Estimating Oil Palm Yields using Vegetation Indices Derived from Quickbird

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Abstract: A single-date archived QuickBird satellite imagery and oil palm yield data collected over a 12-year time series were used to generate empirical oil palm yield models under Malaysian conditions. Vegetation indices and yield data were subject to correlation analysis, followed by regression modeling and model validation using standard metrics. Results showed a strong positive correlation between vegetation indices and oil palm yields, across different planting periods. Among vegetation indices, RVI showed the best correlation with oil palm yield. Empirical models were found to be significant for the 1990-2002 and the 1998-1999 planting periods. Models built using RVI and MSAVI showed a strong fit between estimated yield and observed yield. In the 1998-1999 planting period, however, only RVI and GNDVI showed reliable strength in yield estimation. Overall, findings of this study suggest that selected QuickBird-derived vegetation indices can be used to estimate oil palm yields with reliable accuracy.
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1. Introduction

Oil palm (*Elaeis guineensis*) occupies about 5 million ha of cultivated area in Malaysia, making it the single largest plantation commodity in the country. Malaysia produces about 45% of the world's total palm oil production, and exports almost 80% of its total production. In 2011, the export revenue from crude and processed palm oil surpassed USD25 billion (MPOB 2011).

Due to the economic significance of oil palm as an industrial crop, acquisition of accurate and timely information about its agronomy is critical for realization of best management strategies. The majority of agronomic data, including crop yields, in Malaysian oil palm plantations are obtained manually via field surveys using destructive techniques. These techniques are typically labor-intensive, costly, time-consuming and generally error-prone. Precise, real-time, non-destructive estimation of crop productivity is necessary for large-scale crops such as oil palm to facilitate better pre- and post-harvest operations.

Remote sensing allows for synoptic observation of crop fields repetitively, and is increasingly explored as an effective approach for real-time crop monitoring and crop yield estimation at both local and regional scales (Aboelghar et al. 2011; Liaghat and Balasundram 2010). Remote sensing techniques have the advantage of facilitating instantaneous, non-destructive and quantitative assessment of crop vigor on a large scale. Application of remote sensing techniques to manage agricultural resources is rapidly increasing due to improvement in spatial, spectral, temporal and radiometric resolutions of space-borne satellite platforms. Remote sensing techniques have been used to detect Jack Pine Budworm defoliation in northwestern Wisconsin, USA (Radeloff et al. 1999). They concluded that spectral mixture analysis was a reliable technique to detect insect defoliation. Additionally, remote sensing techniques have been used for detection of rice panicle blast (Kobayashi et al. 2000), detection of anther smut disease (*Microbotryum violaceum)* in *Silene dioica* (Nilsson et al. 1994) and detection of oil palm tree growth variability in Johor, Malaysia (Hashim et al. 2001).

Remote sensing techniques and technologies have enabled precision agriculture to quantify large-scale spatial and temporal variability, which contributes to efficient trouble shooting during crop production. In most cases, the ability to pin down crop production problems and launch timely intervention strategies can result in higher profitability. The use of remote sensing techniques in conjunction with growth simulation models have become increasingly recognized as powerful tools for crop monitoring and yield estimation (Bauman 1992).

Reliable yield estimation is contingent upon the ability to identify key agronomic variables, including crop maturity, vigor and physiological stress. Several studies have been done to estimate crop yield using remote sensing technology. Chang et al. (2005) found that canopy spectral reflectance data obtained at the booting stage can successfully estimate rice (*Oryza sativa*) yield. Goel et al. (2003)

and Uno et al. (2005) estimated corn (*Zea mays*) yield using several vegetation indices that were computed from compact airborne imagery. Rodriguez et al. (2004) showed a significant correlation between field reflectance measurements and wheat (*Triticum aestivum*) yield. Peng and Gitelson (2011) used Moderate Resolution Imaging Spectroradiometer (MODIS) and Medium Resolution Imaging Spectrometer (MERIS) space-borne sensors to estimate gross primary production at regional and global scales. Fang et al. (2011) successfully integrated MODIS-estimated leaf area index and vegetation indices with CSM-CERES-Maize for improved corn yield prediction. In a recent work by Kogan et al. (2012), Advanced Very High Resolution Radiometer (AVHRR)-based vegetation indices characterizing vegetation greenness and vigor, along with moisture and thermal conditions were used to estimate yields of winter wheat, sorghum and corn in Kansas, USA. It was indicated that implementing a 3-4 month lead forecast in operational field practice will aid farmers to manage weather vagaries, pest and disease problems, and nutrient uptake efficiency during a growing season (Kogan et al. 2012). Simultaneously, this would help decision-makers to regulate commodity pricing, marketing, and trade, which in turn will contribute to a more coordinated approach of addressing food security issues.

Vegetative Index (VI) refers to the ratio of reflectance values at different wavelengths, and is commonly used to understand plant vigor. Many VIs have been developed and tested for estimation of biophysical parameters of vegetation (Huete et al. 2002), quantification of vegetative biomass (Jaishanker et al. 2001), estimation of crop acreage (Dadhwal et al. 2003), assessment of crop condition (Kogan 1997), modeling of crop yield (Dadhwal et al. 2003) and precision crop management (Haboudane et al. 2004).

Research on use of remote sensing techniques to understand oil palm productivity is limited. This work, which is part of an ongoing effort to develop remote sensing protocols for precision oil palm management, was aimed at understanding the relationship between spectral information extracted from QuickBird satellite imagery and oil palm yield collected over a 12-year time series.

2. Material and Methods

This study was conducted in a commercial oil palm plantation in Bukit Serampang, Johor, situated in the southern peninsula of Malaysia. The study area is geographically located at 2° 17' - 2° 22' N, and 102° 40' - 102° 42.5' E (Figure 1), and comprises 56 oil palm management blocks with a total acreage of 2724 ha. The average rainfall is about 1850 mm with the highest amount of rainfall occurring in November and December (average > 200 mm), while the lowest occurs in February and June (average < 100 mm). The management blocks are mostly situated on Laterite (Typic Plinthudult) and Marang (Typic Paleudult) soils.
(Figure 1. Geographic location of the study area)

A system/map corrected and pan-sharpened single-date QuickBird image of the study site, acquired in August, 2006 was used. The archived image had a spatial resolution of 0.61 m (after resolution merge) (Laben and Brower 2000), and three spectral bands consisting of green (0.52–0.60 µm), red (0.63–0.69 µm) and near infrared (0.76–0.90 µm). Satellite image analyses were performed on Erdas Imagine 9.1 (ERDAS 2005) using standard protocols. Image georectification was carried out based on 37 ground control points.

Oil palm yield data, recorded as Fresh Fruit Bunches (FFB) and expressed in tons per hectare, of the 56 management blocks were obtained from the plantation management. The management blocks were demarcated based on planting year, which ranged from 1990 to 2002. The change points within oil palm yield time series were determined using the Pettitt test (Memarian et al. 2012; Pettitt 1979).

The four vegetation indices employed in this study were Ratio Vegetation Index (RVI) (Jordan 1969), Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1973), Modified Soil-Adjusted Ratio Vegetation Index (MSAVI) (Qi et al. 1994), and Green Normalized Difference Vegetation Index (GNDVI) (Gitelson et al. 1996). These vegetation indices were extracted in correspondence to the sampled plots within the 56 oil palm management blocks spread over 2724 ha.

The vegetation indices were computed using the following formula:

$$RVI = \frac{\rho_{ir}}{\rho_r} \tag{1}$$

$$NDVI = \frac{\rho_{ir}-\rho_r}{\rho_{ir}+\rho_r} \tag{2}$$

$$MSAVI = \frac{2\times\rho_{ir}+1-\sqrt{(2\times\rho_{ir}+1)^2-8\times(\rho_{ir}-\rho_r)}}{2} \tag{3}$$

$$GNDVI = \frac{\rho_{ir}-\rho_g}{\rho_{ir}+\rho_g} \tag{4}$$

where: ρ_r and ρ_{ir} are spectral reflectance from the red and near infrared bands, respectively, and ρ_g is spectral reflectance from the green band.

Before performing the correlation analysis, the oil palm yield and vegetation index data were tested for normality using Shapiro-Wilk and Kolmogorov-Smirnov tests. The correlation between vegetation index and oil palm yield was computed using Pearson coefficient. This was followed with regression analysis to generate empirical yield estimation models. The explanatory power of independent variables in the model and the estimation accuracy of model were assessed using the Standard Error of Estimates (SEE), F-test, t-test and coefficient of determination (R^2). Empirical yield estimation models were generated based on the calibration data set and statistically significant models were validated using the validation data set.

3. Results

Oil palm yield data were discretized into three evaluation periods based on planting year (Table 1) so as to represent the oil palm stands as immature ($\leq$ 5 years old), young ($\leq$ 7 years old) and mature ($\geq$ 8 years old). As demonstrated by the Pettitt test, there was a significant difference (at $p=0.05$) between mean oil palm yields in the 1990-1997 and 1998-1999 planting periods. Similar difference was found in the 1998-1999 and 2000-2002 planting periods. The Shapiro-Wilk and Kolmogorov-Smirnov tests showed that the yield data were normally distributed (Table 2). However, the vegetation index data did not adhere to a normal distribution (Table 2), hence, they were treated using the Box-Cox transformation technique ($\lambda=5$) to ensure normality. After data transformation, the vegetation index data adhered to a normal distribution (Table 3).

Table 1 shows the yield data discretized based on planting year.

Table 2 shows the Normality test applied on the original yield and vegetation index data.

Table 3 shows the Normality test applied on the transformed vegetation index data.

All vegetation indices showed significant correlation (Table 4) with oil palm yield in the 1990-2002 (entire 12-year time series), 1998-1999 and 2000-2002 planting periods. In these planting periods, oil palm yield was best correlated with RVI. In the 1990-1997 planting period, however, only NDVI showed significant correlation with oil palm yield. Clearly, the 3- to 7-year old oil palm stands demonstrated a strong positive relationship between VIs and yields, as compared to the 8- to 15-year old stands.

Table 4 shows the Correlation (r) between oil palm yield and vegetation indices across different planting periods.

Linear regression models were significant only in the 1990-2002 and 1998-1999 planting periods (Table 5). Goodness of Fit (GOF) for the regression of yield on NDVI and MSAVI in the 1998-1999 interval was larger than 0.8, while that of RVI and GNDVI registered lesser than 0.8. The R^2 values of the empirical models in the 1998-1999 planting period were higher than those in other periods. Figures 2 and 3 illustrate scatter plots and linear trends of the calibration data sets, corresponding to the 1990-2002 and 1998-1999 intervals.

Figure 2 shows the oil palm yield estimation as a function of vegetation index calibrated based on the 1990-2002 planting period.

Figure 3 shows the Oil palm yield estimation as a function of vegetation index calibrated based on the 1998-1999 planting period.

Model validation for the 1990-2002 planting period is shown in Table 6 and Figure 4. All four vegetation indices exhibited strong robustness in estimating oil palm yield where t-test revealed no significant difference between estimated yields and observed yields at the 0.05 level. The models featuring RVI and MSAVI as the estimator variable showed strong fits between estimated yield and observed yield with an r value of 0.96 and 0.89, respectively.

Table 6 shows the Validation of empirical oil palm yield (Y) models calibrated based on the 1990-2002 planting period.

Figure 4 shows the Fit between observed yield and estimated yield in the 1990-2002 planting period.

Model validation for the 1998-1999 planting period is shown in Table 7 and Figure 5. Although the t-test indicated that all four vegetation indices were able to estimate oil palm yields, models featuring NDVI and MSAVI as the estimator variable recorded a weak fit (r values of 0.45 and -0.13, respectively) between estimated yield and observed yield. Meanwhile, models featuring RVI and GNDVI as the estimator variable showed reliable strength in yield estimation with an r value of 0.95 and 0.89, respectively.

Table 7 shows the Validation of empirical oil palm yield models calibrated based on the 1998-1999 planting period.

Figure 5 shows the Fit between observed yield and estimated yield in the 1998-1999 planting period.

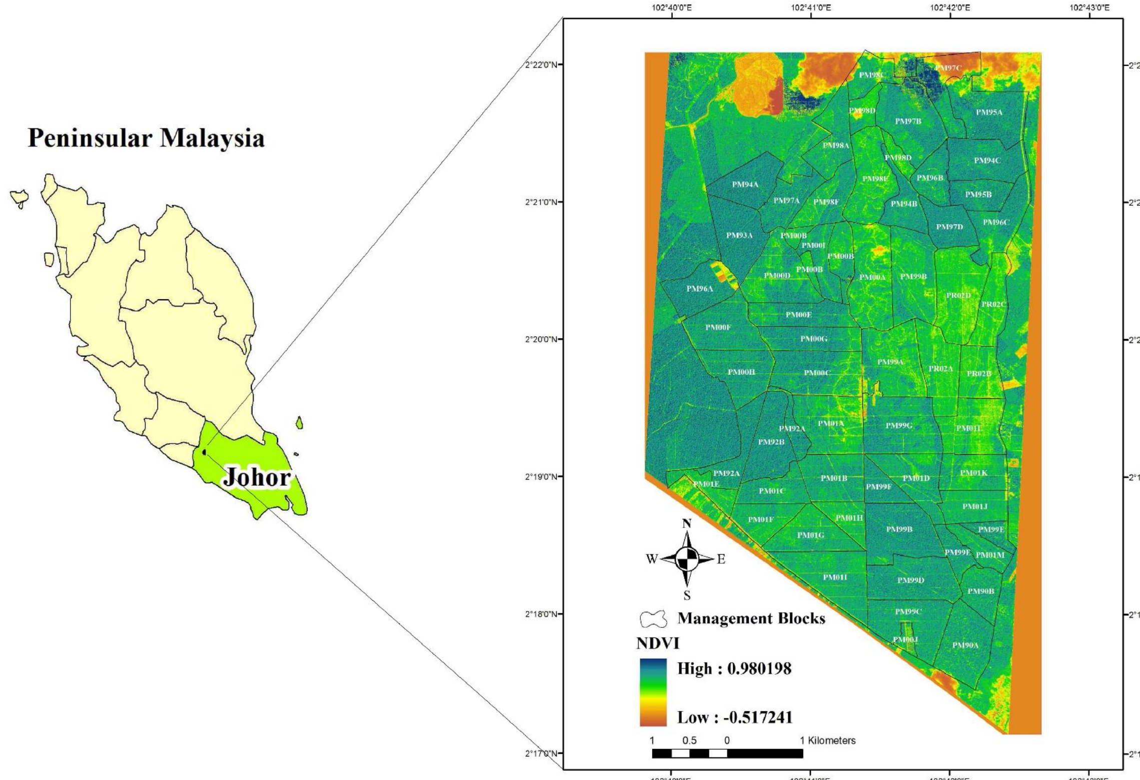


Figure 1. Geographic location of the study area

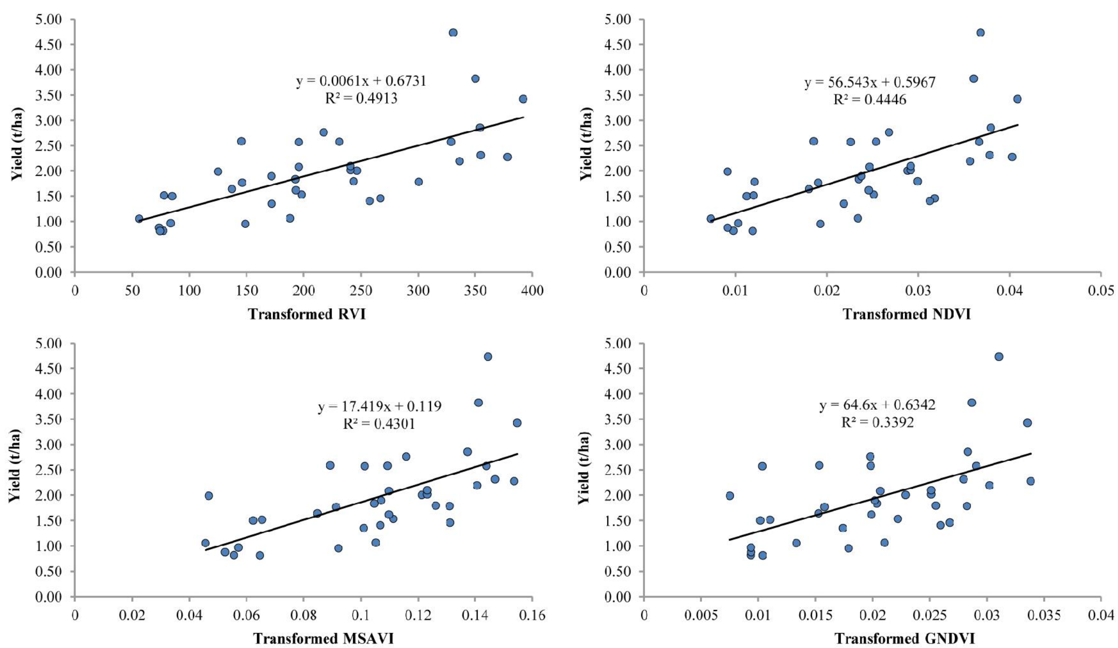


Figure 2. Oil palm yield estimation as a function of vegetation index calibrated based on the 1990-2002 planting period

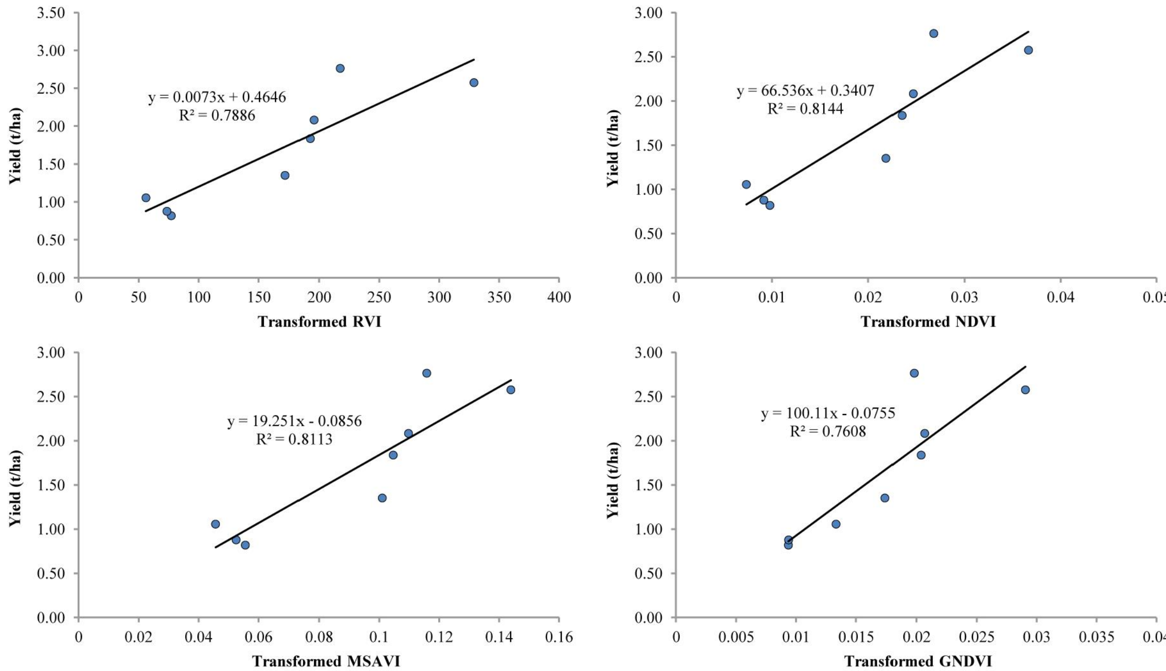


Figure 3. Oil palm yield estimation as a function of vegetation index calibrated based on the 1998-1999 planting period

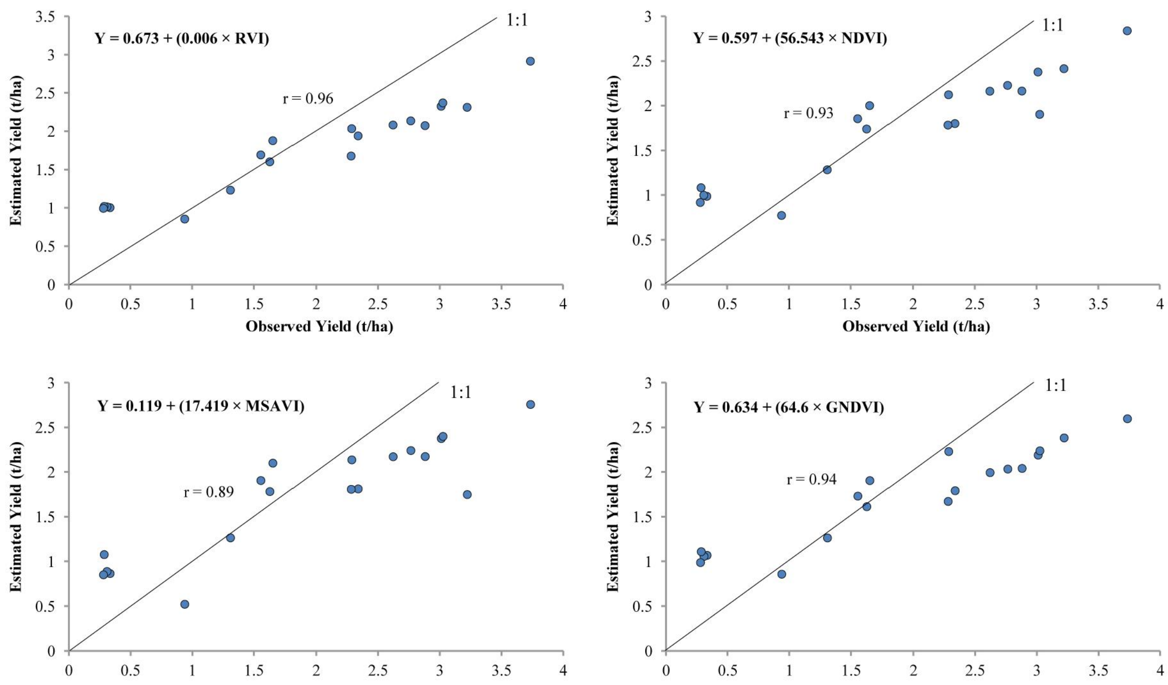


Figure 4. Fit between observed yield and estimated yield in the 1990-2002 planting period

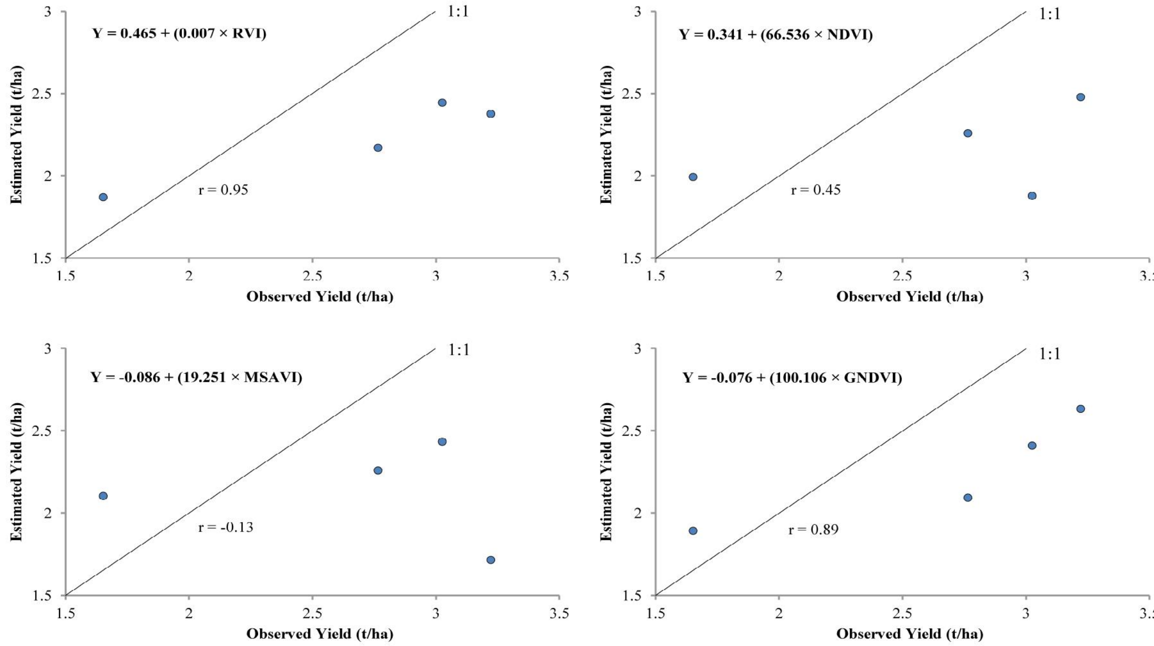


Figure 5. Fit between observed yield and estimated yield in the 1998-1999 planting period

Table 1. Yield data discretized based on planting year

Evaluation period	[1]Palm age	Number of yield records	[2]Mean oil palm yield (t ha^{-1})
1990-1997	8-15	17	2.79
1998-1999	6-7	12	2.00
2000-2002	3-5	27	1.39

[1]In relation to the acquisition date of QuickBird imagery; [2]Refers to fresh fruit bunches

Table 2. Normality test applied on the original yield and vegetation index data

Data	Kolmogorov-Smirnov		Shapiro-Wilk	
	Statistic	Significance	Statistic	Significance
Yield*	0.053	0.200	0.979	0.451
RVI	0.129	0.021	0.934	0.004
NDVI	0.156	0.002	0.916	0.001
MSAVI	0.170	0.000	0.895	0.000
GNDVI	0.158	0.001	0.927	0.002

*Significant at $p < 0.05$

RVI: Ratio Vegetation Index, NDVI: Normalized Difference Vegetation Index, MSAVI: Modified Soil-Adjusted Ratio Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index

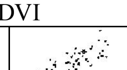
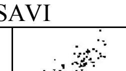
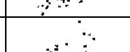
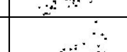
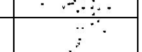
Table 3. Normality test applied on the transformed vegetation index data

VI	Kolmogorov-Smirnov		Shapiro-Wilk	
	Statistic	Significance	Statistic	Significance
RVI*	0.095	0.200	0.963	0.083
NDVI*	0.122	0.037	0.961	0.066
MSAVI*	0.105	0.185	0.949	0.018
GNDVI*	0.101	0.200	0.968	0.137

*Significant at $p < 0.05$

RVI: Ratio Vegetation Index, NDVI: Normalized Difference Vegetation Index, MSAVI: Modified Soil-Adjusted Ratio Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index

Table 4. Correlation (r) between oil palm yield and vegetation indices across different planting periods

Planting year	*n*	RVI		NDVI		MSAVI		GNDVI	
1990-2002	56	0.789**		0.762**		0.744**		0.713**	
1990-1997	17	0.380		0.522*		0.398		0.311	
1998-1999	12	0.895**		0.831**		0.761**		0.884**	
2000-2002	27	0.617**		0.599**		0.611**		0.559**	

*Significant at $p < 0.05$, **Significant at $p < 0.01$

RVI: Ratio Vegetation Index, NDVI: Normalized Difference Vegetation Index, MSAVI: Modified Soil-Adjusted Ratio Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index

Note: Data cloud for each correlation is given next to the respective correlation value

Table 5. Regression of oil palm yield (Y) on vegetation indices based on the calibration data set

Planting period	*n*	Vegetation Index	R^2	GOF	F	p	Regression Equation
1990-2002	37	RVI	0.491	<0.8	33.799	0.000	$Y = 0.673 + (0.006 \times RVI)^*$
(Entire time series)		NDVI	0.445	<0.8	28.013	0.000	$Y = 0.597 + (56.543 \times NDVI)^*$
		MSAVI	0.430	<0.8	26.419	0.000	$Y = 0.119 + (17.419 \times MSAVI)^*$
		GNDVI	0.339	<0.8	17.970	0.000	$Y = 0.634 + (64.6 \times GNDVI)^*$
1990-1997	11	RVI	0.086	<0.8	0.845	0.382	$Y = 1.502 + (0.004 \times RVI)$
(8- to 15-year old palms)		NDVI	0.209	<0.8	2.377	0.158	$Y = 1.327 + (45.037 \times NDVI)$
		MSAVI	0.090	<0.8	0.894	0.369	$Y = 0.72 + (15.268 \times MSAVI)$
		GNDVI	0.062	<0.8	0.595	0.460	$Y = 1.914 + (32.186 \times GNDVI)$
1998-1999	8	RVI	0.789	<0.8	22.376	0.003	$Y = 0.465 + (0.007 \times RVI)^*$
(6- to 7-year old palms)		NDVI	0.814	>0.8	26.321	0.002	$Y = 0.341 + (66.536 \times NDVI)^*$
		MSAVI	0.811	>0.8	25.795	0.002	$Y = -0.086 + (19.251 \times MSAVI)^*$
		GNDVI	0.761	<0.8	19.082	0.005	$Y = -0.076 + (100.106 \times GNDVI)^*$
2000-2002	18	RVI	0.091	<0.8	1.592	0.225	$Y = 1.234 + (0.002 \times RVI)$
(3- to 5-year old palms)		NDVI	0.058	<0.8	0.982	0.336	$Y = 1.292 + (14.139 \times NDVI)$
		MSAVI	0.066	<0.8	1.131	0.303	$Y = 1.166 + (4.482 \times MSAVI)$
		GNDVI	0.038	<0.8	0.633	0.438	$Y = 1.34 + (13.759 \times GNDVI)$

GOF: Goodness of Fit

*Significant at $p < 0.05$ level based on F-test

RVI: Ratio Vegetation Index, NDVI: Normalized Difference Vegetation Index, MSAVI: Modified Soil-Adjusted Ratio Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index

Table 6. Validation of empirical oil palm yield (Y) models calibrated based on the 1990-2002 planting period

Empirical model:	$Y = 0.673 + (0.006 \times RVI)$	$Y = 0.597 + (56.543 \times NDVI)$	$Y = 0.119 + (17.419 \times MSAVI)$	$Y = 0.634 + (64.6 \times GNDVI)$
n	19	19	19	19
SSE	6.409	6.897	7.524	7.993
SEE	0.614	0.637	0.665	0.686
R^2	0.921	0.868	0.789	0.888
t-stat	1.339	1.170	1.338	1.340
p (t-test)	0.197	0.257	0.197	0.197

SSE: Sum of Squared Error, SEE: Standard Error of Estimates

RVI: Ratio Vegetation Index, NDVI: Normalized Difference Vegetation Index, MSAVI: Modified Soil-Adjusted Ratio Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index

Table 7. Validation of empirical oil palm yield models calibrated based on the 1998-1999 planting period

Empirical model:	$Y = 0.465 + (0.007 \times RVI)$	$Y = 0.341 + (66.536 \times NDVI)$	$Y = -0.086 + (19.251 \times MSAVI)$	$Y = -0.076 + (100.106 \times GNDVI)$
n	4	4	4	4
SSE	1.452	2.242	3.082	1.238
SEE	0.852	1.059	1.241	0.787
R^2	0.909	0.202	0.016	0.795
t-stat	1.955	1.638	1.348	1.887
p (t-test)	0.146	0.200	0.271	0.156

SSE: Sum of Squared Error, SEE: Standard Error of Estimates

RVI: Ratio Vegetation Index, NDVI: Normalized Difference Vegetation Index, MSAVI: Modified Soil-Adjusted Ratio Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index

4. Discussions

All four vegetation indices extracted from the QuickBird satellite imagery showed a strong positive correlation with oil palm yields in the 1990-2002, 1998-1999 and 2000-2002 planting periods. However, only NDVI showed significant correlation with oil palm yields in the 1990-1997 planting period. This infers that the QuickBird-derived vegetation indices were more appropriate for yield estimation among younger (3- to 7-year old) palms than that of older ones (8- to 15-year old). Among the vegetation indices, RVI gave the best correlation with oil palm yield.

Based on the correlated response between oil palm yields and vegetation indices, empirical yield estimation models were calibrated and validated across the yield time series. These models were significant in the entire 12-year time series (1990-2002) and the 1998-1999 planting period. However, empirical models in the 1998-1999 planting period resulted in a better linear fit, as compared to models in the 1990-2002 planting period. In validation, the models featuring RVI and MSAVI as the estimator variable showed strong fits between estimated yield and observed yield.

From the perspective of managing oil palm plantations, findings from this study are in agreement with a landmark report by Tucker (1979), who concluded that the correlation of vegetation index and vegetation biomass (yield) will facilitate non-destructive detection of decline in vegetation vigor, greenness or health.

NDVI and RVI are well-known indices and are the most commonly used ratio-based vegetation indices (Gilabert et al. 2002; Jackson and Huete 1991). From this study, RVI showed better correlation with yield than NDVI. Such a finding is in agreement with Aparicio et al. (2002) and Serrano et al. (2000). Both studies concluded that RVI is a better indicator than the traditional NDVI in estimating physiological response in wheat. The capability of RVI in extraction of vegetation information of young oil palm was demonstrated by Salleh (1993).

However, NDVI was found to be better correlated with yields of rice (Mohd et al. 1994) and wheat (Singh et al. 2002), and vegetation cover (Elmore et al. 2000) as compared to other vegetation indices. According to de Wit and Boorgaad (2001), NDVI is the most widely used and well understood vegetation index. This may be driven by the fact that NDVI computation is simple, and possesses the best dynamic range and sensitivity to changes in vegetation cover (Gielen and de Wit 2001). Raun et al. (2001) reported estimates of in-season yield using NDVI that was well correlated in wheat. Likewise, Inman et al. (2007) found that NDVI has potential to estimate grain yield in corn. Previous studies have also shown that crop yields can be successfully estimated using NDVI (Hayes and Decker 1996; Rasmussen 1998) and the relationship between yield and spectral reflectance could be integrated into process-based crop models for better predictive power (Moulin et al. 1998).

Thenkabail et al. (2004) indicated that the best spectral-based yield estimation model in oil palm was based on an IKONOS satellite platform, featuring red and near infrared bands. In our study, all the vegetation indices, except for GNDVI, featured red and near infrared bands. GNDVI employs the green band instead of the red band, which probably explains why GNDVI registered the lowest correlation with oil palm yield.

Murthy et al. (1994) found that vegetation indices computed from satellite imagery taken at panicle initiation and heading stages of rice showed a high correlation with yield. They concluded that satellite-derived vegetation indices could aid yield estimation in large-scale plantings. However, they cautioned that one single-date image representing one particular phenological stage may trigger difficulties in yield estimation due to the different planting dates and crop varieties commonly employed at the field scale.

However, in our study, vegetation indices extracted from the single-date QuickBird imagery performed well in yield estimation of oil palm stands aged between 3 and 7 years old. The strength of empirical models bearing RVI and NDVI within the entire 12-year time series (1990-2002) was possibly due to a larger number of combined observations from the 1998-1999 (n = 12) and 2000-2002 (n = 27) planting periods, as compared to the 1990-1997 (n = 17) planting period. Studies have shown that vegetation indices such as NDVI, RVI and SAVI derived from 3-band multispectral imagery such as Quickbird or UK DMCi II cannot be correlated well with the age of oil palm trees because the leaf area index of the oil palm canopy generally stabilizes after 10-13 years of age (Corley and Gray, 1976). The stabilized development in canopy results in less separability among mature oil palm stands, as sensed by satellite imagery. In addition, the relationship of oil palm canopy area and the age of oil palm stands using WorldView-2 in Africa has demonstrated a good relationship (R^2=0.88) for stands less than 13 years of age but no relationship was observed for older stands (Chemura, 2012). These findings support the fact that less variation in canopy and possibly biomass can be observed via remote sensing of mature oil palm stands (i.e. stands aged 13 years and over). It is also worth noting that the oil palm begins to fruit between 2.5 and 3 years after planting, and continuously produces fruits for the next 22 years with an average production of about 200 kg fresh fruit bunches per tree per year. Peak oil palm yields typically occur from 10 to 12 years after planting.

This study has demonstrated that selected QuickBird-derived vegetation indices can be used to estimate oil palm yields with reliable accuracy. In this work, the ability of selected vegetation indices, derived from a single-date archived high resolution satellite imagery, to estimate oil palm yields at the management block scale was demonstrated. This study provides an important benchmark for applying remote sensing technology in the management of plantation-scale oil palm. Oil palm yield estimation based on empirical models, as described in this work, can be computerized using a simple spreadsheet interface so as to facilitate optimal agronomic intervention, particularly with regard to crop harvesting, crop stress alleviation and input application. However, empirical models generated in such a manner are typically site-specific and may be limited by the macro- and micro-environmental factors operating within the crop field at a given time.

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