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A method of mapping forest fuel types in peat swamp forest

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In response to growing concerns over the burning of peat swamp forests, researchers have begun developing methods of mapping forest fire. Forest fire is one of the major causes of deforestation of tropical peat swamps in Malaysia. A way of identifying which peat swamp forest is vulnerable to forest fire is to develop a fuel type map to classify forest fire into different risk levels. In this study, remote sensing and geographical information system (GIS) techniques were integrated. Landsat Thematic Mapper (TM) image dated April 3rd, 1999, which corresponded to fire incident in this study area was used. The objective of this paper is to map fuel types in peat swamp forests. Results show that greenness and wetness components of Tasselled cap, used in classification, accurately captured greener and wetter area by combining supervised image and Tasselled cap image. The overall kappa statistics was 0.94 for combined supervised and Tasselled Cap classification. High values of kappa statistics for certain vegetation classes were due to the availability of representative pixels in the classes.

Key words: Forest fire, Peat swamp, forest fuel classification.

INTRODUCTION

Conservation is critical to a large tropical peat forests in Southeast Asia, such as those in Kalimantan, Borneo, and Malaysia. Tropical peat lands contribute significantly to terrestrial carbon because of their high carbon content and high carbon accumulation rates, which are higher compared to those of boreal and temperate peat lands. Fires are one of the negative impacts which caused forest and land degradation. Fire produces high carbon emission as a consequence of fire smoke (Miettinen and Liew, 2010). Changes in fire regimes have also increased attention on many national parks and protected area due to forest fire (Crabtree et al., 2009). Forest disturbance caused reduction in live biomass and increase the amount of coarse woody debris and the forest floor (Goulden et al., 2011).

More research is necessary for countries such as Malaysia and Indonesia to ensure adequate fire-monitoring and prevention. The extensive habitat damage and poor air quality are some of the effects of forest fires caused by El Nino (El Nino Southern Oscillation or ENSO1997/1978) in Southeast Asia, South America, and southern United States. Peat lands consist of layers of organic materials containing a significant portion of the world's carbon in which tropical peat lands account for about 15% of the global total. These peat lands are sensitive ecosystems and are vulnerable to seasonal changes within their local and regional climates as well as to disturbances due to human activities. Small scale activities, such as camping, can bring about forest fires, which release carbon into the atmosphere and contribute to environmental degradation.

On the other hand, large scale activities, such as agricultural conversion, pose a threat via extensive land-clearing. Oil palm conversion in particular threatens pristine peat swamp forest and distinctive vegetation species. Peat swamp areas are viewed to be suitable for oil palm plantations. Most of the lands needed for expansion of the oil-palm industry are located in Malaysia

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and Indonesia. Contribution of peat lands to global carbon cycle is relatively high for the temperate zone, and about 15% of the global peat land carbon may reside in tropical peat land. There are about 2.7 million ha of peat and organic soils in Malaysia. Sarawak has the largest area of peat in the country, covering about 1.66 million ha and constituting 13% of the state (Wong, 1991). Pahang was represented as the second largest peat land in Peninsular Malaysia, boasting about 219 561 ha of peat (Law and Silvadurai, 1968). The integration of remote sensing and GIS may improve accuracy and reduce the cost of fuel mapping. With development of new satellite sensors and radars such as ASTER and ALOS PALSAR, respectively, remote sensing becomes an ultimate tool in mapping vegetation types.

Recent research found using MODIS (Moderate Resolution Imaging Spectroradiometer) imagery fire issues such as fire risk assessment can be done in Brazilian Amazon forest (Maeda et al., 2011). In addition, fuel type map can be generated using high resolution satellite data such as Landsat TM (Riano et al., 2002). Therefore, we used Landsat TM image to classify fuel types by using combined maximum likelihood classifier and indices-transformed images to assess the accuracy of the classification. Techniques employed in this study tend to improve classification because it is sensitive to phonological changes (Dymond, 2005).

Therefore, the indices can be used to distinguish the green vegetation with soil from green vegetation and brown vegetation. Crist and Cicone (1984) indicated that Tasselled Cap could discriminate brightness of soil, greenness of vegetation, and wetness of moisture. One of the advantages of using Tasselled Cap is that it incorporates more information into vegetation indices using six different bands of light.

Accurate fuel type maps provide information for fire managers to carry out prevention, detection, and suppression strategies, such as forest cleaning, prescribed burning, and vigilance tower locations (Riano et al., 2002). Fire risk can be reduced by prioritizing fire management through characterization of fuel types. In pre-fire planning, an important factor that should be considered is fuel type.

The relationship of fuel type with fire hazard is unpredictable and varies according to area. Therefore, fuel maps are essential for computing spatial fire hazard and risk and simulating fire growth and intensity across a landscape (Keane, 2001). Fuel mapping is an extremely difficult and complex process, requiring expertise in remotely sensed image classification and GIS. Data that can be used for classification come mainly from satellite images, aerial photography, and field measurements. However, there is still a need to find an appropriate and accurate method for fuel mapping.

Therefore, fuel types need to be well classified by applying continuous improvised methods to facilitate risk hazard assessment in fire prone area.

Forest fire in Malaysia

In Malaysia, large forest land is being continually converted to non-forestry use, and burning is one of the methods being used in the process (AIFM, 1996). Recently, the problems caused by fire in Malaysia have become more serious and need to be addressed in the right perspective. The problems caused by fire are not only affecting the people in Malaysia, but also those who live beyond the Malaysian boundary. The threat of fire to the forests in Peninsular Malaysia is minimal compared to Borneo. Severe forest fires were recorded in Sabah since 1993. In 1998, more than 100 000 ha of forest reserves in Kudat, Sandakan, Kota Kinabalu, Keningau, and Tawau were burned. In Sarawak, forest fires were confined to plantation forests. A small plantation area of *Acacia mangium* and *Shorea macrophylla* were destroyed every year from 1981 to 1994 due to agricultural activities in adjoining farmlands. According to Sarawak Environmental Quality Report (EQR, 2000), March 1998 was when the most severe fire occurred where peat swamp forest near Miri burned. Air Pollution Index (API) reached the “hazardous level” and was later stabilized down to “very unhealthy” in April 1998.

Peat swamp forest found in the lowlands of tropical area represents another forest fire fuel type. With decreasing precipitation and lowering of the water table in the peat swamp biome, the organic layers progressively dry out. During 1982 to 1983 ENSO, a number of observations in East Kalimantan confirmed a desiccation of more than 1 to 2 m of organic layers (Johnson, 1984). While the spread of surface and ground fires in this type of organic terrain is not severe, deep burning of organic matter leads to toppling of trees and complete removal of standing biomass. It is further assumed that smouldering organic fires may persist throughout the subsequent rainfall period and get reactivated as an ignition source in the next dry spell (Goldammer and Seibert, 1989). Severe occurrences of forest fires in peat swamp forests were recorded in Pahang from early 1998 until May 1998, in which more than 10 000 ha of peat swamp forest burned (Forest Research Institute of Malaysia/FRIM, 1998). According to FRIM (1998), peat swamp forest fire in Pahang occurred in heavily disturbed (logged) land forest because of improper water management and prolong dryness.

Open burning of plant residues in large tract of land peat, shifting cultivations, and collection of non-timber forest products by *Orang Asli*, as well as lack of an integrated water management programme also contributed to the forest fire. There are many possible causes of forest fire in Malaysia. FRIM (1998) reported that the possible causes of forest fire, particularly in peat swamp forest in Peninsular Malaysia in 1998 were land clearing for oil palm plantation and other industrial purposes, fishing, camping, and other activities by local and *Orang Asli* communities as well as unknown causes. In a report compiled by Department of Forestry of Peninsular Malaysia (2001), most cases of forest fire in Peninsular Malaysia in 1998 were caused by negligence and carelessness, and six cases were activities by *Orang Asli*. Only one case was caused by spark from high voltage electricity cables.

MATERIALS AND METHODS

Study area

This study was conducted at peat swamp forest of Pekan, Kuantan, Pahang, west of Malaysia. This area is located at longitude 103° 16' E and latitude 3° 44' N, covering approximately 2480.95 ha of land and bordered by a newly established oil palm plantation (Figure 1). The climate of Pahang is typical to Peninsular Malaysia which experiences the equatorial climate. The annual averages of temperatures are between 20.5 and 36°C. The maximum annual rainfall was 3601.6 mm, which occurred in 1993 while the minimum annual rainfall was 1908 mm which was in 1997. For rainy days, the yearly maximum was 222 days (that is, year 1999) while the minimum was 140 days (that is 1997). In 1998, total annual rainfall was 2970 mm. During that year, the monthly maximum rainfall was 1108 mm, which occurred in December while the minimum rainfall was 1.2 mm, which occurred in February (Figure 2 and Table 1). Relative humidity (RH) was between 77 and 89%, and RH of 79% was recorded in February (Figure 3).

Highly disturbed peat swamp forest due to fire allowed fast growing species such as sedges and grasses to replace tree communities. The disturbed peat swamp forest areas consist of (1) totally destructed sites - for example industrial estates and housing areas, (2) destructed sites - for example agricultural areas such as oil palm, (3) successional level – (a) pioneer community, (b) alang alang community (*Imperata cylindrical)* (c) weed community, (d) *Macaranga* community, and (4) secondary forest. Disturbed peat swamp forests also generate more fern colonies at the first stage of regeneration. Huge differences between natural peat swamp vegetation composition, structures, and species are generally a consequence of destroyed hydrological systems such as streams (Manshhor and Asyraf, 2001). A forest fire was recorded on 12th March 1998 at the study area. Although forest fire is a repeated incident in Penor/Kuantan District, it was the first forest fire occurrence in that particular area. According to the Kuantan Forest Department District officers, land clearing activities at Ladang Sri Meranti Oil Palm Plantation was believed to cause the fire, which was located next to the study area.

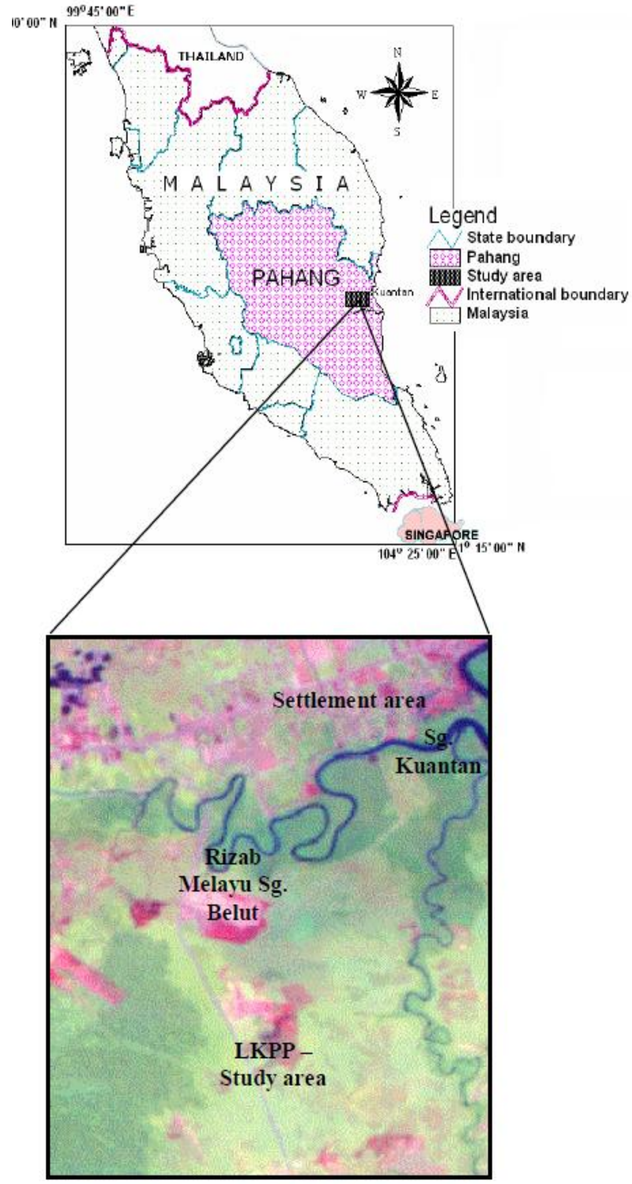

Figure 1. Locations of the study area.

Image processing

In this study, Landsat TM image of 12th April 1999 was retrieved and radiometrically corrected by using normalization. This simple method is based primarily on the fact that infrared data (> 0.7 μm) are largely free of atmospheric scattering effects, whereas the visible region (0.4 to 0.7 μm) is strongly influenced by them. The method involves evaluating histograms of the various bands of scattering, taking place in these wavelengths (Jensen, 1996).

Haze reduction was applied to reduce atmospheric scattering effects in the visible band, that is bands 1 to 3. Haze reduction method is designed to minimize the influence of path radiance effects. One mean of haze compensation in multispectral data is to observe the radiance recorded over the target areas of essentially zero reflectance. For example, the reflectance of deep clear water is essentially zero in near-infrared region spectrum (Lillesand and Kiefer, 2000). Haze reduction routine was applied throughout the scene of the study area.

Fuel type mapping

Landsat TM images acquired in 2000 (for the same area), topography maps, and land use maps were used as reference during the geometric correction procedure. Accurate registration of multi-spectral remote sensing data is essential for analyzing land use and land cover conditions of a particular geographical location. In this study, a first-order polynomial linear transformation function was used, and nearest neighborhood re-sampling algorithm was applied, since this did not alter the radiometric values of individual pixels.

In this study, unsupervised classification technique was applied to supplement the classification process and provide better identification of classes. Unsupervised classification technique is an automatic, fast, and effective tool to label the pixels into simple land process (Jensen, 2005). The iterative process attempts to minimize the distance between clusters' centres, while minimizing the variance

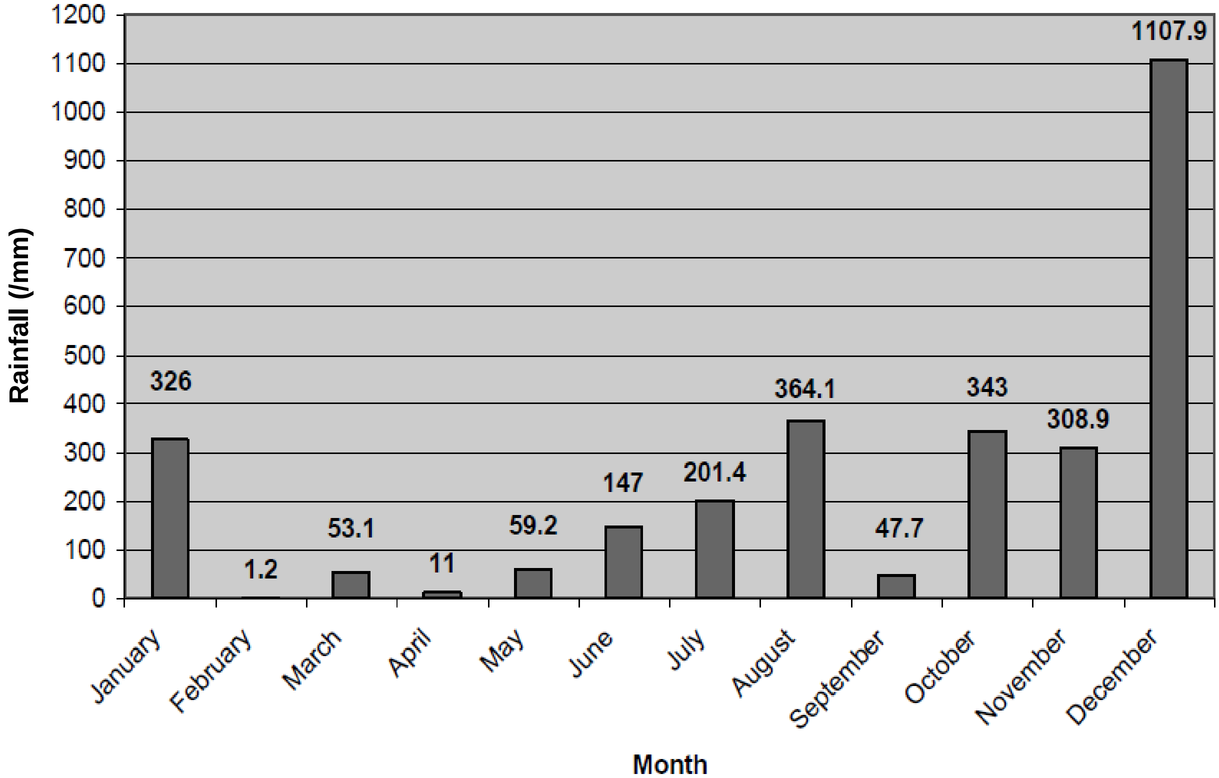

Figure 2. Rainfall of the study area in 1998.

Table 1. Rainfall and rainy days for ten years period (1990 – 1999) in Kuantan, Pahang.

No.	Year	Rainfall (mm)	Rain days
1.	1990	2699.7	167
2.	1991	3048.2	187
3.	1992	2847.5	189
4.	1993	3601.6	194
5.	1994	3408.6	214
6.	1995	3081.3	198
7.	1996	2245.0	185
8.	1997	1908.0	140
9.	1998	2970.0	170
10.	1999	3242.2	222

Source: Malaysia Meteorological Service, 2000.

within each cluster. This technique requires a defined number of classes to which pixels will be assigned. Furthermore, it represent a data class, assigns pixels into candidate clusters, and then moves them from one cluster to another in an interactive classes. It requires a minimal input as low as five pixels or fewer to can separate out all the basic land-cover types, for example, forest from non-forest. The Maximum Likelihood Classifier (MLC) is one of the most important image classification methods that have been widely used in vegetation and land cover mapping. It was used to assess the spectral response patterns, which quantitatively evaluates both the variance and covariance of the spectral data of the training sites when classifying an unknown pixel and placing pixels into the class with the highest probability of belonging (Lillesand and Kiefer, 2000). Moreover, it was also tested for fuel model (Lanorte and Lasaponara, 2008). In this study, more than 60 samples were collected during the classification process. Since the classes were close together, a high collection of training data were required. This is especially true because the classes have a variety of spectral responses or tones. As such, the same pixels of the training data were merged and the processing of training data collection was repeated to match the actual class.

This was an attempt to improve discriminations amongst different

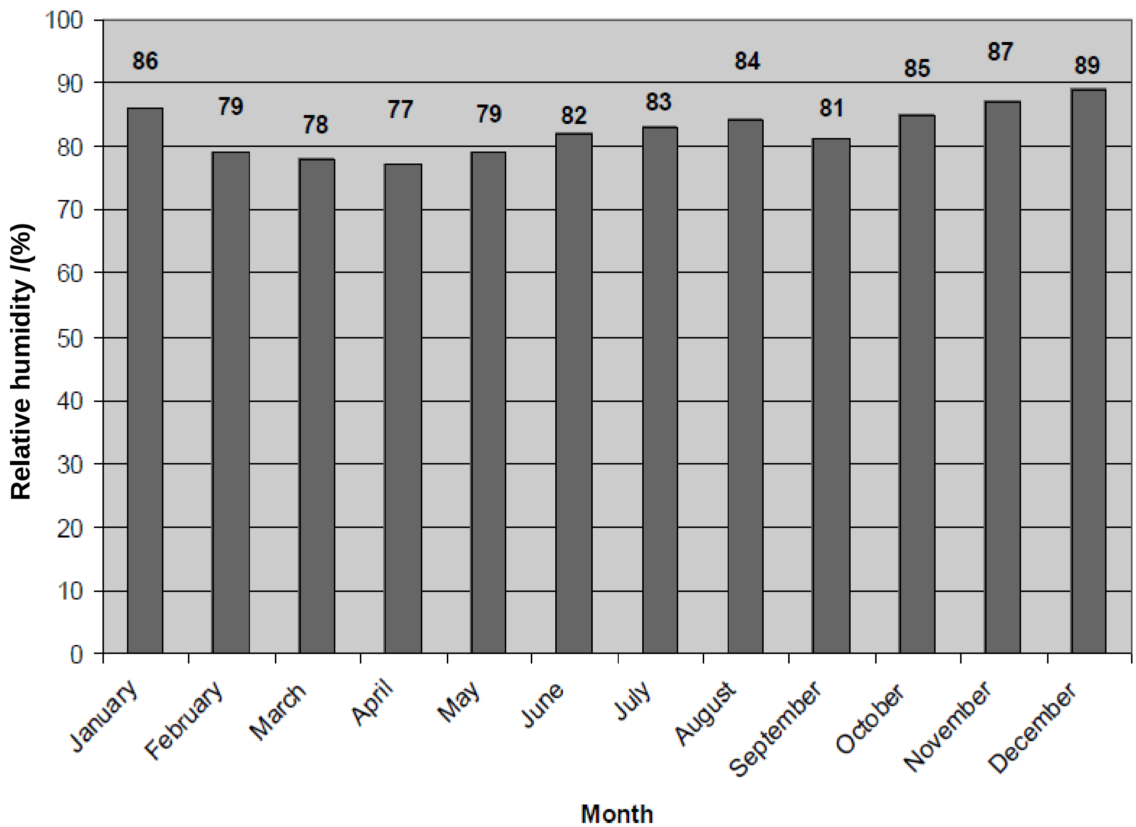

Figure 3. Relative humidity of the study area in 1998.

ground conditions, such as vegetation (peat swamp forest), soil (burn peat), and water (canal). The vegetation types in the study area were analyzed using digital classification systems, specifically, vegetation index of Tasselled Cap (TC) transformation (Christ and Cicone, 1984). Vegetation index measures the amount and distribution of green vegetations by utilizing its capacity to intensely absorb solar radiation in the red spectral region and strongly scatter it in the near-infrared (Gobron et al., 2000).

The nine fuel type classes were categorized based on the criteria set by Manshhor and Asyraf (2001) and also adapted and modified from Prometheus system (Lanorte and Lasaponara, 2007). Particularly, the fuel types of the study area were identified and carefully verified during the field work of this study. Photos for the study area were taken immediately after the acquisition of Landsat TM image data along with the fuel types. In this study, grasslands covered about half of the study area. In Southeast Asia, canals provide accessibility to illegal users who often drain peat swamps for oil palm plantations. Drained peat swamps will lose their ecological functions of soaking and storing water to mitigate floods and as water catchments to buffer coastal lands from the intrusion of salty marine water (Ainuddin et al., 2006). This draining causes oxidation and collapsing of the soil where fine fuels such as grasslands, and slash fuels within the peat will be drier during the drought; thereby increasing the likelihood of ignition by illegal users such as hunters and honey collectors. The category of 'Bushes-1' was a pioneer succession species, which was mostly found in small patches and scattered in highly disturbed peat swamp forest widely across Malaysia and Indonesia (Table 2). Moreover, peat lands were also present over large contiguous areas in both countries (Dymond et al., 2002).

Tasselled cap transformation (TC)

TC has advantages over Normalized Difference Index (NDVI), in that it incorporates more information by using six bands of light (excluding the thermal band). Crist and Cicone (1984) developed this index by producing three data structure axes defining the vegetation information content: brightness, which is the weighted sum of all bands as determined by the phonological variation in soil reflectance; greenness, which is orthogonal to brightness and measures the contrast between the near infrared and visible bands; and wetness, which relates to canopy and soil moisture. The usefulness of the TC components (greenness, brightness, and wetness) was corroborated by Wang and Xu (2009), as well as by Hansen et al. (2001), in a study which estimated the age, structure, and complexity of mature and old-growth forest stands. TC can also be used to re-classify previously analyzed data by bringing a new perspective to the data structure, allowing a more direct view and defining features that correspond to the spectral variations.

Although TC was originally developed for agricultural applications, it has been found to be sensitive to the structural characteristics of forest environments as well. In particular, changes in the TC wetness components have been identified as a reliable indicator of changes in the forest, particularly damages caused by forest fires. Crist et al. (1986) stressed the usefulness of the wetness components in distinguishing forest and natural vegetation from cultivated vegetation at TM spatial resolutions. This capability shows the advantage of TC in detecting the increased shadowing in forest stands, as compared to crop or grass canopies, for forest classifications. TC is also used to overcome several challenges when performing land cover classifications within a tropical forest

Table 2. Description of fuel types observed during field work classified using MLC and Tasseled Cap transformation techniques.

No.	Fuel type	Description
1	Canal-1	Drain in peat swamp forest
2	Cleared land and burnt area-1	Open area of peat swamp forest which had been previously burned which remained with dead stumps
3	Cleared land-1	Open area of peat swamp forest
4	Young oil palm and burnt area	Bare ground with young oil palm plantation
5	Bushes	Area found near the roads invaded by *Imperata*
6	Bushes-1	Area found in peat swamp forest invaded by *Imperata* and *Palmae* groups
7	Peat1 and road	Open peat swamp forest, and secondary and main road
8	Peat	Wetland with variable vegetation types

region. It is a significant challenge, for example, to acquire data in a tropical region on days with high cloud cover and when water vapour is too low. During the rainy season in tropical regions, cloud cover is almost a daily occurrence.

In such situation, the TC wetness measure proved a reliable indicator of forest haze reduction because it enhances image interpretation through minimizing the influence of path radiance data. Unlike other vegetation indices, such as the NDVI, TC is intended to detect relatively low-level changes in high-density forests, such as peat swamps. Land cleared by forest fires can be detected by using the TC index as the algorithm, as many studies have shown it to be an effective means for assessing forest transformations caused by forest fires and clear cuts (Ramsey et al., 2001).

Furthermore, Collins and Woodcock (1996) agreed that the change in information was highly correlated with the wetness components of the TM TC transformation. NDVI, on the other hand, is limited in its ability to detect changes in land cover within forests because biophysical vegetation parameters are difficult to detect in a "saturated" mode (Huete et al., 1997).

RESULTS

Fuel type map

The fuel-type layer was obtained from a combination of supervised classifications and TC transformations of the TM image acquired on 3rd April 1999. Nine categories were defined: (i) Canal; (ii) Water logged; (iii) Cleared land and Burnt area-1; (iv) Cleared land-1; (v) Young oil palm and Burnt area; (vi) Bushes; (vii) Bushes-1; (viii)Peat-1 and Road, and (ix) Peat (Table 3). The fuel-type layers are depicted in Figure 4. Four standard measures of accuracies are: 1) producer's accuracy, 2) user's accuracy, 3) overall accuracy, and 4) the Kappa statistical assessment. The overall accuracy is the percentage of correctly classified samples which were calculated by summing the number of pixels classified correctly and dividing by the total number of pixels (Lanorte and Lasaponara, 2007). All four of these accuracies were computed in order to evaluate the quality of the classifications. The omission error was presented by producer's accuracy which the measure of omission errors is corresponding to those pixels belonging to the class of interest which the classifier has failed to recognize. The user's accuracy on the other hand, refers to the measure of commission errors that correspond to those pixels from other classes which the classifier has labeled as belonging to the class of interest (Richards and Jia, 1999). Kappa accounts for all the elements of the confusion matrix and excludes agreement that occurs by chance.

The Kappa coefficient expresses the proportionate reduction in errors generated by the classification process. Congalton (1991) found that Kappa provides a more rigorous assessment of classification accuracy. Supervised classification of Tasselled Cap transformation images were applied to four-band layers of brightness, greenness, wetness, and haze, for bands 1, 2, 3, and 4, respectively. Since the Tasselled Cap images appeared in different variations in each class, such as 'Cleared land' (mixed burnt area), 'Young oil palm' (mixed burnt area), and other classes, such as 'Bushes' and 'Water logged', were added.

Classification accuracies

Our study area comprised of a land cover with a range of reflectance values (DN), yielding minimum and maximum values of 10 and 100 μm, respectively. A varying range of reflectance values like these can be a problem during land cover classification. For example, both 'Young oil palm and Burnt area' and 'Cleared and Burnt area-1' have highly similar reflectance values of 41 and 39 μm, in band 4, respectively. The Tasselled Cap transformation technique, however, was able to distinguish those similarities. The Kappa statistic is computed as the sum of the diagonals, multiplied by the sum of each row, multiplied by the sum of each column, divided by the sum of each row, and multiplied by the sum of each column. Christ's and Cicone's studies showed that the TC transformation techniques are able to improve land cover classifications for vegetation because the TC is sensitive to phenological changes (Dymond et al., 2002).

In this study, the image was transformed into TC images

Table 3. Overall accuracy and Kappa (K^) accuracy table of supervised classification of TC.

Class name	Reference total (Column total)	Classified total (Row total)	Number correct	Producers accuracy (%)	Users accuracy (%)	Kappa (K^)
Young oil palm and burnt area	88	87	87	98.60	100.00	0.9860
Peat-1 and road	17	18	17	100.00	94.44	1.0000
Bushes	31	40	30	96.77	75.00	0.9677
Bushes-1	20	29	20	100.00	68.97	1.0000
Peat	51	50	48	94.12	96.00	0.9412
Cleared land and burnt area-1	180	176	174	96.67	98.86	0.9667
Cleared land -1	151	122	119	78.81	97.54	0.7881
Canal	7	7	6	85.71	85.71	0.8571
Water logged	11	11	11	100.00	100.00	1.0000
Total	**602**	**602**	**556**			**0.9452**
Overall accuracy				**94.63**		

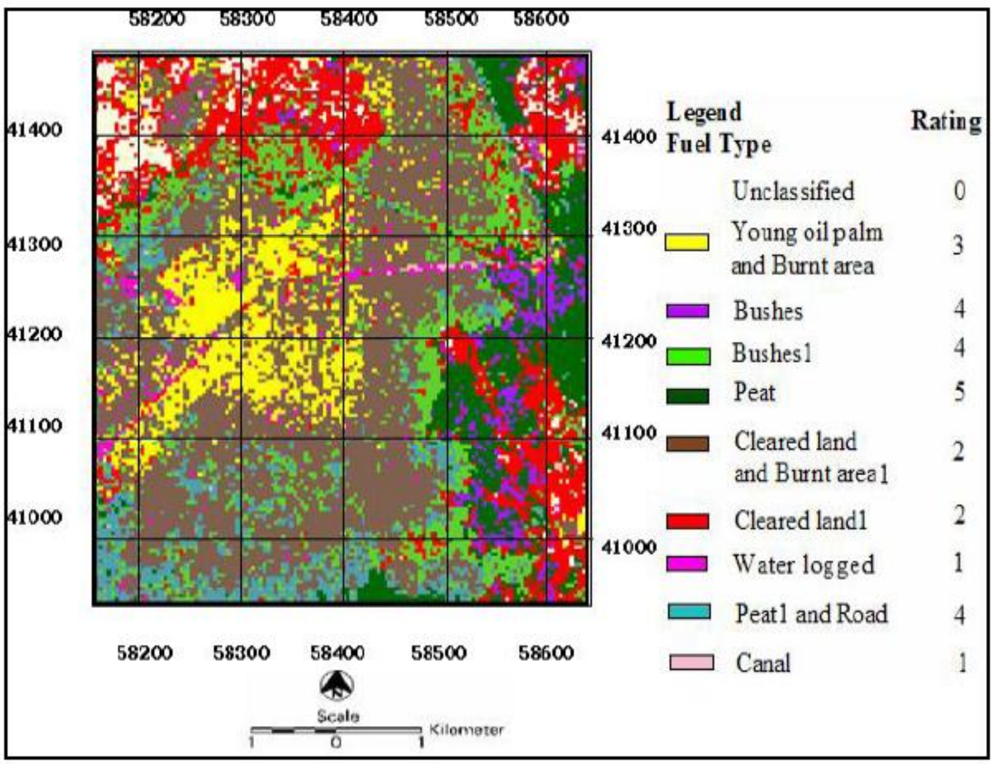

Figure 4. Fuel type map of the study area using landsat TM image of 1999.

for analysis. The images of both indices are presented in Figure 5. Accuracy assessment was created to evaluate the quality of each classification using error confusion matrix and Kappa coefficient statistics. The Kappa coefficient statistics is widely used in accuracy assessment of classification. In this study, the best results were 'Peat-1 and Road', and 'Bushes-1' and 'Water logged', which provided the K^ value of 1.000. 'Young oil palm and Burnt area' and 'Cleared land and Burnt area-1', which were successfully classified after adapting TC method, provided K^ values of 0.9860 and 0.9667, respectively. These indicate that the classification were 98.60 and 96.67% better than expected by chance (Yool and Miller, 2000).

As a result, fuel type was divided into nine types as has been clearly mentioned earlier. The overall classification's accuracy was 94.63% after adding in the TC transformation. The best results were obtained for 'Bushes-1' and 'Water

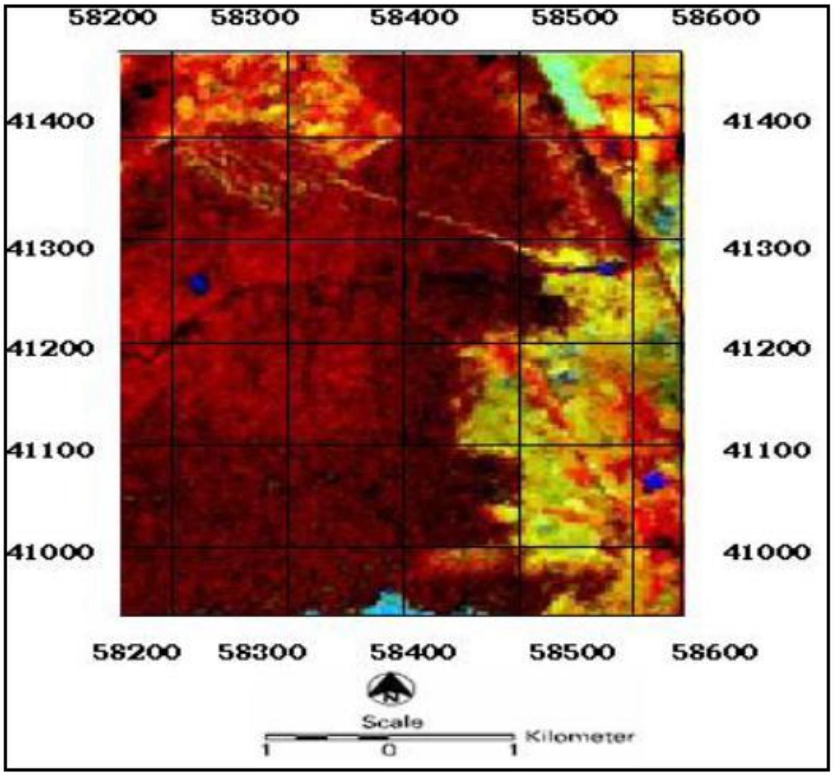

Figure 5. Landsat TM image after Tasseled Cap transformation techniques were applied. The image represents low and high moisture of different land covers at the study area.

logged' with 100% accuracy and 'Young oil palm and Burnt area' with 98.60% accuracy, respectively. Particularly, the overall accuracy of supervised TC transformation classification for this study was 94.63%. This means that class accuracy was 94.63% greater than chance (Yool and Miller, 2000). The Kappa coefficient, which ranges between 0 and 1, was a conservative measure. Based on experience on application projects at the U.K. National Remote Sensing Centre, it was concluded that the classification accuracy for MLC ranges from 60 to 80%, depending upon land use/cover types and sensors. For that reason, this accuracy is acceptable for land cover classification. The Producer's and User's Accuracy are useful in defining the type of classification's errors made and providing the perspective of accuracy (Mazlan and Wan, 2000). Based on the Producer's Accuracy, 'Peat-1 and Road', 'Bushes-1', and 'Water logged' scored a 100% accuracy with Kappa statistics of 0.9669, 0.9676, and 0.9754, respectively. 'Cleared land-1' was low with 78.81% accuracy with Kappa statistics of 0.7571. Factors such as the small area of classes, contributed to the success of the classification. Moreover, 'Canal' was poorly identified with 85.71% with Kappa statistic of 0.8490. For the other classes such as 'Young oil palm and Burnt area', 'Peat', 'Bushes', and 'Cleared land and Burnt area-1' were classified within 94.12 to 98.60% accuracy. The overall result for the accuracy assessment is presented in Table 3. The high level of accuracy was due to the availability of representative pixels in each class. The accuracy was accepted when a study by Dimyati et al. (1996) found out that the accuracy levels for land cover classification was as high as 89 and 89.4% for vegetated and non-vegetated land cover, respectively, including paddy and settlement area. It was also deemed as a superior result when Lillesand and Kiefer (2000) found out that TM sensor was more finely tuned for vegetation discrimination.

Conclusion

This study has successfully generated fuel types of different classifications of fire hazard rating index, using TC transformation techniques. Specifically, using Landsat TM data, the accuracy of 94% was achieved and was acceptable based on the study conducted using similar satellite data. Particularly, an accurate fuel type map is essential in providing information for fire managers to carry out prevention, detection, and suppression efforts.

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