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Abstract:

Oil palm plantations are rapidly expanding in the tropics, which leads to deforestation and other associated damages to biodiversity and ecosystem services. Forest researchers and practitioners in developing nations are in need of a low-cost, accessible and user-friendly tool for detecting the establishment of industrial oil palm plantations. Google Earth Engine (GEE) is a cloud computing platform which hosts publicly available satellite images and allows for land cover classification using inbuilt algorithms. These algorithms conduct pixel-based classification via supervised learning. We demonstrate the use of GEE for the detection of industrial oil palm plantations in Tripa, Aceh, Indonesia. We performed land cover classification using different spectral bands (RGB, NIR, SWIR, TIR, all bands) from our Landsat 8 image to distinguish the following land cover classes: immature oil palm, mature oil palm, non-forest non-oil palm, forest, water, and clouds. The overall accuracy and Kappa coefficient were the highest using all bands for land cover classification, followed by RGB, SWIR, TIR, and NIR. Classification and Regression Trees (CART) and Random Forests (RFT) algorithms produced classified land cover maps which had higher overall accuracies and Kappa coefficients than the Minimum Distance (MD) algorithm. Object-based classification and using a combination of radar- and optic-based imagery are some ways in which oil palm detection can be improved within GEE. Despite its limitations, GEE does have the potential to be developed further into an accessible and low-cost tool for independent bodies to detect and monitor the expansion of oil palm plantations in the tropics.

Key-words: *Elaeis guineensis*, agricultural expansion, tropics, land cover classification, land use change

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1. Introduction

The oil palm (*Elaeis guineensis*) has become one of the most rapidly expanding equatorial crops in the world, with the global extent of oil palm cultivation increasing from 3.6 million ha in 1961 to 17.2 million ha in 2012 (FAOSTAT, 2014). Due to its multiple uses for food and industrial products, global demand for palm oil has increased over the last few decades, and has spurred both private and government sectors to invest heavily in the oil palm industry (World Bank, 2011). While oil palm production has an important role in rural development and supporting local and regional economies (World Bank, 2010), the rapid expansion of industrial oil palm plantations has also led to detrimental social and environmental impacts, especially in the region of Southeast Asia (Sheil et al., 2009), but such impacts are a growing concern in Africa as well (Wich et al., 2014).

Over the last few decades, tropical deforestation as a result of oil palm expansion has been rapid and extensive (Carlson et al., 2013; Koh et al., 2011; Uryu et al., 2008). In Kalimantan, the Indonesian side of Borneo, it is estimated that oil palm plantations were directly responsible for ~57% of 2000 - 2010 deforestation (Carlson et al., 2013); while in Sumatra, deforestation within oil palm concessions accounted for ~19% of 2000 - 2010 deforestation (Lee et al., 2013). Industrial oil palm plantations have also been singled out for impacting peat ecosystems which are important carbon sinks in Peninsular Malaysia, Borneo, and Sumatra (Koh, Miettinen, Liew, & Ghazoul, 2011; Miettinen et al., 2012). Conversion of tropical forests to oil palm plantations leads to biodiversity losses (Fitzherbert et al., 2008), higher carbon dioxide emissions (Dewi et al., 2009), and warmer stream environments as well as higher sedimentation in aquatic systems (Carlson et al., 2014). As forests around the world are increasingly exploited and subsequently converted for oil palm plantations (Butler, 2013; Hoyle and Levang, 2012), it is important to have a classification system which is able to detect oil palm land cover across the tropics in near real-time.

Mapping of oil palm land cover using satellite remote sensing data has been carried out in many studies across the tropics (Gutiérrez-Vélez et al., 2011; Li et al., 2015; Miettinen and Liew, 2010; Shafri et al., 2011; Srestasathiern and Rakwatin, 2014). There are two broad categories of using optics based methods to study land cover classification from remote sensing data: phenology-based and image-based methods (Li et al., 2015). Phenology-based methods such as Gutiérrez-Vélez et al. (2011) use temporal changes in vegetation greenness to detect the area deforested by large-scale oil palm expansion in the Peruvian Amazon. Image-based methods utilize spectral signatures as well as textural information to differentiate oil palm trees from their surroundings (Carlson et al., 2013; Thenkabail et al., 2004). Oil palm plantations can be manually digitized from satellite images, based on the unique textural information of oil palm plantations (e.g., long rectangular blocks for industrial plantations, geometric shape of oil palm canopy, presence of roads) along with expert knowledge on the land use system (Carlson et al., 2013; Uryu et al., 2008). Other studies have also tried to automate the detection of oil palm plantations based on spectral image analysis which classifies pixels based on their spectral class thresholds (Shafri et al., 2011). Some challenges related to detecting oil palm plantations using optics based methods include the difficulty in separating oil palm plantations from other spectrally similar land cover types (e.g., forests, rubber trees) (Morel et al., 2011) as well as the frequent presence of cloud cover in the tropics which hinders image analysis (Li et al., 2015). Recent use of radar data which is all-weather and all-time capable has shown great potential and suitability for oil palm mapping (Miettinen and Liew, 2010). Phased Array type L-band Synthetic Aperture Radar (PALSAR) data has been used by Miettinen and Liew (2010) for distinguishing between woody plantations including rubber (*Hevea brasiliensis*), wattles (*Acacia spp.*), and palms (oil palm and coconut (*Cocos nucifera*)). The use of both radar and optical data for image classification may provide enhanced information on land cover and use (Joshi et al., 2016). Microwave energy scattered by vegetation depends on the size, density, as well as orientation and dielectric properties of elements that are comparable to the size of the radar wavelength, while optical energy reflected by vegetation depends on the leaf structure, pigmentation and moisture (Joshi et al., 2016). Hence, radar data provide more information on the structural properties of the land, while optical products, commonly available in the form of multispectral images, offer information on spectral reflectance and can be used to accentuate land cover using different indices (e.g., Normalized Difference Vegetation Index) (Joshi et al., 2016).

These methods of classifying oil palm land cover require training in remote sensing, expensive software to process satellite images, and expensive hardware with fast computer processing power and large storage capacities (Friess et al., 2011). While it is important that such mapping exercises be carried out cautiously, these methods do require a significant amount of time, and are disadvantageous for independent monitoring bodies (e.g., environmental non-governmental organizations (NGOs) in developing countries) which wish to monitor oil palm expansion in tropical landscapes. An increasing number of producer and consumer companies have pledged to purchase certified sustainable palm oil to ensure that their supply chains do not involve tropical deforestation or zero-deforestation policies (May-Tobin et al., 2012). Certified sustainable palm oil is produced based on a set of environmental and social criteria set out by a standards body such as the Roundtable of Sustainable Palm Oil (RSPO; http://www.rspo.org/). The use of earth observation technologies is one of the ways to monitor the credibility of producer companies who have pledged themselves to zero-deforestation policies.

The advent of digital globes such as Google Earth has played an important role in facilitating public access to geospatial analysis and simple spatial analysis tools (Butler, 2006; Friess et al., 2011). Google Earth Engine (GEE) (http://earthengine.google.org) takes open source geospatial analysis one step further by providing a cloud computing platform for earth observation data analysis. It combines a public data catalogue, which consists of a nearly complete set of Landsat imagery from its start in 1972 until the present day, with a large-scale computational facility optimized for parallel processing of geospatial data (Hansen et al., 2013). In a recent global forest mapping exercise by Hansen et al. (2013), a total of 20 terapixels of Landsat data were processed on GEE, using one million CPU-core hours on 10,000 computers in parallel, in order to characterize year 2000 percent tree cover and subsequent tree cover loss and gain through 2012. This process was completed in a matter of days on GEE but would have taken 15 years for a single computer to finish (http://googleresearch.blogspot.ch/2013/11/the-first-detailed-maps-of-global.html). GEE also hosts an imagery classification system in the cloud which enables one to run supervised learning algorithms across huge datasets in real time. These algorithms are trained to identify different land cover classes using hand-drawn points and polygons on the input dataset (satellite image). This land cover classification method is rapid and accessible through the World Wide Web. Hence, GEE's computing infrastructure revolutionizes time-consuming remote sensing processes, facilitates access of remote sensing resources and tools to the public, and paves a new way forward for rapid land cover classification.

To explore the potential of GEE's imagery classification system as a low-cost, accessible and user-friendly oil palm detection tool, we used GEE's classifiers to detect and map the establishment of industrial oil palm plantations in Aceh province, Indonesia. To assess the performance of GEE's classification methods, we verified land cover maps produced by GEE with a set of randomly selected training points. In so doing, we aim to evaluate GEE as a potential oil palm monitoring system for scientists and NGOs in tropical developing countries.

2. Study site

Our study site is located at Tripa (3°50’31 N, 96°33’17 E), which is on the west coast of Aceh province, Indonesia. The Tripa landscape covers an area of ~1,020 km^2, and falls under the administration of two districts, Nagan Raya and Aceh Barat Daya. Our study area (314 km^2) is part of the Tripa landscape. In the early 1990s, Tripa was covered with pristine peat swamp forests and hosted as many as 1,000 Sumatran orangutans (*Pongo abelii*) (Wich et al., 2011). This landscape is characterized by large peat domes and deep peat with peat depth greater than 3 meters (Wich et al., 2011). However over the last two and a half decades, the Tripa ecosystem has seen a rapid decline in forest cover mainly due to oil palm agricultural expansion at both the scale of industrial and smallholder plantations (Tata et al., 2010). Due to the predominance of oil palm agriculture in this landscape and rapid transitions of forest to oil palm land cover, we used Tripa as a case study for testing GEE’s imagery classification system for detecting industrial oil palm plantations.

3. Data and Methods

We searched for Landsat 8 top-of-atmosphere reflectance (TOA) images from 1st January 2014 to 31st December 2014 from GEE’s data catalogue and selected the image with the least cloud cover as the image used for supervised classification of oil palm land cover. Landsat 8 images are taken every 16 days and have a resolution of 30 m, making them useful for monitoring land cover change over time.

We aimed to assess GEE’s ability to separate immature oil palm, mature oil palm, non-forest non-oil palm, and forest land cover classes. We plotted 450 training points for each land cover class. The classes of the training points were specified by the lead author who has experience working in Tripa and is familiar with the land cover in this landscape. We first identified industrial oil palm plantations using rectangular grid lines which indicate oil palm development (Uryu et al., 2008). Of these plantations, ‘Immature Oil Palm’ displayed a lighter shade of green compared to ‘Mature Oil Palm’. In the absence of rectangular grid lines which indicate the absence of industrial oil palm development, burnt areas and vegetation mosaics were classified under ‘Non-forest non-oil palm’ land cover. ‘Forest’ land cover displayed a contiguous vegetation cover with a dark shade of green. Other additional land cover classes included ‘Water’ and ‘Clouds’.

We used 60% of these training points to train the GEE classifiers while the remaining 40% were used to conduct accuracy assessments. We used different spectral bands from the Landsat 8 TOA image for image classification. We included red, green and blue bands (RGB), Near Infra-Red (NIR), Short Wave Infra-Red (SWIR), Thermal Infra-Red (TIR), and all bands (including RGB, NIR, SWIR and TIR) for image classification. During image classification, all pixels in the input image were assigned to a class, according to their spectral signature. GEE has 10 classifiers, CART, Random Forest, Minimum Distance, GMO MaxEnt, Naïve Bayes, SVM, Perceptron, IKPamir, and Winnow, for image classification. Each of these classifiers uses a different algorithm to assign pixels to classes and perform land cover classification in a pixel-based manner. Out of the nine classifiers listed above, GMO MaxEnt, Naïve Bayes, SVM, Perceptron, IKPamir and Winnow produced land cover maps which had little distinction among the different classes. Hence, we excluded the above six classifiers and compared GEE maps produced by classifiers CART, Random Forest, and Minimum Distance (Table 1).

A validation error matrix was produced in GEE and the overall, producer’s and user’s accuracy were calculated. Since we were more interested in understanding how GEE classification detects industrial oil palm, we focused more on the producer's and user's accuracy for immature and mature oil palm land cover classes. We calculated the Kappa coefficient which tests whether a land cover map is significantly better than if a map had been generated at random (Congalton, 1996). Kappa values are generally characterized into 3 groupings: 0.80 represents strong agreement, 0.40-0.80 represents moderate agreement, and below 0.40 represents poor agreement (Congalton, 1996). However, the Kappa coefficient has come under recent question as a useful metric for accuracy assessments (Pontius and Millones, 2011), and should be interpreted with caution. All geospatial analyses were conducted in GEE API (https://code.earthengine.google.com/). The Earth Engine code for this analysis is available under Supplementary Material.

4. Results

GEE classifiers are able to detect industrial oil palm land cover from Landsat 8 images. In particular, the CART and Random Forest (RFT) classifiers provided the highest overall accuracy scores using ALL bands and RGB bands and outperformed the Minimum Distance (MD) classifier (Table 2; Figure 1). Based on the overall accuracy scores, CART classification using ALL bands came in first (93.6% with a Kappa coefficient of 0.92), followed by Random Forest (RFT) classification using ALL bands (91.2% with a Kappa coefficient of 0.89), and CART classification using RGB bands (Table 2). The near infrared (NIR) and thermal infrared (TIR) bands performed poorly compared to the ALL, RGB and SWIR bands.

GEE classifiers CART and RFT using ALL and RGB bands provided the best producer's and user's accuracy scores for distinguishing immature oil palm (Table 3). The producer's accuracy for immature oil palm was the highest under the CART classifier using ALL bands (94%), followed by the RFT classifier using ALL bands (88%), and RFT classifier using

RGB bands (83%). The user's accuracy for immature oil palm was highest for CART classifier using RGB bands (92%), followed by CART classifier using ALL bands (88%), and RFT classifier using RGB bands (86%).

GEE classifiers CART and RFT using ALL and RGB bands also provided the best producer's and user's accuracy scores for distinguishing mature oil palm (Table 3). Interestingly, the producer's accuracy score for MD classifier using SWIR bands was the second highest (Table 3). The producer's accuracy for mature oil palm was highest for CART classifier using ALL bands, followed by MD classifier using SWIR bands (82%), and RFT classifier using ALL bands (80%). The user's accuracy for mature oil palm was highest for CART classifier using ALL bands (88%), followed by RFT classifier using ALL bands (87%), and RFT classifier using RGB bands (71%).

5. Discussion

GEE classifiers are able to detect industrial oil palm land cover from Landsat 8 images, which are a useful source of publicly available satellite images for near real-time monitoring of land use change. Based on the high overall accuracy and moderate Kappa coefficients, CART and RFT classifiers outperformed the MD classifier to produce classified land cover images of an oil palm dominated landscape. Under MD classification, the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature is calculated, and the class of the candidate pixel is then assigned to the class for which the spectral distance is the lowest. Hence, the MD approach works well when the distance between the means is large compared to the spread of each class with respect to its mean. Since the land cover classes being segregated here are very similar (immature oil palm, mature oil palm, non-forest non-oil palm, forest), the distance between the means may be small and result in the poor performance of the MD classifier. In contrast, CART and RFT classifiers are machine learning classifiers and use a decision tree as a predictive model to classify candidate pixels into classes. They are strictly nonparametric and are less sensitive to the distributions of the input data (Friedl and Brodley, 1997).

While near infrared bands from high resolution imagery have been used to successfully detect diseases in oil palm trees (Santoso et al., 2011; Shafri et al., 2011; Thenkabail et al., 2004), they are less useful in itself for distinguishing land cover classes in our study. The use of both infrared bands and visual bands (ALL) as well as visual bands themselves were most useful in distinguishing land cover classes in our study. Distinguishing oil palm plantations from secondary vegetation and flooded forests has been shown to be a challenge due to both land covers being spectrally and structurally similar (Morel et al., 2011; Santos and Messina, 2008). Hence pixel-based image analysis without the use of non-spectral information such as the shape and texture of the image pixels may be insufficient for detecting oil palm plantations. In the case of differentiating industrial oil palm from forests, an object-based classification approach, which takes into consideration spectral, shape and contextual relationships of groups of image pixels, will be more effective (Carlson et al., 2013; Uryu et al., 2008). A combination of PALSAR and Landsat images have also been shown to be effective for differentiating oil palm plantations from forests (Li et al., 2015; Miettinen and Liew, 2010). Synthetic Aperture Radar (SAR) data from the European Union Space Agency is available on GEE and can be considered in combination with Landsat images for future detection of industrial oil palm plantations. Detecting immature oil palm and smallholder oil palm plantations is an important area for future research to detect oil palm expansion in its early phase, and for keeping track of smallholder-led expansion which is occurring more frequently in places such as Cameroon (Nkongho et al., 2014) and Sumatra, Indonesia (Ekadinata et al., 2013).

Our results show the potential use of GEE’s imagery classification system as a tool for oil palm land cover mapping but also reveal the limitations of this classification system especially in relation to the level of accuracy for detecting immature and mature oil palm plantations from other land cover types with similar spectral signatures. In most oil palm mapping studies, manual digitization of satellite imagery, accompanied by intensive field visits are commonly employed to detect oil palm from other land cover types (Carlson et al., 2013; Uryu et al., 2008). Such techniques ensure a higher level of accuracy and are able to differentiate immature, young plantations from other land cover types such as shrub or agricultural land. However, such high level accuracy mapping techniques also require substantial expertise, resources and time, which is difficult to do on a frequent basis. Hence, there is a tradeoff between time and resources, and the level of accuracy of oil palm mapping within GEE’s imagery classification system. The oil palm classification method demonstrated in GEE is useful to provide a quick understanding of oil palm plantations present in the landscape. This in itself is advantageous for independent monitoring bodies to conduct a survey of the landscape in question and conduct more detailed assessments if necessary.

In this study, we assessed the use of GEE’s classifiers for detecting industrial oil palm plantations in Tripa, Indonesia. Expanding the scope of our study to include other regions of Indonesia (e.g., Kalimantan and Papua) as well as other parts of the world (e.g., Cameroon and Peru where oil palm is expanding rapidly (Butler, 2013; Mousseau, 2013)) would be a useful next step to test GEE’s oil palm mapping for different contexts of oil palm development. The ultimate goal would be to develop an online tool where preliminary detection of mature, industrial oil palm plantations can be made publicly available to various stakeholders (e.g., researchers, non-governmental organizations, government officials, as well as industry players) to increase monitoring efforts and improve transparency on whether palm oil production is linked to tropical deforestation. Hence, a near real-time detection for oil palm expansion will allow for better monitoring of oil palm expansion within the tropics, and has potential implications for the traceability of zero-deforestation palm oil products. Despite its limitations, GEE classification system does have the potential to be developed further into an accessible and low-cost tool for detecting industrial oil palm plantations in the tropics.

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Tables

Table 1. GEE's classifier algorithms which were used in our study.

Classifier	Description
Classification and Regression Trees (CART)	CART is a non-parametric decision tree learning technique which produces prediction models from training data. The models are obtained by recursively partitioning the data space and fitting a simple regression or classification model within each partition to predict continuous or categorical dependent variables respectively.
Random Forests (RFT)	Random forests are an ensemble learning method which generates successive decision trees that are independently constructed using a random sample of the data. The best split at each node of the decision tree is based on a subset of randomly selected predictor variables. The number of trees required for a robust result depends on the number of predictors. The GEE default input parameters used for the Random Forest classifier were: number of Rifle decision trees to create per class = 1; number of variables per split = square root of the number of variables; minimum size of a terminal node = 1; and fraction of input to bag per tree = 0.5.
Minimum Distance (MD)	Minimum Distance uses spectral characteristics of the training samples which have been chosen as representatives of the different object classes. The Euclidean Distance between the candidate pixel values and the mean values of each class is calculated and the candidate pixel is allocated to the class with the shortest Euclidean Distance.

Table 2. Overall accuracy and Kappa coefficient for GEE classified maps produced by classifiers CART, RFT and MD using different combinations of spectral bands (RGB, NIR, SWIR, TIR, ALL). Table ranked based on descending overall accuracy.

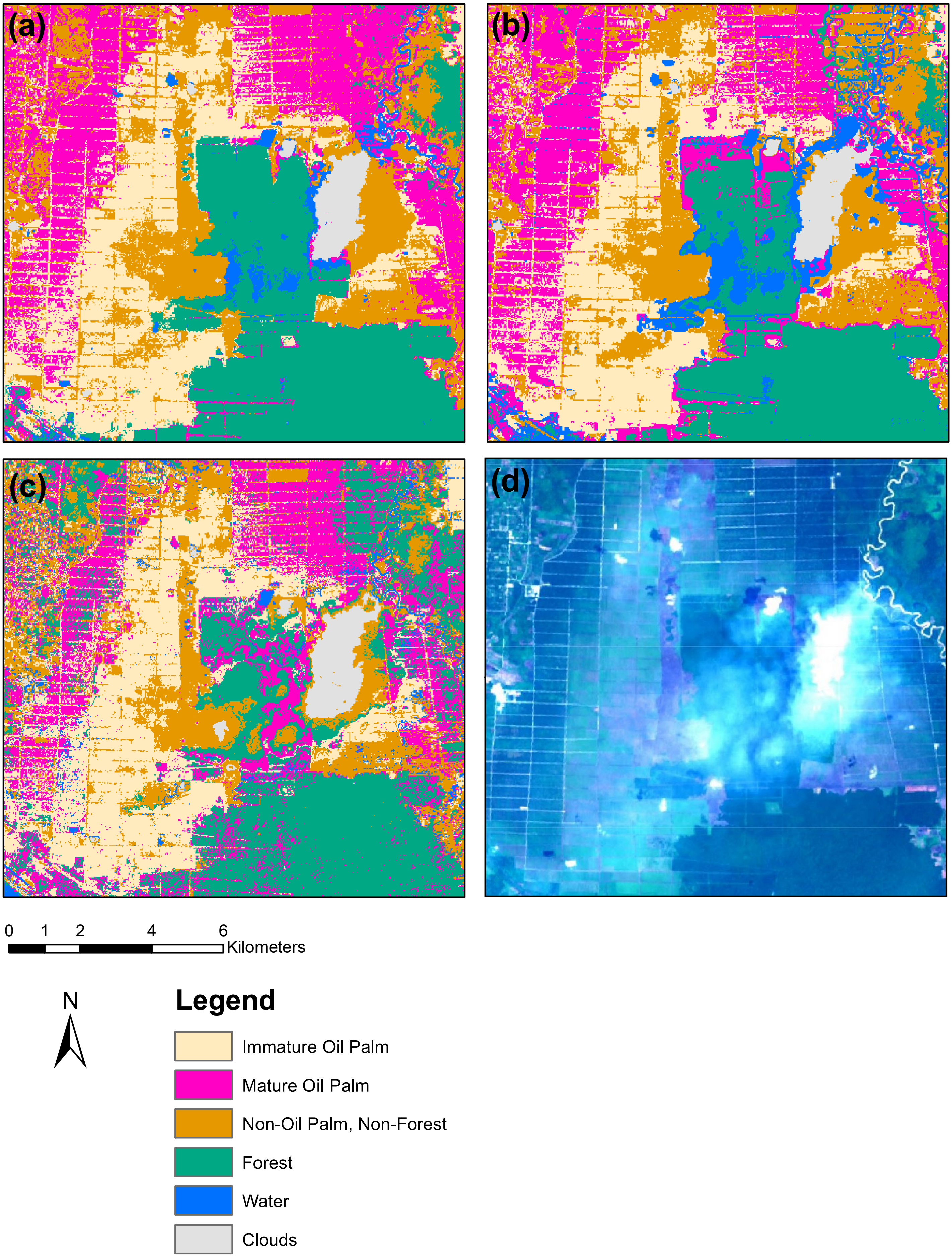
Bands	**Classifier**	**Overall accuracy**	**Kappa coefficient**
ALL	CART	93.6%	0.92
ALL	RFT	91.2%	0.89
RGB	CART	84.9%	0.82
RGB	RFT	81.2%	0.77
SWIR	CART	70.1%	0.64
SWIR	RFT	66.5%	0.60
SWIR	MD	63.6%	0.56
RGB	MD	62.6%	0.55
TIR	CART	62.3%	0.55
ALL	MD	59.7%	0.52
TIR	RFT	57.0%	0.48
TIR	MD	56.3%	0.47
NIR	MD	46.9%	0.36
NIR	CART	45.5%	0.35
NIR	RFT	39.0%	0.27

Table 3. Producer's (%) and User's (%) accuracy of GEE classified maps for all land cover classes using different spectral bands and classifiers. ‘Prod’ refers to Producer’s accuracy and ‘User’ refers to User’s accuracy. Shaded and underlined values represent the three highest values for immature and mature oil palm producer’s and user’s accuracy.

		Land classes											
Bands	**Classifier**	**Immature Oil Palm**		**Mature Oil Palm**		**Non-forest non-oil palm**		**Forest**		**Water**		**Clouds**	
		Prod	**User**	**Prod**	**User**	**Prod**	**User**	**Prod**	**User**	**Prod**	**User**	**Prod**	**User**
ALL	**CART**	94%	88%	88%	88%	87%	92%	99%	98%	96%	97%	97%	98%
	RFT	88%	84%	80%	87%	85%	81%	98%	99%	96%	97%	100%	98%
	MD	22%	32%	72%	60%	53%	43%	78%	63%	72%	69%	56%	100%
RGB	**CART**	82%	92%	77%	70%	80%	80%	85%	78%	87%	93%	99%	98%
	RFT	83%	86%	72%	71%	68%	74%	85%	76%	81%	83%	98%	97%
	MD	80%	64%	68%	57%	49%	72%	63%	56%	57%	49%	58%	99%
SWIR	**CART**	66%	57%	65%	59%	70%	66%	94%	92%	84%	85%	39%	58%
	RFT	48%	52%	65%	56%	58%	60%	94%	92%	82%	87%	50%	51%
	MD	57%	51%	82%	54%	29%	55%	100%	81%	77%	95%	36%	45%
TIR	**CART**	54%	52%	62%	69%	50%	55%	79%	68%	62%	64%	67%	66%
	RFT	49%	49%	56%	58%	46%	43%	66%	69%	61%	60%	66%	66%
	MD	28%	42%	76%	59%	50%	44%	76%	56%	66%	60%	43%	96%
NIR	**CART**	20%	28%	49%	37%	35%	45%	66%	55%	67%	62%	35%	39%
	RFT	20%	25%	45%	36%	30%	31%	48%	44%	57%	64%	35%	34%
	MD	20%	29%	23%	41%	32%	37%	77%	54%	65%	63%	63%	45%

Figure Caption

Figure 1. Classification results of Classification and Regression Trees (CART) using ALL bands (a), Random Forests (RFT) using ALL bands (b), and CART using RGB bands (c) of Landsat 8 TOA image from 2014 (d).



(a)
(b)
(c)
(d)
0
1
2
4
6
Kilometers
N
Legend
Immature Oil Palm
Mature Oil Palm
Non-Oil Palm, Non-Forest
Forest
Water
Clouds