as King Ashton and only found in tropical rainforest region. The previous research of biochemical studies showed their interest on their own type of species such as wheat (Song, 2008), mixed forest (Huber et al, 2008) and black Sprus (Zhang et al, 2008). Among researcher, traditional techniques for extracting biochemical still most popular however applying those data is costly and time-consuming. Sometimes, the use of traditional technique could bring low accuracy data due to limited collections number of sample from site location. Therefore, spectral changes caused by absorption or reflectance of leaf biochemical substances in the near-infrared to mid infrared frequency detector could give an effort for better estimates of canopy biochemical properties.

The previous report of biochemical related to sensor from broadband optical sensor such as Landsat TM (Song , 2008) and MODIS until to the use of narrowband spectral data such as satellite sensor Hyperion, CHRIS/PROBA (Stagakis et al, 2010), Airborne Imaging Hyperspectral (AISA) and Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (Asner et al, 2008) was successful use for collecting biochemical information. But, each sensor owns different radiometric sensitivity that has promise to observe biochemical canopy species in unique changes of radiometric performance. The specific biochemical research also found in estimation of pigment chlorophyll (Penuelas et al, 1995), nitrogen (Serrano et al, 2002) and vegetation water content (Gao, 1996).

In this paper, we focused more on biochemical studies included of pigment chlorophyll, carbon, nitrogen and moisture status for our local species of neobalanocarpus heimii sp. Using both in-situ data and ASTER data the 50 ha forest study plot in Pasoh forest reserve in Negeri Sembilan, Malaysia was used in this study. Later, the results of two method of biochemical extraction using empirical and semi-empirical methods are compared to determine the relationship of biochemical information for neobalanocarpus heimii sp.

2 Brief theoretical concept of biochemical parameters and remote sensing

In general, there are four types of model developed for biochemical extraction using remote sensing data. The first model built was a descriptive model where this model is not competent to extract biochemical information but only gives an idea of how chemical and structural properties of leaves influence in reflected energy sensed by the sensor. Then, a second type of model was a physical model. The model was introduced to alter descriptive model which based on kubelka-munk (KM) theory and plate-based model. The both new models provide reverse the nature of leaf biochemical by the coefficient of absorption and dispersion of energy (Slater, 1980). However, differrent approach is given by plate-based model which determine biochemical information by the absorption energy received by the sensor of rough surface while KM model determines biochemical information by the energy reflected from four sided top layer of cuticle, parenchyma, and mesophyll span and lower layer of cuticle (Allen et al. 1968; Yamada and Fujimara ,1988).

Then, the physical model PROSPECT was introduced (Jacquemoud and Scratched, 1990). In PROSPECT, three input parameters, namely water content, chlorophyll concentration and leaf mesophyll structure are used for estimating biochemical of plant. Dawson et al (1998) enhanced PROSPECT to LIBERTY for additional biochemical components such as carotenoids, anthocyanins, proteins and lignin. LIBERTY was purposely developed for structure of plant leaves, such as conifer needles while PROSPECT-was developed for flat leaves structure. Fourty et al (1996) reported that most of reversed physical model is insufficient for determination of detailed biochemical compositions due to lack of absorption features.

The statistical-based empirical model was then introduced and has been widely used since then. These models provide better understanding of the intereactions of spectral reflectance with leaf structure and plant biochemical properties. Hence, such analyses allow in-situ biochemical observations be regressed against and the corresponding reflectances of satellite remotely sensed data (Matson et al, 1994 and Serrano et al, 2002). Asner and Martin (2008) suggested that partial least square (PLS) statistical method for regression analysis approach. This idea was also supported by Smith et al (2003) which shown PLS advantages compared to Stepwise Linear Regression.

Sometimes, regression model could provide weak correlation between data spectra and ground biochemical. Therefore, Shi (2004) suggest transformation of the spectral such as continuum removal to overcome the problem with strength signal. Shi (2004) also found that continuum removal able to produce better result than other spectral transformation such as Reciprocal spectra, Logarithm spectra, apparent absorption spectra, spectra 1st derivative, 2nd derivative spectra or its original reflectance, R. Other research by Kokaly et al (2003) also agreed that transformation spectra like continuum removal able to isolate the field of forest plant species composition. While, Schmidt and Skidmore (2003) in their studies found that continuum removal in the visible spectrum provide best spectral separation plants. However, Peterson et al(1988) was report that the use of transformation spectra such as 1st derivative spectra, dRi and apparent absorption spectra, RA able to showed an equal results compare to transformation spectra of 2nd derivative spectra, d2Ri. While, research by Jacquemoud (1995) found that the use of apparent absorption spectra, RA can provide better result than original reflectance, R data itself. Significant result also reported in Sims and Gamon (2002) studies where transformation of spectra by derivative was a good approach to separate the pigments in certain spectral bands, thus reducing space between plants and shadows. Table 1 showed algorithm for spectra transformation.

Table 1 transformation spectra algorithm

Type of transformation spectra	Algorithm
Reciprocal spectra , RR	= 1 / R
Logarithm spectra , RL	= log (R)
Apparent absorption spectra, RA	= log (1/R)
1st derivative spectra, dRi	$= (R_{i+1} - R_i) / \Delta\lambda$
2nd derivative spectra, d²Ri	$= (dR_{i+1} - dR_i) / \Delta\lambda$
Continuum removal, R'	= R/ Rc

(Sources: Shi, 2004)

Latest model of semi-empirical method was introduced to replace the use of empirical method. Thenkabail et al (2000) was explained that semi-empirical model using vegetation index promoted signaling pathway based on theory of wave spectra ratio between the reflectance range in visible and infra-red spectrum energy. They also reported that the use of this model is very sensitive to the plant and estimating of green cover. The model also was concise and clear to enhance the reversal of power by the wave spectra of the material in plant biochemistry (Jackson and Huete ,1991). Furthermore, the use of this vegetation index model are prepare to reduce the impression of topography, atmospheric, background soil, leaf orientation, soil moisture and the position angle of the sun. The history of biochemical model used in estimating leaf or plant biochemical showed in Table 2.

Table 2 Some of biochemical model developed for remote sensing data

Type of modeling	Brief explaination of model
Descriptive model	Theory-based models : ray tracing and stochastic model
Physical model	Model-based simulation: Kubelka-Munk, Plate based, PROSPECT, LIBERTY (Slater, 1980; Allen et al, 1968; Yamada and Fujimara ,1988; Jacquemoud and Scratched, 1990; Dawson et al, 1998)
Empirical model	Model-based statistic: Partial least square (PLS), Stepwise Linear Regression (SLR) (Matson et al, 1994; Serrano et al, 2002; Asner and Martin ,2008 ; Smith et al, 2003)
Semi-empirical model	Model-based statistic: Vegetation index (Thenkabail et al , 2000; Jackson and Huete ,1991)

3 Methodology and Approach

ASTER satellite data- were acquired in 14 spectral bands; in visible (520-600, 630-690) nm, infrared (760-860, 1600-1700) nm, shortwave infrared (2145-2185, 2185-2225, 2235-2285, 2295-2365, 2360-2430)nm and thermal infrared(8125-8475, 8475-8825, 8925-9275, 10025-10095) nm. The relationship ASTER's reflectances and in-situ biochemical of selected vegetation targets were analyzed chlorophyll pigment, carbon, nitrogen and moisture status. The spectra range 520 to 690nm was used to estimate chlorophyll pigment, while spectra range 760nm to 1300nm is examined for carbon and nitrogen; canopy moisture status using spectra range of 1300 to 2500nm. The corresponding in-situ spectroradiometer observations of the target vegetation class *neobalanocarpus heimii sp.*, was performed in the experimental near real-time to the ASTER data acquisition. Both the ASTER and in-situ data sets were then input into semi-empirical employing the related vegetation indices given in equation in table 3.

Table 3 The original of vegetation index modified according to Aster spectral range and the result was verify using overall accuracy and kappa statistic.

Vegetation Index(VI)	Aster	Overall accuracy	Kappa statistic	Equation	References
Chlorophyll Pigment -Broadband spectral	**EVI**	-	-	**2.5((Rnir-Rred) / (Rnir+6Rred-7.5Rblue+1))**	**Huete et al. (2002)**
	Green NDVI	**80.7278%**	**0.7312**	**(Rnir-Rgreen) / (Rnir + Rgreen)**	**Gitelson et al. (1997)**
	NDVI	77.0889%	0.6828	**(Rnir+ Rred) / ((Rnir + Rred)**	**Tucker (1979)**
	SR	67.2507%	0.5578	**(Rnir / Rred)**	**Jordan (1969)**
Chlorophyll Pigment -Narrowband spectral	**CARI**	80.3235%	0.7233	**(R700 (a670 + R670 +b)) / (R670 $(a^2+ 1)^{0.}$** Dimana a= (R700-R550)/150; b= R550-a550	**Kim et.al (1994)**
	GI	62.264%	0.4871	**R554/R677**	**Tejada et.al (2005)**
	GVI	61.7251%	0.4748	**(R682-R553) / (R682+R553)**	**Gandia et al. (2004)**
	mCARI	61.7251%	0.4797	**[(R700-R670) - 0.2(R700-R550)](R700/R670)**	**Daughtry et.al (2000)**
	mCARI2	37.8706%	0.2109	**1.2 [2.5(R800-R670)-1.3(R800-R550)]**	**Haboudane et al. (2004)**
	mNDVI	-	-	**(R800-R680) / (R800+R680-2R445)**	**Sims dan Gamon (2002)**
	Mndvi2-705	-	-	**(R750-R705) / (R750+R705-2R445)**	**Datt (1999)**
	Msavi	81.2668%	0.7392	**$0.5[2R800+ 1 - \sqrt{(2R800+1)^2- 8 (R800-R670)}]$**	**Qi et al. (1994)**
	mSR	-	-	**(R800-R445) / (R680-R445)**	**Sims dan Gamon (2002)**
	Msr2-705	-	-	**(R750-R445) / (R705-R445)**	**Datt (1999)**
	mTVI	78.0323%	0.6893	**1.2[1.2(R800-R550)- 2.5 (R670-R550)]**	**Haboudane et.al (2004)**
	NDVI705	-	-	**(R750-R705) / (R750+R705)**	**Gitelson dan Merzlyak (1994)**
	OSAVI	79.6496%	0.7174	**1.16(R800-R670) / (R800+R670+0.16)**	**Rondeaux et.al (1996)**
	RDVI	**81.5364%**	**0.7431**	**$(R800-R670) / \sqrt{(R800+R670)}$**	**Roujean dan Breon(1995)**
	REP	-	-	**700+ 40[(((R670+R780)/2) –R700)/ (R740-R700)]**	**Guyot et.al. (1988)**
	SIPI	-	-	**(R800-R450)/ (R800-R650)**	**Peneulas et.al (1995)**
	SIPI2	-	-	**(R800-R440)/ (R800-R680)**	**Peneulas et.al (1995)**
	SPVI	82.3450%	0.7508	**0.4[3.7(R800-R670)-1.2(R530-R670)]**	**Vincini et.al (2006)**
	SR1	-	-	**R750/R700**	**GitelsondanMerzlyak(1997)**
	SR2	67.2507%	0.5578	**R752/R690** GitelsondanMerzlyak(1997)	
	SR3	75.0674%	0.6545	**R750/R550**	**GitelsondanMerzlyak(1997)**
	SR4	69.5418%	0.5791	**R672/ R550**	**Datt (1998)**
	TCARI	73.3154%	0.6324	**3[(R700-R670)-0.2(R700-R550)(R700/R670)]**	**Haboudane et.al (2002)**
	TSAVI	79.6496%	0.7183	**$a(R875-aR680-b)/[R680+a(R875-b)+0.08(1+a^2)]$** Dimana a= 1.062, b=0.022	**Rondeaux et.al (1996)**
	TVI	79.5148%	0.7107	**0.5[120(R750-R550)-200(R670-R550)]**	**Broge dan Leblanc (2001)**
	VOG1	-	-	**R740/R720**	**Vogelmann et.al (1993)**
	VOG2	-	-	**(R734-R747)/ (R715+R726)**	**Tejada et.al (2001)**
	VOG3	-	-	**(R734-R747)/ (R715+R720)**	
Nitrogen	**NDNI**	-	-	**[log(1/R1510)-log(1/R1680)]/[log(1/R1510)+log (1/R1680)]**	**Serrano et.al (2002)**
	NDLI	-	-	**[log(1/R1754)-log(1/R1680)]/[log(1/R1754)+ log(1/R1680)]**	**Serrano et.al (2002)**
Carbon	**CAI**	-	-	**0.5[(R2000-R2200)/(R2100]**	**Daughtry (2001)**
Water	**WBI**	-	-	**R900/R970**	**Penuelas et.al (1993)**
	NDWI	42.8571%	0.2472	**(R857-R1241) / (R857+R1241)**	**Gao (1996)**
	MSI	**43.1267%**	**0.2591**	**R1599/ R819**	**Hunt dan Rock (1989)**
	NDII	24.3935%	0.0482	**(R819-R1649) / (R819+ R1649)**	**Hardisky et.al (1983)**

4 Results

The biochemical experiment based on semi-empirical method reliable to verify result using coefficient of determination, regression model and p-value statistic. During this study, we do a test on 39 different types of vegetation index to represent each biochemical information consist of pigment chlorophyll, carbon, nitrogen and water status. However, our result showed only three type of vegetation index test on Aster data give a good result. The vegetation index result first was evaluated based on overall accuracy and kappa statistic. The Green NDVI showed overall accuracy test result of 80.73 percent with kappa statistic 0.731 and RDVI showed overall accuracy test result of 81.54 percent with kappa statistic 0.743 for biochemical pigment chlorophyll studies. While, the MSI showed overall accuracy test result of 43.13 percent with kappa statistic 0.259.The overall result of vegetation index test during this studies was showed in Table 3. From this model, we do regression of biochemical between ground and sensor data and applied differ transformation spectra test. Surprising, our result showed a standard transformation spectra of 1st derivative give a best result on biochemical tested on Green NDVI, RDVI and MSI (Table 4). The result for Green Ndvi showed coefficient of determination is equal to 0.079, regression model is equal to 0.006 and P-value is equal to

0.566. While, the RDVI showed coefficient of determination is 0.256, regression model is 0.066 and P-value 0.066 and MSI showed result coefficient of determination is equal to 0.139, regression model is equal to 0.019 and P-value is equal to 0.311. Although this semi-empirical method does not give a good model for biochemical information however those result give some idea on later biochemical process could be analyze based on 1st derivation transformation spectra on vegetation index. The 1st derivative spectra help to increase the strength of the biochemical spectra signal.

Table 4 Biochemical analysis of neobalanocarpus heimii sp. (NEOBHE) with n= 56 based on semi-empirical method

Semi-empirical method (Ground versus Aster VI)	NEOBHE, N=56	R	RA	RR	RL	dRi	d2Ri
Green NDVI	Multiple R	0.060	0.053	0.046	0.053	**0.079**	0.070
	R^2	0.003	0.003	0.002	0.003	**0.006**	0.005
	P-value	0.662	0.700	0.738	0.700	**0.566**	0.616
RDVI	Multiple R	0.157	0.165	0.154	0.165	**0.256**	0.231
	R^2	0.025	0.027	0.024	0.027	**0.066**	0.053
	P-value	0.249	0.224	0.256	0.224	**0.059**	0.093
MSI	Multiple R	0.074	0.063	0.052	0.063	**0.139**	0.131
	R^2	0.005	0.003	0.002	0.003	**0.019**	0.017
	P-value	0.587	0.646	0.704	0.646	**0.311**	0.344

5 Conclusion

This study demonstrates that biochemical experiment on neobalanocarpus heimii sp. does not perform well in providing biochemical information using Aster data. The biochemical studies may be improved by using high spectral resolution data such as Hyperion satellite data. The ability to predict canopy biochemical properties using relationship developed in this study, however remains to be test.

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7 References

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