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Anthropogenic influences on deforestation of a peat swamp forest in Northern Borneo using remote sensing and GIS

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Abstract

Aim of study: To study the anthropogenic factors that influence the fire occurrences in a peat swamp forest (PSF) in the northern part of Borneo Island.

Area of study: Klias Peninsula, Sabah Borneo Island, Malaysia.

Material and methods: Supervised classification using the maximum likelihood algorithm of multitemporal satellite imageries from the mid-80s to the early 20s was used to quantify the wetland vegetation change on Klias Peninsula. GIS-based buffering analysis was made to generate three buffer zones with distances of 1000 m, 2000 m, and 3000 m based on each of three anthropogenic factors (settlement, agriculture, and road) that influence the fire events.

Main results: The results showed that PSF, barren land, and grassland have significantly changed between 1991 and 2013. PSF plummeted by about 70% during the 19-year period. Agriculture exhibited the most significant anthropogenic factor that contributes to the deforestation of the PSF in this study area with the distance of 1001-2000 m in 1998 fire event and 0-1000 m in 2003. Additionally, the distance to settlement played an increasingly important role in the fire affected areas, as shown by the increase of weightages from 0.26 to 0.35.

Research highlights: Our results indicate that agriculture is the most influential anthropogenic factor associated with the fire-affected areas. The distance to settlement played an increasingly important role in the fire affected areas and contributes to the deforestation of the PSF in these study areas.

Additional keywords: land cover change; driver of change; forest fire; overlay analysis; Wetland Sabah; mapping fire risk.

Abbreviations used: PSF (peat swamp forest); GIS (geographic information system).

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Introduction

Wetland ecosystem disturbances that are intensified and persistent lead to fast changes in the forest cover and the deterioration of the environment's services in the tropics. One of the most seriously threatened wetland ecosystems is the peat swamp forest (PSF). It consists of a crucial natural ecosystem for climate stabilization. About 60% of the tropical peat area is in Southeast Asia, and PSF has been estimated to have a higher amount of carbon with a storage of 5,800 tons ha^{-1} carbon in a 10-m deep peatland compared to 300 to 500 tons ha^{-1} of carbon in other types of tropical forests (Moore et al., 2013; Too et al., 2018). This indicates that peatlands can store a tremendous amount of carbon. According to Minasny et al. (2019), the world cover over the peatland extent ranges from $1 \cdot 10^6$ to $4.6 \cdot 10^6$ km^2, and contains 30% of global soil carbon. The large peatland carbon pool of more than $68 \cdot 10^{13}$ tons (77%) is located in Southeast Asia, which is equal to 11-14% of the global peat carbon (Condro et al., 2018). The Southeast Asian peatlands is estimated to store at least $42 \cdot 10^9$ tons of soil carbon and the drainage can contribute to 1.3% to 3.1% of current global emissions (Hooijer et al., 2010).

Despite the importance of maintaining wetland as a balanced ecosystem to society, particularly in the context of sustainable development (Akhbar et al., 2022), there are very few wetland ecosystems that have not been influenced by anthropogenic activities (Mallick & Chakraborty, 2018). Anthropogenic influences on wetland ecosystems are of global concern. Exploitation of forest resources and forest-to-agriculture conversion cause forest degradation and fragmentation to take place and increase the potential for forest fire occurrence. Although forest fire is considered an ecological factor, intended fires, either for land clearing, hunting activities, or human habits, can be destructive to ecosystems (Chuvieco et al., 2014; Menon & Vishnu-Menon, 2022). Quantifying burned areas over time as well as identifying the causes of fire occurrences are crucial for forest resource management.

Satellite remote sensing technology proves effective in monitoring changes in forest cover. Previous research on PSF mapping in Borneo utilizing remote sensing has predominantly concentrated on multi-temporal vegetation indices (Trisasongko et al., 2020; Vijith et al., 2020). These studies commonly utilize the image differencing technique for identifying burned areas (Phua et al., 2007; Phua & Tsuyuki, 2021). Additionally, supervised classification of satellite imagery has been employed to quantify changes in land cover and discern the factors driving such changes (Kamlun et al., 2016; Kamlun & Arndt, 2019; Mahdavi et al., 2018; Gómez et al., 2019). Nevertheless, achieving a high level of overall accuracy for wetland areas posed challenges due to the presence of clouds and haze in specific satellite imagery. This problem can be addressed by using optical imagery with higher temporal resolution, which provides users with the ability to select cloud-free images (Gallant, 2015). Light Detection and Ranging (LiDAR) technology has also been extensively used to assess the three-dimensional canopy structure of Borneo (Nordin et al., 2019; Wedeux et al., 2020; Wong et al., 2020). These data provide valuable insights into forest height, canopy density, and biomass, aiding in better understanding and management of these ecosystems.

Spatial analysis functions are also an advantage that are available in the Geographic Information System (GIS). This approach can be used to better understand the causes of land cover changes. GIS has been extensively used to examine fire risk (Alkhatib, 2014; Yakubul et al., 2015). A fire risk zone is a location where a fire is likely to start and from where it can easily spread. Forest fires can be managed only when the fire risk can be mapped (Novo et al., 2020). Mapping fire risk is very important to prevent further degradation of wetland forests from human activities during a prolonged drought. In tropical regions, studies that relate a forest fire to its occurrence drivers are lacking. Human settlement and land use activities are often associated with forest fire occurrences (Phua et al., 2014; Condro et al., 2018; Haryati Silviana et al., 2019). This research aims to study the underlying anthropogenic factors of fire occurrences in a PSF in the northern part of Borneo Island following recurrent El-Niño events. The approach used was integrating remote sensing, supervised classification techniques, and spatial analyses in GIS to identify the factors causing the forest fire to take place.

The integration of remote sensing with other tools and methods has been crucial in understanding the dynamics of PSFs and supporting conservation efforts. Many existing studies have focused on mapping PSFs in Borneo using remote sensing, but they often lack temporal resolution. There is a need for more frequent and up-to-date data to monitor changes in these ecosystems, especially in the context of ongoing deforestation and land-use changes. While remote sensing technology has advanced, access to high-quality and high-resolution imagery, especially in remote and often cloud-covered areas like PSFs in Borneo, remains a challenge. Researchers have faced difficulties in obtaining consistent and timely data.

Material and methods

Study area

The study area, Klias Peninsula, is located in the northern part of Borneo Island, approximately between 115˚45’ and 115˚72’N latitude and 5˚42’ and 5˚15’E longitude. It is about 100 km southwest of Kota Kinabalu city (Fig. 1). The Klias Peninsula is a large lowland coastal plain that lies at the foothills of the Crocker Range and has an extensive wetland of ~130,000 ha. Annually, this area receives an average rainfall of 3500 mm. However, several fires during the El-Niño drought in 1983, 1991, 1998, and 2003 (March) severely affected the wetland, especially PSF. Also, owing to forest-to-agriculture conversion, the PSF has become highly fragmented. Furthermore, repeated fires result in poor remaining stands of PSF, receiving tremendous pressure for its conversion to agricultural uses by the local communities.

The population in Beaufort district in 1980 was 36,404 people. In 2000, the population had increased to 64,756 people. This shows that the mean population increment is 3.5% a year. There are about 127 villages in the Beaufort area, and more than half of these settlements are located near the wetlands. The agricultural (70%) sector is the main contributor to economic development in this area, followed by the industrial and business sectors (20%) and fishery and husbandry (10%).

Data acquisition and pre-processing

Figure 2 shows the overall approach in this study. Topographic maps with a scale of 1:50,000 were obtained from the Department of Survey and Mapping Malaysia (JUPEM). A land cover map (1:100,000) for 1996 was also obtained from the Sabah Land and Survey Department. Then, multi-temporal satellite images were acquired in this study: Landsat TM for June 14, 1991, and November

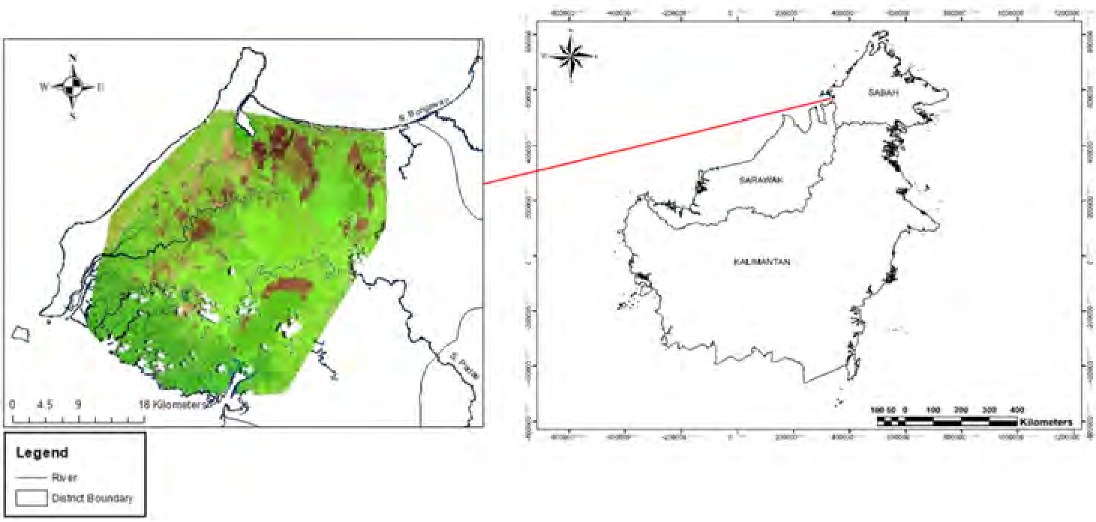

Figure 1. Location of Klias Peninsula, Sabah, in Northern Borneo Island (right). The left image is the SPOT4-HRVIR on March 26, 2003, RGB: 4, 3, and 2.

2, 1999 (Landsat7 ETM+) dates. The 1991 image is free of clouds and haze. However, the 1999 satellite image contains about 10% of haze, and cloud outside of the forest reserve on a relatively small area within the forest reserve was also affected by haze. Two other satellite images used were Landsat7 ETM+ for January 14, 2003 (pre-fire), and SPOT4-HRVIR for March 26, 2003 (post-fire). A relatively small amount of cloud is present in the image, while the KFR contains 10% of haze for the Landsat ETM+ 2003 image. Meanwhile, the March 26, 2003 (SPOT4-HRVIR) image was 20% affected by the cloud. Landsat MSS for June 29, 1985, and SPOT 4-HRVIR for March 26, 2003, images have 15-20% cloud cover. Topographic maps (1:50,000) obtained from JUPEM were used to rectify both images to a Universal Transverse Mercator (UTM) projection. The georeferenced residuals for the Landsat MSS 1985 in both x and y directions were 0.0137 m and 0.0046 m. The 1991 image RMS error for the registration was 2.6625 m and 2.7834 m both for x and y directions. 1999 ETM+ image georeferenced residuals were 2.3780 m and 2.3694 m for the x and y directions, respectively. The 2003 Landsat ETM+ RMS error for registration was 2.5899 m and 3.0797 m for x and y directions, respectively. As for 2003 SPOT 4 image rectification, the errors for the registration for x and y directions were 2.3780 m and 2.3694 m. The resolutions for the five sensor data ranges were different: MSS 1985 (79 m), TM 1991 (30 m), ETM+ 1999 (30 m), ETM+ 2003 (30 m), and SPOT 2003 (20 m). All images were resampled to 30 m using nearest neighbor resampling for land cover classification.

Land cover classification

A supervised classification with a maximum likelihood algorithm was applied to multi-temporal satellite images to generate the land cover maps. ERDAS imagine v 9.1 application specific algorithms for all the pixels in the image data set; values were assigned to define land cover classes (Theres & Selvakumar, 2022). Nine land cover categories (PSF; mangrove; grassland; shrubland; barren land; oil palm; rubber; water; and cloud and shadow) were defined. The spectral signatures of the known land cover categories were developed using digitised training sites from ground truthing activities. The training areas for Landsat MSS 1985, Landsat TM 1991, and Landsat ETM+ 1999 were collected using the topographic maps, which were updated in 1993, and the land cover map of 1996 (1:100,000), and the history of land use was obtained from community interviews. The training areas for Landsat ETM+ 2003 and SPOT4 2003 were collected based on the interpretation of the RGB colours of the unchanged land cover classes. After the land cover classification, a 3×3 majority filter was applied to reduce the salt and paper effect.

Anthropogenic factors

Distance to roads, villages, and agriculture represent the anthropogenic factors that influence land cover changes. These factors were digitised and extracted from the land cover classification map and topographic maps for the years 1998 and 2003. Buffering analysis was carried out for each factor to generate buffer zones of different distances: 1000 m, 2000 m, and 3000 m (Luo et al., 2020). Then, an intersect overlay was performed to determine the anthropogenic factors influencing the PSF changes due to fires. The influence was determined by assigning a weight using Eq. (1). The weightages were used to identify the most important anthropogenic factor that was associated with the PSF change area due to fires in 1998 and 2003.

$$W_i = a_i \times \frac{1}{\Sigma a_i} \qquad (1)$$

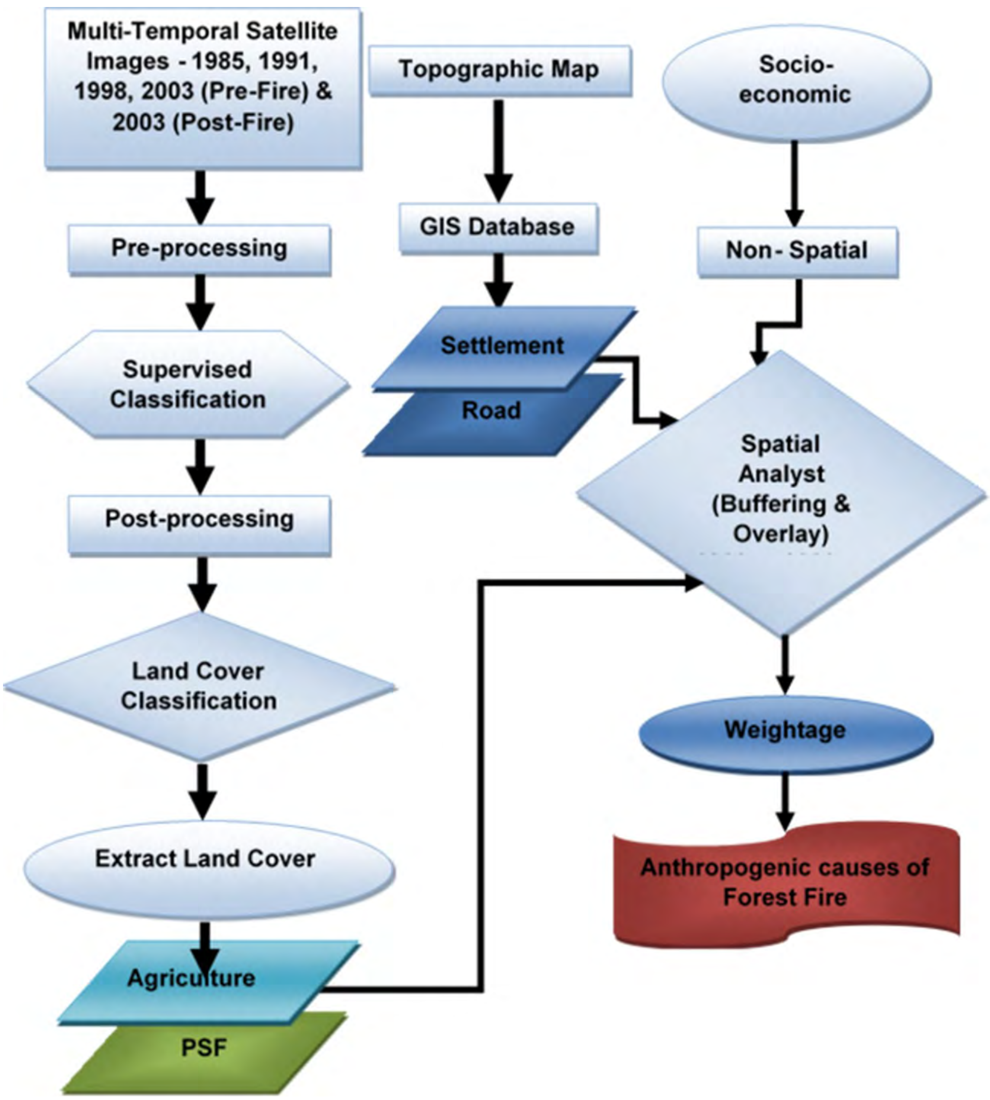

Figure 2. Flowchart on integrating remote sensing and the GIS approach to identify the factors causing forest fire occurrences

where W_i = weightage; a_i = anthropogenic activity factor, Σa_i= values from 1 to the total number of anthropogenic activity factors.

The changes in area due to the 1998 and 2003 fires within the buffer zones of 1000 m, 2000 m, and 3000 m for each anthropogenic activity factor was calculated. The change in area for each anthropogenic factor overlay was normalized by dividing it by the total area within each buffer specific to that anthropogenic activity factor. Subsequently, the overlaid area was normalized again by dividing it by the total area of the corresponding buffer zone for each anthropogenic factor. The outcomes for all three factors were aggregated to derive the anthropogenic activity factor (a_i). To calculate the weighted value (W_i), each anthropogenic activity factor (a_i) was further divided by the overall total for all anthropogenic factors, including a_1 (roads), a_2 (settlements), and a_3 (agriculture).

Results and discussion

The comprehensive evaluation of land cover changes in the Klias Peninsula spanning from 1985 to 2003 exhibited a dynamic landscape marked by substantial alterations in the forest cover. The overall accuracy rates for various years, including MSS 1985, TM 1991, ETM 1998, SPOT January 2003, and SPOT March 2003, ranged from 89% to 96%, with corresponding kappa coefficients ranging between 0.88 and 0.95. A visual representation in Figure 3 vividly illustrates the rapid transformations in land cover classes during this period.

Over the 18-year span, the Klias Peninsula underwent significant changes, with fire emerging as a major threat to Primary Successional Forests (PSFs) in both West and East Malaysia in Borneo (Chew et al., 2022). In 1985, the PSF covered over 20,000 ha, but the 1998 El-Niño-induced forest fires devastated more than 75% of this area. The Binsuluk Forest Reserve witnessed significant deforestation

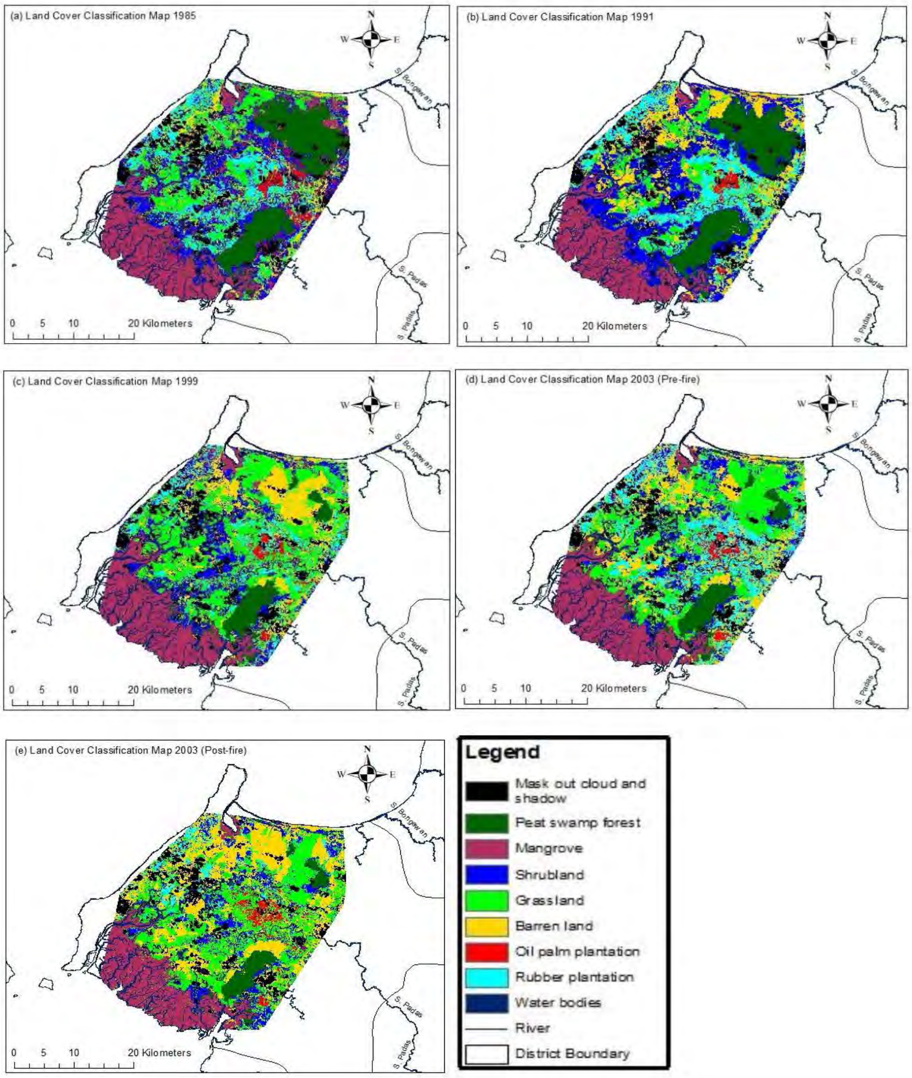

Figure 3. Land cover classification of Klias Peninsula: (a) 1985, (b) 1991, (c) 1999, (d) 2003 (pre-fire), (e) 2003 (post-fire).

during this event (Kamlun et al., 2016). A subsequent fire during the prolonged drought in 2003 further impacted PSFs, reducing the total area to 5,364 ha (Phua et al., 2007).

The classification results demonstrate that PSFs, barren land, and grassland were the most affected land cover types during this period. Notably, the land cover classification highlights a drastic decrease in PSF from over 10,000 ha in 1991 to about 8,000 ha in 1999. This loss was accompanied by a remarkable increase in grassland, showcasing the transformation of the forest landscape into extensive grassland due to fire disturbances. The years 2003 witnessed a decrease in PSF by 25%, and the most significant vegetation change was the twofold increase in barren land, which expanded from 14,750 to 30,108 ha (Fig. S1). The susceptibility of PSFs to fire is attributed to their peat composition, which has limited water-holding capacity. Drought conditions result in reduced water levels, creating favourable conditions for ignition. Repeated fires degrade the forest, giving way to scrub and grassland, as indicated by previous studies (Goldstein et al., 2020; Taufik & Tw, 2022; Palaiologou et al., 2020; Darusman et al., 2021).

Analyzing the impact of anthropogenic factors on PSF changes, Table S1 demonstrates that agriculture, roads, and settlements within varying distance classes significantly contributed to PSF reduction during fire events in 1998 and 2003. Agriculture, especially in the 0-1000 m distance class, played a pivotal role in the 2003 fire, highlighting human activities, particularly land clearing for oil palm plantations, as a major cause of fires. The weightage of distance to agriculture remained consistently high for both fire events, underscoring its continued significance in driving deforestation. While roads ranked second as a contributing factor in the 1998 fire, the importance of settlements increased over time, becoming the second most influential factor in 2003. The weightage of distance to agriculture decreased, while the weight of distance to population increased, reflecting the evolving dynamics of human activities in the region. Proximity to population centres emerged as a crucial factor in fire ignition and spread, emphasising the need for monitoring these anthropogenic factors over time, especially during El-Niño events (Nunes & Raposo, 2021; Chuvieco et al., 2014).

The GIS-based approach utilised in this study offers a valuable tool for identifying high-deforestation areas, supporting the enforcement of fire prevention regulations (Arif & Nakagoshi, 2006; Robins, 2020). The findings confirm agriculture as the most important anthropogenic factor for deforestation of the PSF in the study area, with the weight of distance to agriculture being the highest among the three factors for both fire events. The distance from the road factor ranked second with a weightage of 0.27 for the 1998 fire. Although trailing after the two factors, the distance to settlement factor was only 1% lower than the road factor. Moreover, it is worth noting that the weight of distance to agriculture has decreased while the weight of distance to population has increased over the study period. Local people in Borneo always use fire for cultivation and to upkeep their home gardens (Brookfield & Byron, 1990). The weightage of distance to these anthropogenic factors should be monitored over time for preventive fire management, especially during an El-Niño event. The GIS-based approach allows identification of high-deforestation areas, thus supporting the enforcement of existing fire prevention regulations (Brookfield & Byron, 1990).

Fire is an imminent threat to PSFs during an El-Niño event because it is easily spread under prolonged and extremely dry conditions. Land cover maps derived from multitemporal satellite imagery showed PSF in the Klias Peninsula was severely affected by the fires. The PSF has decreased from 20,281 ha to 5,364 ha between 1985 and 2003. This study confirmed the influence of agriculture as the most influential anthropogenic factor associated with the fire affected areas. The distance to settlement played an increasingly important role in the fire affected areas, as shown by the increase in weights from 0.26 to 0.35. The results also showed that agriculture is the most significant anthropogenic factor that contributes to the deforestation of the PSF in these study areas with a distance of 1001-2000 m in 1998 fire event and 0-1000 m in 2003.

This study revealed the importance of controlling slash-and-burn activities near the settlement areas as well as in the agricultural plantations. There is also no doubt that the degradation of the peat swamp forest due to forest fires that occurred during prolonged El Niño events remains a serious matter. Monitoring PSF changes is crucial for sound political and policy decision making.

Supplementary material (Table S1 and Fig. S1) accompanies the paper on *Forest System´*s website

Data availability: Not applicable.

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