Detection of fire impact and vegetation recovery over tropical peat swamp forest by satellite data and ground-based NDVI instrument

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Multitemporal Principal Component Analysis (MPCA) was used for processing Landsat TM/ETM+ satellite images. MPCA was able to merge spectral data corresponding to TM-1996 (pre-fire in 1997), ETM-2000 (post-fire 1997 and pre-fire 2002), and ETM-2003 (post-fire in 2002), which was crucial for detecting the fire impact and vegetation recovery. Results indicate that the burnt areas of 1997 and 2002 were 89,086 ha (16.5%) and 31,859 ha (5.9%), respectively, within the study area of 540,000 ha. SPOT-VEGETATION 10-days Maximum Value Composite (MVC) data were also used and compared with Normalized Difference Vegetation Index (NDVI) from ground-based NDVI. Our research demonstrates the strong relationship between Landsat TM/ETM+, SPOT-VEGETATION data and ground-based NDVI to identifying land cover changes and vegetation recovery over the tropical peat swamp forest area in Central Kalimantan, Indonesia that is affected by forest fires occurred in 1997 and 2002.

1. Introduction

The Peatlands are technically defined as all lands where 80% of the area is covered by peat soil; a soil containing at least 30% by weight of organic matter, in cumulative layer of 40 cm or more (FAO, 1988), and typical landcover in wetland. Peatlands are an essential part of the Earth’s biosphere, accounting for approximately 3% of the total land area (Weiss et al. 2002). Tropical peatland constitutes over 8% (33–49 Mha) of global peatland area of 386–409 Mha, but because of the relatively greater depth of tropical peatland it may store more than 70 gigatonnes (Gt) or up to 20% of global peatland carbon (Maltby and Immirzi 1993, Melling et al. 2005). Tropical peat soils are distributed over Southeast Asia and form peat swamp forests. The tropical peat swamp forest is important as not only for its wealth of diverse bio-resources but also its huge carbon pool (Tawaraya et al. 2003). Tropical peat swamp forests and deforested peatlands are important stores of carbon whose release in large quantities through burning can contribute significantly to climate change processes (Page et al. 2002).

In 1995, the Indonesian government initiated a large-scale land-use conversion project to develop one million hectares of wetland for rice and transmigration settlements: the so-called Mega Rice Project (MRP) in Central Kalimantan, Indonesia (Boehm and Siegert 2001, Boehm et al. 2002, Tetuko et al. 2003). The hot-spot distribution was detected in 1997 in the MRP area by NOAA–AVHRR data in which intensive human activities were conducted, including opening forests and other areas

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for agriculture, canal development, transmigration house construction, shifting
cultivation, and other activities. In 1997, a drought began in Southeast Asia. It was
related directly to its contemporary El Niño-Southern Oscillation (ENSO) event
(Schimel and Baker 2002, Wooster and Strub 2002), and the 1997 disaster torched
more than 2.7 million hectares in Central Kalimantan (Aldhous 2004). Similar
problems caused by ENSO event occurred in 2002, when peat and vegetation fires
broke out again in Central Kalimantan from July 2002 and lasted for several months
(Siegert et al. 2004). It has become obvious that the incidence of more frequent ENSO
events, coupled with major land development projects that involve drainage of the
surface peat, is leading to an increased risk of repeated fire events in tropical peatland
areas. Furthermore, forest fires are an important cause of environmental alteration and
land degradation or conversion through human activities. Indonesian forests have
been affected by intense burning for plantation agriculture and exploitation practices
for commercial logging since the 1970s. Interactions between land clearance activities
and drought have engendered massive, uncontrolled vegetation fires that have burned
large areas of forest and agricultural land, most severely in the Kalimantan Island.

Remote sensing is a powerful tool to monitor the earth surface in different spectral
bands of the visible, infrared, and radar frequencies. Changes of the areas of interest
can be detected easily over time. Satellite imagery provides a viable source of data
from which updated land cover information can be extracted to inventory and monitor
changes in vegetation cover (Roberts et al. 1997, Boehm and Siegert 2001). Some
researchers have reported that post-fire satellite-based surveys have confirmed the
Kalimantan Island was most severely affected by the 1997–1998 fires, with fire
activity split into two intense burning periods, separated by the 1997–1998 monsoon
rains that commenced in November 1997 (Siegert and Hoffmann 2000). Page et al.
(2002) estimated that 0.19–0.23 Gt of carbon were released to the atmosphere through
peat combustion, with a further 0.05 Gt released from burning of its overlying
vegetation in the Kalimantan Island. Using quick look imagery from the SPOT
satellite, the total area of forest cleared or damaged directly by the fires has been
estimated at 30,600 km². In East Kalimantan, 5.2 ± 0.3 million hectares, including 2.6
million hectares of forest, was burned with varying degrees of damage (Siegert and

Therefore, the objective of this study was to evaluate the impact of fires and
vegetation recovery affected by fire events in 1997 and 2002 in a devastated tropical
peat swamp forest area in Central Kalimantan, Indonesia using Landsat TM/ETM+
and SPOT-VEGETATION images data from the study area site. In addition, this
study also applies and compares trend analyses of the NDVI values of satellite data
and ground-based NDVI (Huemmrich et al. 1999, Harada et al. 2004) from a
micrometeorological tower.

2.   Methods

2.1  Study area

This study was conducted in a tropical peat swamp forest area around Palangka Raya,
the capital city of Central Kalimantan Province, Indonesia (see figure 1). Central
Kalimantan lies within the Inter-Tropical Convergence Zone (ITCZ) were the largest
province on the island of Kalimantan (Borneo) and experiences a wet tropical climate.
The area is 153,564 km², comprising mostly jungle (ca. 126,200 km², 82.18%),
swamps (11.80%), rivers and lakes (2.97%), and agriculture land (3.05%). Central
Kalimantan is hot and humid, the mean daily temperature ranges from 24 to 30°C and
annual rainfall varies between 2,500 to 2,800 mm (Takahashi 2002, Tawaraya et al. 2003, Page et al. 2004).

Ground surveys and field investigations were carried out in the study area in July and October 2003, July and December 2004. They were combined with data from an aerial survey using a helicopter to comprise an area of 75 km × 72 km, or approximately 540,000 ha. The location of the Landsat TM/ETM+ scenes, SPOT-VEGETATION coverage and a micrometeorological tower for ground-based NDVI detailed in table 1.

Three principal peat swamp forest sub-types have been described from the study area based on tree species composition and forest structure (Page et al. 1997, Shepherd et al. 1997, Morrogh-Bernard et al. 2003). The zone beyond the limit of river flooding on the margins of the peat dome, up to a distance of 6 km from the river on peat up to 6 m thick is dominated by a mixed swamp forest. This forest canopy has three strata with a maximum height of 35 m. The principal tree species of the upper canopy are *Gonystylus bancanus*, *Shorea* spp. (meranti), *Cratoxylon glaucum* (gerongang) and *Dactylocladus stenostachys* (mentibu). Mixed swamp forest grades into low pole forest, which continues for a further 7 km from Sebangau river or so. Low canopy forest has only two strata and very few trees of commercial value. The principal species of the upper canopy are *Combretocarpus rotundatus* (tumeh), *Palaquium* sp., *Dyera costulata*, *Ilex cymosa*, *Dyospyros* sp. and *Calophyllum* spp. (Tuah et al. 2003). Owing to the higher light levels penetrating the canopy, and the permanently high water table in this forest zone, there is dense undergrowth of *Pandanus* and *Freycinetia* spp. (pandans).

Mammal sightings in this area in 1993 and 1994 confirmed the presence of orangutans (*Pongo pygmaeus*) at an apparently high density (Page et al. 1997) in addition to several other endangered or threatened mammals, including agile gibbon (*Hylobates agilis*), maroon langur (*Presbytis rubicunda*), sun-bear (*Helarctos malayanus*), leopard cat (*Felis bengalensis*), and marbled cat (*F. marmorata*).

### 2.2 Data collection and processing

For multitemporal analysis, a series of three images was obtained from Landsat TM/ETM+ (Path-118/Row-062), acquired on 10 May 1996, 16 July 2000 and 14 January 2003. We employed three multitemporal images corresponding to: pre-fire-event 1997 (TM 10 May 1996); post-fire-event 1997 and pre-fire-event 2002 (ETM 16 July 2000); and post-fire event 2002 (ETM 14 January 2003) using Multitemporal Principal Component Analysis (MPCA) methods. In MPCA method, the three-plus-three, four-plus-four, five-plus-five and six-plus-six bands (TM/ETM 1, 2, 3, 4, 5 and 7) of each date (eight bands) are used to calculate principal components (PC1996–2000 and PC2000–2003) in a total of 23 band combinations. The PCA method provides a systematic means of compressing multi-spectral image data with the aim of reducing redundancy in the different bands. The MPCA offers some advantages: (1) most of the variance in a multi-spectral data set is compressed into one or two PC images; (2) noise may be relegated to less-correlated PC images; and (3) spectral differences between materials may be more apparent in PC images than in individual bands (Garcia-Haro et al. 2001). Within this frame, PCA was applied in combination with field survey data, which permitted estimation of point samples of new recovery/degradation (Maldonado et al. 2002). PCA is a common technique that can be applied in the interpretation of a large number of reflectance spectra because it can
identify the components responsible for the spectral variability, as expressed by the
eigenvectors (Smith et al. 1985, Galvao and Vitorello 1995).

The sun-synchronous SPOT4 satellite was launched in March 1998 with, onboard,
the wide field of view imaging radiometer VEGETATION, which was specially
designed to monitor land surface parameters. VEGETATION is a linear-array push-
broom system with 1,728 detectors for each of the four channels providing a swath
width of about 2,250 km. The spectral bands and sensor characteristics of SPOT4-
VEGETATION are given in table 2. In-flight radiometric calibration of each of the
four sensors is based on different methods: Onboard calibration lamp is selected as
reference for monitoring changes in the cameras sensitivity over time. Calibration
over Rayleigh scattering, sun glint, clouds or deserts are the complementary
 calibration methods. The estimated calibration accuracy is around 5% for absolute
calibration, better than 2% for multi-temporal calibration and less than 3% for inter-
band calibration (Henry and Meygret 2001). The ground resolution is 1.15 km
independent of the viewing incidence angle. In ground processing, all pixels are re-
sampled onto a regular grid (1 km x 1 km) in a polar stereographic projection. The
SPOT-VEGETATION “level P” products that we used provide reflectance values at
the top of the atmosphere after geometric and radiometric corrections.

SPOT-VEGETATION 10-days MVC data from April 1998 to March 2003 (5
years) were obtained to detect of land cover and vegetation recovery that were
attributable to the forest fire events in 1997 and 2002. NDVI values and angular data
selected on the basis of the maximum NDVI value over 10-days periods (Bartalev et

An analysis was carried out using ground-based NDVI values (Harada et al. 2004,
Hirano et al. 2004) calculated from observed downward and upward (reflected)
photosynthetically activity radiation (PAR) measured at the top of
micrometeorological tower using the method of Huemmrich et al. (1999). A tower of
50 m height was constructed about 300 m inside from the northeast corner of the
tropical peat swamp forest (2º 20’ 41.6” S, 114º 2’11.3” E). The frequent observations
of NDVI values have been derived using data from the radiation sensors mounted on
the tower (Huemmrich et al. 1999, Wang et al. 2004). In this study, measurements of
incident and reflected PAR and incident and reflected shortwave radiation as equation
(1) were used in the calculation of NDVI. The definition of NDVI utilizes in leaf
absorption in the visible wavelengths (ρ\text{\textsubscript{Vis}}) and near-infrared wavelengths (ρ\text{\textsubscript{NIR}}):
\[
\text{NDVI} = \frac{(\rho\textsubscript{NIR}−\rho\textsubscript{Vis})}{(\rho\textsubscript{NIR}+\rho\textsubscript{NIR})}
\] (1)

The PAR measurements were converted from micromoles of photons to joules by
multiplying by 0.25 J \(\mu\text{mol}^{-1}\). This conversion factor based on the energy of photons
of green light and converts the PAR data to units of Wm\(^{-2}\). PAR reflectance (ρ\text{PAR})
was the ratio of reflected and incoming PAR (\(E_{\text{PARRef}}\) and \(E_{\text{PARin}}\) respectively) as
shown in equation (2).
\[
\rho\text{PAR} = \frac{E_{\text{PARRef}}}{E_{\text{PARin}}}
\] (2)

The PAR irradiance values were subtracted from shortwave irradiances for both
incoming and reflected fluxes to calculate an optical infrared reflectance (ρ\text{OIR}). Thus,
ρ\text{OIR} is calculated from \(E_{\text{SWRef}}\), the reflected shortwave radiation, and \(E_{\text{SWin}}\,\)the
shortwave irradiance:
\[
\rho\text{OIR} = \frac{(E_{\text{SWRef}}-E_{\text{PARRef}})}{(E_{\text{SWin}}-E_{\text{PARin}})}
\] (3)

These reflectances were substituted into equation (1) to calculate the NDVI values:
NDVI = \frac{(\rho_{OIR} - \rho_{PAR})}{(\rho_{OIR} + \rho_{PAR})} \tag{4}

In the next section, the measurement result of NDVI values from this micrometeorology tower will compare with the NDVI values of satellite data (SPOT-VEGETATION 10-days MVC).

3. Results and Discussion

3.1 Principal component analysis

In MPCA method, four bands (TM/ETM 2, 3, 4, and 5) of each date (eight bands) for calculating principal components (PC1996–2000 and PC2000–2003) were taken. These four bands contain most of the spectral information in vegetation-related studies (Huemmrich et al. 1999, Almeida and Filho 2004), including two visible and a near infra-red bands (TM/ETM 2, 3, and 4), and a middle infra-red (TM/ETM 5). The second, third and fourth components showed the most striking in relation to the fire features of interest.

Principal components 1 to 5 (PC1 to PC5) amount 99.2% of PC1996–2000 (figure 2a) and 99.0% of PC2000–2003 (figure 2b) from the original data. The remaining component (PC6, PC7, and PC8) were quite sensitive to noise along with variation of vegetation coverage or do not display any features of significance to the study. Furthermore, some researchers found that the eigenvector characteristics of three additional principal components (PC6, PC7, and PC8) gave little more information than the first five PCs because they have eigenvalue variabilities less than 1% and did not show a useful specific form in further land cover change detection (Singh and Harrison 1985, Garcia-Haro et al. 2001).

PC1 images represented the brightness component and gave the preliminary visual information about change of land cover between two observation dates, whereas the later components highlight changes. PC1 show similar weights for all band ratios (see table 3 and table 4) and it images allow the distinction between peat swamp forests (black), regenerated vegetation or burnt areas (grey) and exposed soil, urban, clouds (white). The eigenvector of PC1 showed all positive values and containing more than 50% of accumulative variance (Richards 1994, Segah et al. 2005). Pixels that have essentially the same cover type in both dates (PCs 1996 and 2000; PCs 2000 and 2003) e.g., vegetation and vegetation, fire burnt and fire burnt, show as midgrey, depending upon the component. These effects are easily verified by substituting typical spectral reflectance characteristics into the equations that generate the components. Each component is a linear combination of the original eight bands of Landsat TM/ETM+ data, where the weighting coefficients are the components of the corresponding eigenvector of the 8 x 8 covariance matrix. These eigenvectors along with their associated eigenvalues which are the variance of the components. PC2 was the greenness/vegetation component, characterized by algebraic sign on red and near infrared band. PC2 images expresses the changed of areas also with white appearance, especially stability in the greenness value. PC3 showed the difference of brightness between two images, characterized by opposite sign of eigenvectors. The fourth axis (PC4), constituting the axis of temporal change, presents a great variation between both dates.

Visual observations confirmed that PC4 was higher in the burnt areas. Furthermore, to map the burnt areas and isolate noise, we found that the burnt areas of 1997 and 2002 were 89,086 ha (16.5%) and 31,859 ha (5.9%), respectively, from 540,000 ha of the study area that was classified using maximum likelihood classification, as shown
in figure 3. Change enhancement offered in the PCs allows the creation of thematic map for detecting land cover change (Segah et al. 2003). Three areas were classified (burnt, forested, and non-forested) for each PC4 of PC\textsubscript{1996–2000} and PC\textsubscript{2000–2003}. These results show that transformation of PCs will increase the computation capability from classification by the declining dimension from original data.

Since there are rich sources of information and abundance of data present in the six bands of LANDSAT TM/ETM+, techniques based on MPCA can be used to gain insight into their overall structures and the relationships of the parts of the bands. In the future, selection of the suitable image bands for change detection using MPCA and determination of the threshold of each bands are both important to produce highly accurate change detection results. Although the MPCA is the simplest and easiest to implement method, it proved to be too scene-dependent, which has also been reported by several authors (Singh and Harrison 1985). In addition, MPCA produce a more direct interpretation linked with the vegetation damage and recovery processes after forest fires in the study area. Plant/vegetation response to fire also could be monitored and modeled by mean of the NDVI variations, in order to quantify the different recovery rates. Also, such regeneration processes in tropical peat swamp forest area in Central Kalimantan may be compared among different areas to search for parameter involved in the vegetation recovery after fire.

3.2 \textit{SPOT-VEGETATION} and ground-based NDVI

\textit{SPOT-VEGETATION} is a satellite sensor that is designed specifically to address the requirements of land cover mapping at about 1-km spatial resolution. Using \textit{SPOT-VEGETATION} 10-days MVC data, we determined a change rate of 5 years NDVI from April 1998 to March 2003 by the difference of two \textit{SPOT-VEGETATION} 10-days MVC, labelled NDVI\textsubscript{April98} and NDVI\textsubscript{March03}. The high-values of the difference between the two NDVIs, i.e. high values of NDVI\textsubscript{March03–April98} were detected as burnt areas. This value shows that the NDVI increases because of vegetation recovery after the forest fire event. The value indicated that vegetation can get self-recovery under this climate condition after intensified human disturbance was alleviated (Wen et al. 2005). Results of this \textit{SPOT-VEGETATION} 10-days MVC image analysis demonstrate the potential of multi-temporal vegetation images for identifying and mapping of burnt areas in the study area, especially the seasonal dynamics of vegetation spectral indices which can be used to discern vegetation recovery at different times and scales (see figure 4). The use of multitemporal image will allow assessment of forest areas that burn repeatedly due to the dryness and flammability of the previously burnt vegetation and soils, these fires having carbon emissions per unit area that may deviate substantially from those of infrequently burned forest (Zhang et al. 2003).

Figure 5 and figure 6 showed the relation between \textit{SPOT-VEGETATION} 10-days MVC and 10-days mean of ground-based NDVI value measured at the field micrometeorological tower in 2002. These figures elucidate the longevity and intensity of the 2002 drought, especially during July–October 2002. There is a high correlation of fires with the annual rainfall regime. These figures also shown the precipitation and relative humidity in the study area also followed a similar and distinct seasonal pattern, with the decreasing of NDVI values from \textit{SPOT-VEGETATION} 10-days MVC and 10-days mean of ground-based NDVI in July to October 2002. In 2002 however, the dry season period in Kalimantan was markedly drier than normal: rain was absent at some locations for many weeks, as that in 1997.
Figure 7 shows the average of vegetation index values derived from the SPOT-VEGETATION 10-days MVC from April 1998 to March 2003 over the study area in Central Kalimantan, Indonesia. In the study area, NDVI value increases gradually since 1998 to 2003 following the vegetation recovery on the study area which is affected by two times fire events in 1997 and 2002. The NDVI usually began to increase with a low value in January and increased near linearly to the peak in June and finally decreasing linearly to the lowest value in October (see figure 7). Although the peak and the lowest values of NDVI appear in the same time in the year, June and October from 1998 to 2003, the NDVI pattern was different among years.

Wooster and Strub (2002) also found a high correlation of fires in the Kalimantan Island in 1997 with the annual rainfall regime. The occurrence of forest fires was higher during the dry season of May–October 1997. Takahashi (2002) reported that, from the 10-year record of the ground water level in a peat swamp forest in Central Kalimantan, the levels of drought in 1997 and 2002 were categorized as markedly dry years. The big forest fires in 2002 have occurred in the study area of peatland in Central Kalimantan between July and October. The result was massive fire damage to the forest by fire, as detected in this study by Landsat TM/ETM+ and SPOT-VEGETATION 10-days MVC data. Anomalous 1997 and 2002 meteorological conditions were related directly to the ongoing ENSO event, which was reportedly the most intense of that century (Wooster and Strub 2002).

Compiling the analyses of characteristics of NDVI values and climate data, the drought effects on the study area in 2002 are detected and monitored successful. In general, we found that the type of method implemented markedly affected the quantitative and qualitative estimates of land cover change by forest fires. Available ground information from field and aerial survey indicated that the combination of human activities (land clearing, illegal logging, etc.) and forest fire induced the land cover change.

Our analysis shows that the result for burnt areas obtained by MPCA method was mutually consistent if compared with SPOT-VEGETATION 10-days MVC simple difference image. MPCA method of Landsat-TM/ETM+ seemed to be reliable because they merge spectral data corresponding to TM-1996 (pre-fire in 1997), ETM-2000 (post-fire 1997 event/pre-fire 2002 event), and ETM-2002 (post-fire in 2002), which is crucial for detection of vegetation recovery. In addition, they produce a more direct interpretation linked with the vegetation damage and recovery processes after forest fires in the study area, especially in ex MRP area. Tani et al. (2005) reported that the burnt areas expanded inside large forest and also along MRP canals, which is a feature of damaged by fire of 1997 and also in 2002.

Our results emphasize that SPOT-VEGETATION 10-days MVC data were useful for regional burnt area mapping. Unlike AVHRR, SPOT-VEGETATION sensors have no thermal channels. Therefore, they cannot be used confidently to locate active fires. The excellent SPOT-VEGETATION 10-days MVC geometric and radiometric characteristics make it attractive for mapping burnt areas. Furthermore, Eastwood et al. (1998) demonstrated the strong potential of SPOT-VEGETATION 10-days MVC data for this application prior to its launch. Nevertheless, using SPOT-VEGETATION for global description of fire effects is insufficient for accurate assessment of damaged ecosystems and probable carbon emissions. SPOT-VEGETATION offers new potential and was shown to be an effective approach for monitoring the burnt areas (Stroppiana et al. 2003).

We found that the higher resolution remote sensing data are necessary, especially for identification and delineation of each ecosystem and for evaluation of the level of
degradation in each of them. The results proved that the analyses using Landsat TM/ETM+ and SPOT-VEGETATION 10-days MVC together with ground-based NDVI from a micrometeorological tower were effective for identifying land cover changes and vegetation recovery in the study area that was affected by forest fires in 1997 and 2002. Ground-based NDVI values were obtained daily for vegetation monitoring of the tropical peat swamp forest in Central Kalimantan. Using these values, we obtained a more detailed description of seasonal changes in NDVI for specific locations. Diaz-Delgado and Pons (2001) reported that the vegetation response to fire could be monitored and modeled by means of NDVI variations, in order to quantify the different of recovery rates.

Analyses using multitemporal and multispectral satellite data and field measurement by ground-based NDVI instruments would be applicable to large areas at different time-scales. Monitoring changes in fire frequency are therefore vital for forest management and predicting climate change impacts. An important lesson of the 1997 and 2002 fire events is that sustainable management of peatlands and the prevention of forest fires must be emphasized, for instance, through better water management and restoration of degraded peatland areas.

4. Conclusion

This study used MPCA method of Landsat-TM/ETM+ and SPOT-VEGETATION 10-days MVC data, and to compare with the NDVI value of radiation sensor data of ground-based NDVI from a micrometeorological tower. The forest canopy change can be detected from multispectral satellite data using a variety of analysis methods. The classification results indicate that the burnt areas of 1997 and 2002 were 89,086 ha (16.5%) and 31,859 ha (5.9%), respectively, using MPCA method within the study area of 540,000 ha. These analyses are proved to be effective for identifying land cover changes and vegetation recovery in the study area that was affected by forest fires in 1997 and 2002.

Analyses using multitemporal and multispectral satellite data and field measurement by ground-based NDVI of micrometeorological instruments further allow for automated change indication and are applicable to large areas on different time-scales. Furthermore, for better understanding and a more accurate interpretation of land cover change and vegetation recovery study, more intensive and long term measurements need to be done.

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References


FIGURES CAPTION

Fig. 1. Map of study area in Central Kalimantan Province, Indonesia with an extent of 75 km x 72 km or approximately 540,000 ha.

Fig. 2. The accumulated proportion and eigenvalue of PCs for 1996–2000 (a) and 2000–2003 (b).

Fig. 3. Detected areas burned by fires in 1997 (a) and 2002 (b) with maximum likelihood classification using PCs.

Fig. 4. The simple difference of 5 years SPOT-VEGETATION 10-days MVC data (NDVI$_{April98}$ and NDVI$_{March03}$) image. The high value of NDVI$_{March03-April98}$ could detect as the burned areas of 1997 and 2002 fire event. This value shows that the NDVI increase as a consequence of the vegetation regeneration/recovery after the forest fire event.

Fig. 5. Relationship between NDVI values of SPOT-VEGETATION 10-days MVC and 10-days mean of ground-based NDVI from micrometeorological tower in 2002. Solid line represents regression line.

Fig. 6. 10-days average NDVI values of SPOT-VEGETATION and 10-days mean of ground-based NDVI from micrometeorological tower in 2002. Peat and vegetation fires broke out in July 2002 and lasted for several months indicated from the decreasing of vegetation index from both measurements.

Fig. 7. Vegetation index values derived from the SPOT-VEGETATION 10-days MVC from April 1998 to March 2003 over the study area in Central Kalimantan, Indonesia. This value shows that the NDVI increases because of vegetation recovery after the forest fire event. The value indicated that vegetation can get self-recovery under this climate condition after intensified human disturbance was alleviated.
<table>
<thead>
<tr>
<th>Satellites/Sensor</th>
<th>Location</th>
<th>Observation dates</th>
</tr>
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<tbody>
<tr>
<td>Landsat TM/ ETM+</td>
<td>Path-118 and Row-62</td>
<td>10 May 1996</td>
</tr>
<tr>
<td></td>
<td></td>
<td>16 July 2000</td>
</tr>
<tr>
<td></td>
<td></td>
<td>14 January 2003</td>
</tr>
<tr>
<td>SPOT-Vegetation 10-day MVC</td>
<td>Central Kalimantan, Indonesia</td>
<td>April 1998 – March 2003</td>
</tr>
<tr>
<td>NDVI Value of Radiation Sensors Data*</td>
<td>Micrometeorological tower, Central Kalimantan, Indonesia</td>
<td>July 2001 – October 2003</td>
</tr>
</tbody>
</table>

* Solar Radiation: radiometer for four separate components (Kipp & Zonen, CNR-1), Reflected Solar Radiation (Albedo): radiometer for four separate components (Kipp & Zonen, CNR-1), PAR: quantum sensor (LI-COR, LI190) and Reflected PAR: quantum sensor (LI-COR, LI190) was mounted at 40.6 m of the field micrometeorological tower at 2°20’41.6”S, 114°2’11.3”E.
Table 2. SPOT4-VEGETATION sensor geometric and radiometric characteristics.

<table>
<thead>
<tr>
<th>Geometrical characteristics</th>
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<tbody>
<tr>
<td>Orbital altitude</td>
<td>822 km</td>
</tr>
<tr>
<td>Period of resolution</td>
<td>101.46 min</td>
</tr>
<tr>
<td>Field of view</td>
<td>±50º</td>
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<tr>
<td>Swath width</td>
<td>2250 km</td>
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<tr>
<td>Ground resolution</td>
<td>1.15 km</td>
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<td>Pixel size</td>
<td>1 km</td>
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<table>
<thead>
<tr>
<th>Spectral bands</th>
<th>Wavelength (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B0 (blue)</td>
<td>0.43–0.47</td>
</tr>
<tr>
<td>B2 (red)</td>
<td>0.61–0.68</td>
</tr>
<tr>
<td>B3 (near infra-red, NIR)</td>
<td>0.78–0.89</td>
</tr>
<tr>
<td>B4 (short-wave infra-red, SWIR)</td>
<td>1.58–1.75</td>
</tr>
</tbody>
</table>

Note: There is no B1 channel onboard VGT in order to keep the same notation from SPOT1 to SPOT5.
Table 3. Eigenvector Characteristics of each Principal Components (Landsat-TM 10 May 1996 and Landsat-ETM 16 July 2000).

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Table 4. Eigenvector Characteristics of each Principal Components (Landsat-ETM 16 July 2000 and Landsat-ETM 14 January 2003).

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$y = 0.06x + 0.65$

$n = 36$