UNIVERSIDAD DE MURCIA

FACULTAD DE BIOLOGÍA

Tropical Forests: Climate Variability, Vegetation Productivity and Human Disturbance

Bosques Tropicales: Variabilidad Climática, Productividad de la Vegetación y Perturbación Humana

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I am Malaysian, born in 1978. Studying and doing research are my passion. I had an opportunity to study in the University of Murcia, Spain because I was offered Erasmus Mover scholarships for 33 months. This opportunity gave me a chance to conduct my study at one of the European country.

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My father, he is the one who loves knowledge. The difficult time that he gone through for raising us was my spirit and inspiration. I am praying every day for his kindness, sincerity and responsibility.

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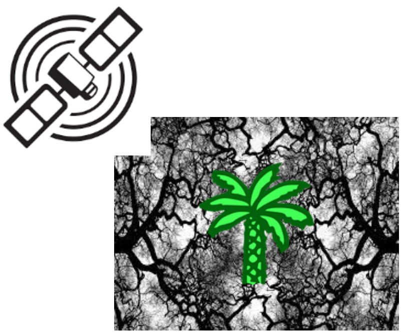
My friends, Zubaida, Fatima, Kaouthar, Hasna and whoever that shared my problems during tough situation; you’re superb mom that changed my weakness to be a stronger person.



Thank you to all & God bless you

Table of Contents

Bosques tropicales: variabilidad climática, productividad de la vegetación y perturbación humana

Resumen

Resumen General

Los bosques tropicales desempeñan un papel importante para mantener el ambiente y mitigar el calentamiento global del planeta. Al mismo tiempo, la agricultura es crítica para soportar tanto la vida humana como la mayor parte de la economía de los países asiáticos del suroeste, especialmente en Malasia. Esta tesis presenta los factores más destacables que contribuyen en las perturbaciones de los bosques tropicales y el desarrollo de la agricultura en la región, y desarrolla un sistema de modelado de bajos costes que se podrían usar para evaluar los impactos humanos en la Producción Primaria Neta (PPN). El estudio ayudará a entender mejor las consecuencias de las perturbaciones humanas, incluyendo el crecimiento de la población y los cambios climáticos, y de modo especial las sequía en los bosques y en las tierras de agricultura en el suroeste de Asia. Por ello se usa las imágenes de resolución moderada MODIS junto con otros datos públicos disponibles para desarrollar este modelo. La tesis identifica los tres factores más cruciales: la variabilidad del clima, la productividad de la vegetación y las perturbaciones humanas, incluyendo el crecimiento de la población. Este crecimiento poblacional es la causa de la mayor parte de los problemas ambientales de los bosques tropicales, y por lo tanto facilitar orientaciones que puedan ayudar para el buen desarrollo de la Política Nacional de los Bosques y de la Biodiversidad.

El capítulo 1 introduce la metodología de análisis de imágenes de MODIS para el desarrollo de los modelos SIG, así como la clasificación de las capas de información de los usos del suelo. El capítulo 1 se basa en la viabilidad del uso de las imágenes MODIS combinado con el uso del suelo, los mapas topográficos y las imágenes de ALOS que sirve para clasificar las capas de uso del suelo. Particularmente para la resolución de mapas de los bosques naturales y las plantaciones.

El capítulo 2 enfoca los cambios de la vegetación en los bosques naturales y las plantaciones sometidos a las condiciones de la sequía. El capitulo 2 desarrolla el monzón

del suroeste de Malasia (M-SWM) sometido a las condiciones de la sequía usando los índices de de la Malasia Peninsular.

En el capítulo 3 se valora el impacto de las actividades humanas en estas áreas en producción primaria neta (conocido como HNPP). El capitulo3 enfoca el impacto de la actividad humana en la producción primaria neta que clasifica los niveles del impacto humano en las zonas forestales.

El capítulo 4 evalúa el consumo de la producción primaria neta per cápita, los recursos de extracción de los bosques y la contaminación que provienen de la actividad agricultura en dos bosques tropicales del suroeste de Asia situados en Malasia y Tailandia. El capítulo 4 compara el impacto de la proyeccion del crecimiento de la poblacion en el NPP, la extraccion de los recursos forestales y la contaminación en los bosques de Malasia y Tailandia en los proximos 30 años (2045).

Resúmenes de los Capítulos

Capítulo 1. Capacidad de integrar la imagen de MODIS y ALOS para el aceite palma, caucho y mapeado de las regiones en los bosques tropicales.

El objetivo de este estudio es para desarrollar las técnicas de mapeado del uso (ej. bosques perennes verdes, palma de aceite de palma y caucho) del sector agricola en los bosques tropicales en la Reserva de los bosques de Pasoh (Malasia Peninsular). En particular, quisieramos determinar la capacidad de los datos de MODIS para el mapeado de la cobertura de la tierra. En este trabajo se indica que si se usa el sistema y el programa adecuado para analizar los datos Modis y teniendo en cuenta que (estos estan disponibles sin costes y los costes de ejecución son reducidos, es una herramienta adecuada para analizar los bosques tropicales. Otros datos públicamente disponibles, como el uso de la tierra, el mapa topográfico y los datos de alta resolución de la imagen ALOS y MODIS permite producir un mapa de usos preciso con bajo coste. El método que desarrollamos en este trabajo puede permitir a los responsables de los bosques tropicales conseguir un uso sostenible de los bosques (SFM) en Malasia con un mínimo coste de la mano de obra.

Capítulo 2. La supervisión de la vegetación bajo las condiciones de sequía usando Los indices de MODIS para los bosques naturales y las zonas de la plantación en Malasia peninsular.

Tras determinar la viabilidad de nuestros enfoques metodológicos, en este capítulo proponemos el uso de datos de MODIS para acceder a los efectos de la sequía en la vegetación de los bosques y las zonas de plantación en las localidades seleccionadas en Malasia peninsular. Nuestro método era para analizar los data de Modis usando (1) el criterio monzón de Suroeste, (2) la precipitación estandarizada tal como está definida en el índice de la precipitación estándar (SPI), (3) la precipitacion mensual, (4) la temperatura mensual, y (5) los índices de MODIS de NDVI y MSI con el objetivo de desarrollar el sistema de clasificación para la evaluación de la sequía en las zonas propensas a la sequía.

La clasificación de la sequía desarrollada aquí es útil para clasificar los niveles de la sequía y posibilitar la creación de las herramientas de su evaluación efectiva, lo que podría ayudar al departamento de meteorología de Malasia para determinar los meses con la probabilidad de la extrema sequía.

Capítulo 3. Cartografía del impacto humano en la producción primaria neta usando datos MODIS para mejorar el desarrollo de la política de gestión.

Nuestro tercer paso es determinar el impacto humano utilizando los datos de los flujos de la biomasa del año 2000 (Global patrón) proporcionados por el Instituto de Ecología Social, Viena (Krausmann et al. 2008). Los humanos dependen de los bosques, desde el cual extraen recursos para la vida o los convierten en tierras de agricultura . Ambas actividades pueden causar la desaparición de los bosques. Es importante estudiar la apropriación de la produccion primaria neta para identificar la disponibilidad de la energía en el ecosistema de los bosques tropicales. Este capítulo desarrolla el mapa del impacto de los humanos en NPP, incorporando la actividad humana y su influencia para estimar la Producción Primaria Neta extraída por el hombre (HANPP) (Krausmann et al. 2008).

El mapa final puede ser útil para aplicar una estrategia adecuada de conservación en la que se pueda minimizar el impacto humano en las zonas con vías de acceso para preservar la productividad primaria del bosque.

Capítulo 4. El cultivo de palma aceitera en los bosques tropicales en el contexto del crecimiento de la población humana

Para concluir esta tesis, evaluamos el consumo de la producción primaria neta per cápita para las zonas de los bosques y las tierras de agricultura de Malasia y Tailandia. La población humana está creciendo en un promedio de 2,5% por año. La presión adicional de la guerra civil y la pobreza en los países de Suroeste conduce cambios en patrón del consumo de los recursos naturales. Incluso Tailandia, con un crecimiento de población de solamente 0,3% para el año 2020, está afectada por el crecimiento del nivel de la vida, lo que ha conducido al aumento del consumo. La pérdida de los bosques debido a la perturbación humana en esta región es una gran preocupación ya en ella se encuentra un punto caliente (hotspot) de biodiversidad del mundo. Para examinar este punto evaluamos el impacto del crecimiento de la población, extracción de los recursos de los bosques y los patrones humanos de consumo de recursos naturales, los efectos de agroquímico en la productividad primaria neta en dos bosques tropicales situados en Malasia y Tailandia. En este estudio se compara las zonas donde se proyectan el porcentaje más alto o el más bajo de crecimiento de la población en el momento actual y en el año 2045. Los resultados de este estudio pueden ayudar a los gestores a desarrollar políticas adecuadas para la sostenibilidad de los bosque tropicales del sureste de Asia.

Introducción general

Las tierras forestales y agrícolas: cambio climático, potencial económico y perspectivas de futuro.

La sequia es un fenómeno y uno de los cambios climáticos impactantes en Asia del suroeste y está reconocida como uno de los factores que causan la mortalidad humana y reduce la producción agrícola. Varios científicos se han preocupado por el impacto de los cambios climáticos en esta región, así que varios estudios se han elaborado en torno al fenómeno del ENSO (Oscilación del Niño en el Suroeste), que causó el fenómeno de la sequía relacionada con la mortalidad (Boyd et al. 2001; Buckley et al. 2007; DID 2005; Khandekar et al. 2000; Nunes et al. 2012; Samanta et al. 2010). Desde el 1998, la sequía no deja de provocar el deterioro de los bosques de Malasia, ocasionando una nube de humo transfronteriza entre los países vecinos de Indonesia que ha sido especialmente peligroso para la salud humana. El polvo atmosférico que cubre Malasia y los otros países vecinos desde hace meses, amenazando la salud y la vida humana que se ha manifestado como un desastre en el área regional (Othman et al. 2014).

La función de los bosques tropicales como un sumidero de carbón, permitiendo el almacenamiento de una gran cantidad de carbono, está amenazada por las actividades humanas y por la atmosfera (Bonan 2008; Joseph et al. 2012; Ngo et al. 2013). Estos bosques consisten en partes fotosintéticamente activas (la mayoría son cloroplasto) y partes no fotosintética con función de soporte o transporte (ej. ramas y tallos) (Joseph et al. 2012). Los bosque tropicales proveen alimento, combustible y refugio para todo el ecosistema (Milesi et al. 2005; Zhao et al. 2005).

Varios estudios han destacado la disminución brusca de la pluviosidad durante la estación seca del monzón del suroeste, ocasionando los niveles más bajos de centenares de embalses y ríos de la región (Associated Press 2005; Wan Zin et al. 2013). Estos cambios afectan al rendimiento de las especies forestales (Corlett 2014) y a la estructura de los bosques. Por lo tanto, la sequía afecta a la agricultura, la salud humana, espacialmente en las zonas más vulnerables que están próximas a los bosques. Dado que la precipitación está disminuyendo constantemente durante los últimos años, las futuras sequías pueden agravar la situación y disminuir tanto en la producción agrícola como la cualidad de la vida humana (Wan Zin et al. 2013).

Teniendo en cuenta los riesgos de la sequías severas sería muy útil entonces seguir las medidas vigentes de la prevención de la sequía que se podría aplicar en la zonas agriculturas, los gestores forestales podrían supervisar los sistemas en otras zonas como los bosques de los pantanos de turba y los funcionarios de servicios de medio ambiente podrían preparar medidas de emergencia como ofrecer información sobre la escasez del agua en las zonas urbanas.

El desarrollo de la agricultura basado en la transformación de los bosques en tierras cultivables ha sostenido la economía de varios países, incluido Malasia. Además, varios estudios han destacado que esta transformación del bosque, especialmente las asociadas a la obtención de aceite de la palma ha mejorado la economía del país, aliviando la pobreza entre los pequeños propietarios de tierras (Dayang Norwana et al. 201 1) y creando miles de puestos de trabajos en los pueblos (Arif and Tengku Mohd Ariff 2001). Un estudio reciente destacó que el éxito de Malasia en esta zona tiende motivar a otros países como Tailandia a transformar la mayoría de sus cultivos del árbol de caucho (*Hevea brasilienses*) a palmeras de aceite, una conclusión que ha sido apoyada por Sayer et al.(2012) y Tan (2014) . Un reportaje realizado por MPOB (2014) ha destacado que Malasia, que es la mayor exportadora del aceite de palma en el mundo, se han plantado 5 millones de hectáreas del aceite de palma. El estudio de esta transformación del uso de la tierra no sólo tiene gran interés científico sino que además es un desafío para el desarrollo sostenible del suroeste asiático. La figura1 demuestra la distribución de los países del suroeste asiático (Wright 2010).

Como el aceite de palma tiene un coste bajo, producir más aceite por hectárea que la producción de otras plantas sería un excelente cultivo para los pequeños propietarios de tierras (Sheil et al. 2009). La sequía causa descensos fuertes en la producción (Rieley and

Page 1995). Sin embargo reemplazar los bosques predominantes por cultivos de palma reduce la habilidad del ecosistema para retener la lluvia, ya que el agua se vierte más rápidamente al río. Otros cultivos de suroeste de Malasia como el café , el arroz y el caucho, han sufrido recientemente sequías severas (Vu and Chaichalearmmongkol 2015). No obstante, el árbol de caucho clones es algo más que resistente a factores externos como la sequía. A lo largo de los últimos diez años, la sequía ha causado varios desastres regionales (Associated Press 2005; Buckley et al. 2007; DID 2005), por ello existe una necesidad urgente para la evaluación de la sequía en el Suroeste de Asia. Se debería realizar más investigaciones en torno de las catástrofes de la sequía para determinar los métodos eficaces y para apoyar la agricultura de Malasia, sobre todo en lo relacionado con la producción del cultivo del aceite de palma. Esta metodología debería ser económicamente factible para las zonas de los bosques tropicales con cultivos comerciales. Para llevar a cabo esta investigación, una herramienta fundamental es la utilización de imágenes de satélite MODIS que permite realizar mapas de los cambios de uso del suelo y proponer un equilibrio correcto entre la producción del aceite de palma y la conservación de los bosques tropicales.

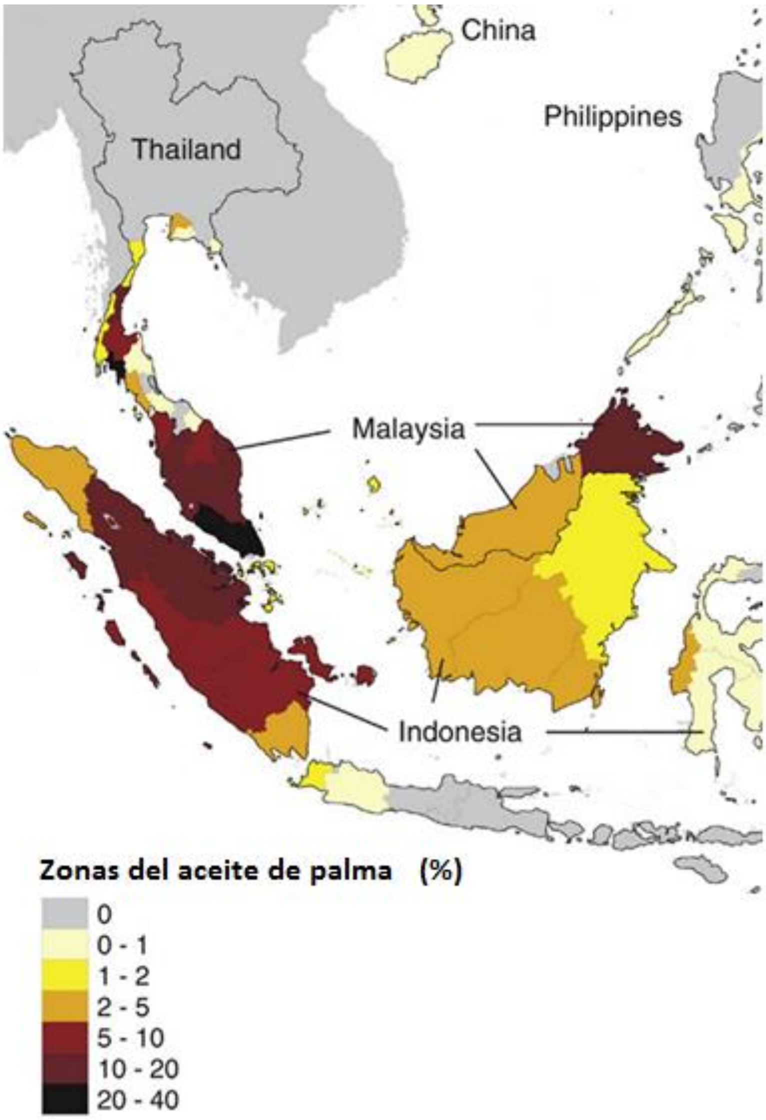


Fig. 1: Distribución de la producción del aceite de palma en los países del suroeste de Asia enfocado en Malasia, Tailandia y Andonesia (datos incompletos para Filipina). Se ve claramente el gran porcentaje de la tierra cultivada está en Malasia y Tailandia. Fuente: Fitzherbert et al. (2008).

Evaluación del impacto humano en los bosques tropicales

El crecimiento rápido de la población, la migración internacional y la pobreza ha aumentado las amenazas ambientales en los bosques tropicales (International Peace and Conflict Studies 2015). Por ejemplo, los campos de emigrantes en zonas profundas de los bosques podrían amenazar la diversidad genética de los árboles, así como las fuentes de agua de los nativos de *Orang Utan* (Meijaard and Sheil 2013). Estos bosques tropicales suponen un componente crítico para el ecosistema global, como una fuente importante para recursos reciclables o no reciclables, y tiene un significado social y cultural.

Prácticamente la totalidad de suroeste de Asia está experimentando un crecimiento rápido de la población. Sin embargo, algunos países (por ejemplo, Tailandia) están experimentando un declive de la población (con 0.3 % de la cifra del crecimiento predicha hasta 2020). Dos reportajes recientes que han cubierto Tailandia (UNPFA 2011) y Malasia (Department of Statistics 2012) demuestran la proyección del crecimiento de la población en suroeste de Asia, que alcanza aproximadamente 30 millones en el año 2020. Este crecimiento ha aumentado la necesidad de alojamiento. Además, a medida que la demanda para una la larga residencia se multiplica y las actividades recreativas aumentan, ejerciendo así más presión en los bosques que gozan de turismo y de alojamientos. Las viviendas de calidad, los parques de los bosques, caminatas por la naturaleza y el flujo comercial son ejemplos de estas nuevas facilidades.

Hoy en día, la perturbación humana ha dejado sus huellas en los bosques tropicales que han reducido su capacidad de ofrecer los servicios ambientales óptimos (Berenguer et al. 2014; Gibson et al. 2011; Mon et al. 2012). La degradación de los bosques tropicales en los países de suroeste de Asia es particularmente alarmante puesto que estos bosques son sistemas claves para mantener el ecosistema tropical.

Además, la larga escala de la plantación del aceite de palma ha causado la fragmentación de los bosques debido al aumento de las carreteras sobre todo después de que el fuego haya disminuido la superficie de los bosques y la sustitución de los cultivos tradicionales (Fitzherbert et al. 2008). Estas incursiones han aumentado la accesibilidad de estos bosques exponiéndolos a los cazadores y a sectores comerciales No obstante, aunque los inversores y los responsables de la política reconocen la importancia de los bosques tropicales para mantener los servicios ecosistemas, en la práctica continúan los cambios en la cobertura de la tierra en los bosques tropicales de suroeste de Asia desde el año 2005 (Wicke et al. 2011). Investigaciones realizadas sobre el impacto del ser humano en las áreas de bosques de China (Su et al. 2012; Yue et al. 2005), Jamaica (Newman et al. 2014) y Serbia (Bajat et al. 2011) deberán ser un modelo para conducir este análisis en sureste de Asia. Varios investigadores han estudiado los efectos del estilo urbano en los bosques tropicales (Broadbent et al. 2008), de la utilización de herbicidas en plantaciones de palma (Langner and Siegert 2009). También se ha indicado que estos herbicidas pueden tener un efecto adverso en los ríos en Malasia (Dayang Norwana et al. 2011).

Se han usado varios enfoques para evaluar el impacto de los bosques (Haberl et al. 2004; Krausmann et al. 2008; Ma et al. 2012), como la evaluación de las carreteras interurbanas, protección legal (Newman et al. 2014) y la intensificación de la agricultura (Firbank et al. 2008). No obstante, la identificación del impacto del área urbana en los recursos de los bosques (por ejemplo la proximidad del establecimiento de los sectores comerciales) es importante para la conservación en sus estados naturales (Phua and Minowa 2005). La densidad humana podría ser el indicador más usado para el desarrollo del modelo de los bosques sometido a la modificación humana (Bistinas et al. 2013). Afortunadamente, los datos públicos disponibles locales e internacionales (ej. datos de población de la ONU) permite disponer de bancos de datos disponibles para la realización de estudios poblacionales.

(a)

(b)

(c)

Fig. 2. Fotos de bosques tropicales en el norte este Peninsular de Malasia. a) claro con un camino; (b) resultado de la plantación del aceite de palma (foto cogida en 26 Julio 2015); y (c) racimo de dátiles frescos. De los racimos de dátiles, además de aceite de palma, también se obtiene fibra utilizada por la industria de la producción de derivados de madera. Fuente: Institute of Tropical Forestry and Forest Products (INTROP).

Numerosos autores han indicado que la producción primaria neta es un indicador muy útil para medir las necesidades inmediatas de los humanos y otros organismos en el ecosistema tropical (Vu et al. 2014;Yang et al. 2014; Potter et al. 2013; Zhao and Running 2010). Este indicador ha sido reconocido para la medida del intercambio del carbono entre la tierra y la atmosfera, que podría ser usado como un indicador biofísico para evaluar el requerimiento de la energía para los próximos años. Algunos autores han usado el concepto del HANPP (Productividad Primaria Neta Extraída por el Hombre) para la análisis del impacto humano en los bosques (Haberl Haberl et al. 2004; Krausmann et al. 2008). Este tipo de estudios es útil para mejorar la conservación y gestión de los bosques (Imhoff et al. 2004) que deberían estar enfocados en los bosques de altos riesgos (por ejemplo aquellos localizados cerca de las áreas urbanas , carreteras y zonas de construcción) en la mayor conservación del valor de los bosques (Sharifi 2004) y la mayor conectividad del valor ecológico (Ferretti and Pomarico 2013;Pomarico 2013).

El concepto HANPP necesita ser adaptado a su uso en los bosques tropicales del sureste de Asia, porque estos bosques están fuertemente influidos por las comunidades de las localidades rurales que los usan para sectores que no son relacionados con los sectores de la producción forestales (NTFPS). En estos bosques tropicales, el estudio del HANPP ha sido escaso debido a la percepción de que estas zonas está bajo la Política Nacional de Biodiversidad (MOSTE 1998) de Malasia y asume que áreas ya están "protegidas".

Teledetección: herramientas para la conservación de los bosques

Los bosques tropicales se están convirtiendo en un estudio crítico para la investigación sobre la conservación y el uso sostenible de los bosques (Phua and Minowa 2005; Reza et al. 2013). El estudio debería concentrarse en la utilización de la información de las imágenes de alta resolución espectral y temporal suministrada por los satélites. Esta es la mejor opción para la observación de los bosques tropicales porque hace hincapié en las dificultades existentes en las zonas de montañosas gran altitud o en pendientes pronunciadas. En estas zonas la metodología usualmente utilizada en tierra es imposible o muy costosa.

Realizar mapas rápidamente de los usos del suero requiere un dato de satélite de alta cualidad como las proporcionadas por las imágenes MODIS. Gran parte de la cartografía del uso del suero pertenece al departamento forestal de la península de Malasia y otros estudios que enfocan en pequeña escala han utilizado imágenes de alta resolución (Jusoff 2009). En este contexto las imágenes de MODIS, son buena fuente para supervisar los datos de la cobertura de la tierra y los cambios climáticos (por ejemplo, la sequía, inundación, los daños provocados por el viento). Su buena calidad ha sido reconocida y utilizada en diversos estudios tropicales (Galvão et al. 2011; Ladle et al. 2010; Luus and Kelly 2008; Xiao et al. 2006). Tiene también una ventaja de la fácil interpretación y coste bajo (Wang et al. 2009; Li et al. 2012; Sheldon et al. 2012).Sin embargo, la información proporcionada por las imágenes MODIS puede verse comprometida en condiciones de lluvias intensas o cielo nuboso las condiciones nubosas. En estas condiciones es necesario complementarlo con los datos del tele detector de satélite de alta resolución como ALOS PALSAR y IKONOS (Dong et al. 2013; Sheldon et al. 2012).

Por otra parte, los datos del tele detector del satélite convencional como NOAA AVHRR no son adecuados para el estudio de la capa del estrés hídrico, pero MODIS es capaz de tener una configuración espectral adecuada para esta tarea (Fensholt et al. 2004). MODIS es capaz de ofrecer propiedades espectrales importantes, derivado de la longitud de onda la corta (infrarrojo) para el estudio del contenido en agua (Cheng et al. 2006; Xiao et al. 2006; Xie et al. 2010; Zhang et al. 2006). Varios estudios han empleado datos de MODIS del canal 5 (1230-1250 nm) y el canal 6 (1628-1652) y han demostrado la correlación con el estrés hídrico (Fensholt y Proud 2012; Galvão et al. 2011; Propastin et al. 2012).

La figura 3 muestra el enfoque triangular de sostenibilidad adaptado de Mata-Lima et al. (2012), donde se muestra la interrelación entre las políticas económicas, sociales, ambientales y la tecnología disponible para lograr la sostenibilidad en los ecosistemas.

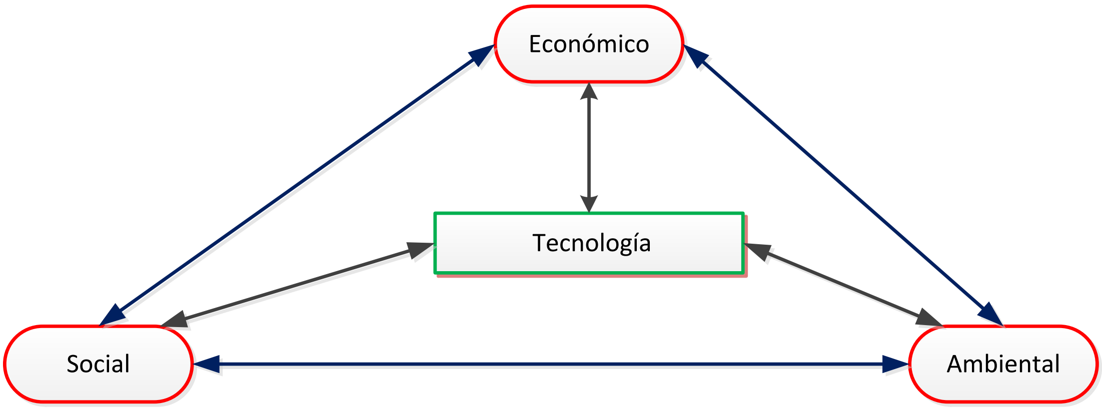


Fig 3. Enfoque de sostenibilidad dirigida en un estudio de Mata-Lima y Alvino-Borba (2012).

En este sentido hay un coste asumible y razonable utilizando la metodología de Sistema de Información Geográfica (GIS) para realizar mapas, visionar y evaluar los recursos naturales con la resolución de imágines de satélite (Macary et al. 2014; Valente and Vettorazzi 2008; Yates and Chen 2014; GEC 2010).

Objetivos de la tesis

Los objetivos de esta tesis son:

i. Evaluar la realización del mapeado de la imagen MODIS de los diferentes usos/cobertura de suelos de la Reserva del bosque Pasoh (península de Malasia) utilizando el método de clasificación de no supervisión (capítulo 1).

ii. Desarrollar el sistema de evaluación y clasificación de la sequía en Malasia suroeste durante la estación del monzón en una zona propensa a la sequía usando los datos del satélite recogidos del MODIS (capítulo 2).

iii. Evaluar la perturbación humana en NNPP y desarrollar un mapa de apropiación humana NPP usando el criterio de la actividad humana (capítulo 3).

iv. Comparar el impacto de crecimiento de la población humana en los dos bosques tropicales de Malasia y Tailandia (capítulo 4).

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Tropical forests:
Climate variability, vegetation productivity and human disturbances

Abstract

Tropical forests play an important role in maintaining the environment and mitigating global warming. At the same time, agriculture is critical to support human life as well as a major part of the economy in Southeast Asian countries, particularly Malaysia. This thesis presents the major factors contributing to disturbances in tropical forests and agricultural land in the region, and develops a low-cost modeling system that can be used to assess human impacts on Net Primary Productivity (NPP). The study will assist in better understanding and appreciating the consequences of human disturbances, including population growth and climate change, particularly drought to the forests and agricultural lands in Southeast Asia. Moderate resolution MODIS image along with other publicly available data, are employed to develop this model. The thesis identifies the three most crucial factors: climate variability, vegetation productivity and human disturbance including population growth that cause most of the problems in tropical forests, hence providing insights that can be helpful in developing effective national forest and biodiversity policies.

Chapter 1 introduces the method of using MODIS image for developing land use/land cover classification maps. Chapter 2 focuses on monitoring vegetation in natural forests and plantations under drought conditions. Chapter 3 assesses the impact of human activities in these areas, on net primary productivity (known as HANPP), and Chapter 4 to assess net primary productivity consumption per capita, forest resource extraction and pollution from agricultural activity in two tropical forests of Southeast Asia, one in Malaysia and one in Thailand.

Chapter 1 assesses the feasibility of using MODIS images, combined with land use and topographical maps and ALOS imaging, for classifying land cover for the study area, particularly for mapping natural forests and plantations.

Chapter 2 develops the Malaysia Southwest Monsoon (M-SWM) drought classification using MODIS indices for Peninsular Malaysia.

Chapter 3 provides an assessment of human activity impact on net primary productivity that rating human impact levels for forest areas.

Chapter 4 compares projected human population growth impacts on NPP, forest resource extraction and pollution on Malaysian and Thai forests, for the next 30 years (to 2045).

General Introduction

Forest and agricultural lands: Climate change, economic potential and the future

Drought is one of the climate change phenomena impacting Southeast Asia and is recognized as one factor causing human mortality and reduced agricultural production. Many scientists are concerned about climate change impacts in this region, and various studies on tropical forests have documented a multi-occasion of ENSO (El Niño Southern Oscillation) phenomenon, which has caused a drought-related mortality phenomenon (Boyd et al. 2001; Buckley et al. 2007; DID 2005; Khandekar et al. 2000; Nunes et al. 2012; Samanta et al. 2010). Every year of drought since 1998 has resulted in the deterioration of Malaysian forests and transboundary smoke haze from the neighbouring country of Indonesia is has been especially harmful. Dusts covering Malaysia and other neighbouring countries for months, threatening human health and livelihoods which has several times been declared a regional disaster area (Othman et al. 2014).

Tropical forests function as a carbon sink, enabling the sequestering of a large amount of carbon from human activities from the atmosphere annually (Bonan 2008; Joseph et al. 2012; Ngo et al. 2013). These forests consist of both photosynthetically active (mostly chloroplast) and non-photosynthetic vegetation (foliage, branches and stems) (Joseph et al. 2012), making them a food generator and a fuel and shelter provider, for the whole ecosystem (Milesi et al. 2005; Zhao et al. 2005).

Many studies have found that during the dry season of the Southwest Monsoon rainfall declines sharply, causing hundreds of reservoirs and rivers to drop to the lowest water level in the region (Associated Press 2005; Wan Zin et al. 2013). This induces changes in species phenology (Corlett 2014) and forest size structure, and also leads to differential impacts on forest species performance. The catastrophe affects forest, agricultural land, human health and livelihoods especially in the most vulnerable areas located adjacent to the forests. As mean precipitation consistently decreases, future drought may worsen this situation and affecting both crop production and the quality of human life (Wan Zin et al. 2013).

Determining the months with severe drought risk can therefore be very useful whereby dryness-prevention measures can be implemented in agricultural areas, forest managers can monitor systems in the other areas such as peat swamp forests and environmental officers can also prepare emergency measures such as early water-shortage warnings for urban areas.

Increasing the acreage of agricultural lands by converting forests to farmland has sustained the economies of many countries, including Malaysia. Furthermore, many studies have found that the expansion of oil palm areas has improved the country's economy, allevating poverty among small landholders (Dayang Norwana et al. 2011) and creating thousands of jobs in villages (Arif and Tengku Mohd Ariff 2001). A recent study found that Malaysia's success in this area likely motivated other countries such as Thailand to convert their major crop from rubber trees (*Hevea brasiliensis*) to palm oil trees that other studies by Sayer et al. (2012) and Tan (2014) have supported this conclusion. A report by MPOB (2014) has found that as the world's biggest palm oil exporter Malaysia has already planted 5 million ha of oil palms and this acreage continues to increase making research concentrating on monitoring land cover changes in Southeast Asian countries both a necessity and a challenge. Figure 1 shows the oil palm distribution for Southeast Asian countries, depicted as a colour-coded map.

Because oil palm has lower production costs, produces more oil per acre than other oil producing plants it is an excellent crop for small landholders (Sheil et al. 2009). Drought, however, causes a severe drop in production (Rieley and Page 1995) and replacing the overlying forest with oil palms reduces the ability of the ecosystem to hold rainfall, as water is flushed more quickly into the rivers. Other Southeast Asian crops such as coffee, rice and rubber, have suffered from recent severe droughts (Vu and Chaichalearmmongkol 2015), although rubber tree clones are somewhat more resilient to stress from external factors such as drought (Rantala 2006). Over the past ten years, drought has caused several regional disasters (Associated Press 2005; Buckley et al. 2007; DID 2005), therefore clearly there is an urgent need for drought assessment for Southeast Asia and more research should be carried out on the drought catastrophes in the region, to determine effective methods of sustaining Malaysian agriculture, especially the critical crop of oil palm products. Such methods need to be economically feasible and sustainable and applicable to tropical forest areas where the most critical cash crops are grown. To carry out such research, high spectral and temporal resolution satellite image such as MODIS (Franklin and Wulder 2002) can be used to rapidly map land cover changes and propose the correct balance between palm oil production and forest conservation.

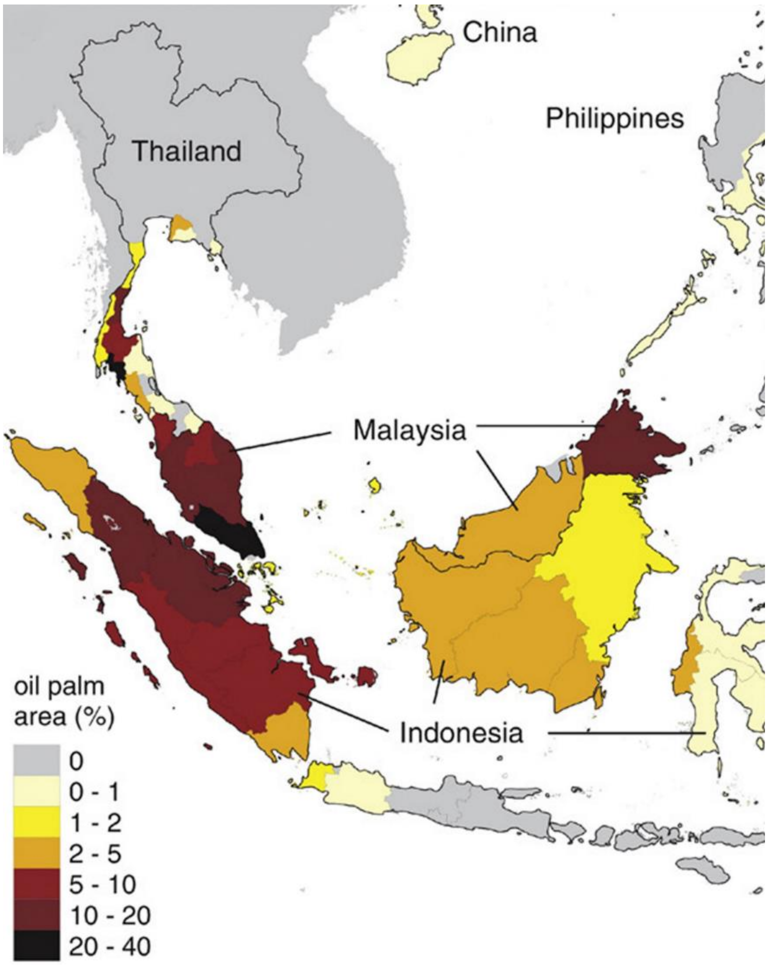


Figure 1. Distribution of oil palm production in the Southeast Asian countries focused for Malaysia, Thailand and Indonesia. Clearly, the highest percentages of cultivated land are in Malaysia and Thailand. Note: The map showed incomplete data for Philippines. Source: Fitzherbert et al. (2008).

Evaluation of human impacts on tropical forests

Rapid population growth, international migration and poverty have increased the environmental threats to tropical forests (International Peace and Conflict Studies 2015). For example, migrant camps deep in the forests can create new clearings in remote areas threatening genetic diversity among the trees, as well as water and food resources for native *orang utan*(Meijaard and Sheil 2013). These tropical forests comprise a critical component of the global ecosystem, are an important source of renewable and non-renewable resources, and have social and cultural significance.

Although some countries (*e.g.,* Thailand) are experiencing a population declination (with 0.3 percent growth rate and no significant growth predicted at least until 2020), overall Southeast Asia is experiencing rapid population growth. Two recent reports covering Thailand(UNPFA 2011) and Malaysia (Department of Statistics 2012) show population growth projections for Southeast Asia of nearly 30 million by 2020 which this growth increases the need for housing. Furthermore, as standards of living raise the demand for larger residential lots and recreational activities increases, putting further pressure on forests and other rural areas from more upscale housing and tourism. Nature-friendly houses, forest parks, nature walks and commercial waterfalls are some examples of these new facilities.

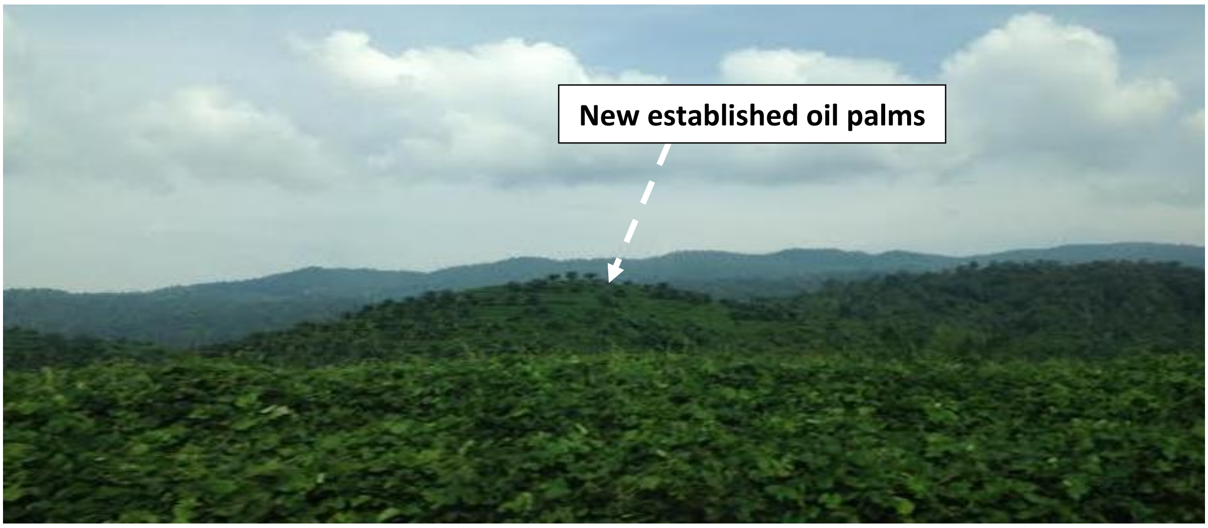
Today, human disturbance has left major impacts on tropical forests which reducing the capacity of the forests to supply optimum environmental services (Berenguer et al. 2014; Gibson et al. 2011; Mon et al. 2012). The degradation of tropical forests is particularly worrisome in Southeast Asian countries, as these forests are one of the keys to maintaining the tropical ecosystems.

Furthermore, large scale oil palm plantations have caused forest fragmentation with road development particularly after forests have been degraded by fire and the displacement of other crops into forest regions (Fitzherbert et al. 2008). These incursions even the most remote forest areas have increased accessibility to the forests and exposed them to hunters and commercial timber extraction (Wright 2010). Figure 2 shows a forest in the north eastern region of Peninsular Malaysia that was first opened with a road and then converted into an oil palm plantation, and a photo of a fresh fruit bunch from an oil palm; these bunches supply fibre for the wood-based product industry. Given all of these agricultural, housing and recreational pressures tropical forests should obviously be a high conservation priority. Yet, although investors and policy makers acknowledge the importance of tropical forests in sustaining ecosystems services, in practice there continued to be many changes in the land cover in Southeast Asian tropical forestss since 2005 (Wicke et al. 2011). Research on the human impact on forest areas conducted in China (Su et al. 2012; Yue et al. 2005), Jamaica (Newman et al. 2014), and Serbia (Bajat et al. 2011), should be a model for conducting such analysis in Southeast Asia.

Thus, many researchers have documented the degradation of tropical forests and some have emphasized the urban-edge effect (Broadbent et al. 2008), the effects of agrochemicals used for combating the grassland species of *Imperata cylindrica* in oil palm plantations(Langner and Siegert 2009), and the increasing agrochemical runoff in rivers in Malaysia (Dayang Norwana et al. 2011).

Numerous approaches have been used for exploring the human impact on forests (Haberl et al. 2004; Krausmann et al. 2008; Ma et al. 2012), by assessing single impact factors such as distance to roads, legal protection (Newman et al. 2014) and agricultural intensification (Firbank et al. 2008). However, because identifying an area's impact on forest resources (e.g., proximity to settlements and commercial timbers) is important for conserving the forest and its natural resources (Phua and Minowa 2005), human density can be a more useful indicator for developing a human-modified forest model (Bistinas et al. 2013). Fortunately, publicly available data pools shared by several institutions (e.g., gridded population data from the United Nations) make data gathering easier than it used to be, for this kind of study.

(a)



(b)

(c)

Figure 2. Photos of (a) tropical forest in North eastern Peninsular Malaysian opened with a road; (b) resulting oil-palm plantation (photo taken on 26 July 2015); and (c) fresh fruit bunch. Source: Institute of Tropical Forestry and Forest Products (INTROP).

There are extensive references on net primary productivity, a highly useful indicator for measuring the immediate needs of humans and other organisms in tropical ecosystems. This indicator has been recognized for the measurement of carbon exchange between land and atmosphere, which can be used as a biophysical indicator to assess energy requirements for future years. Studies by several authors, Vu et al. (2014) and Yang et al. (2014) applied NPP in their global studies, as did Potter et al. (2013) and Zhao and Running (2010) which many of these researchers highlighted specifically the impact on NPP from the human interference perspective. Others have used NPP by means of remote sensing techniques for human impact analysis: for example a study by Haberl et al. (2004) and Krausmann et al. (2008), who introduced the concept of HANPP in their study. This type of research is useful for better forest conservation and management (Imhoff et al. 2004), which should be focused on high risk forests (i.e., those located near urban areas, highways, and construction areas), high conservation value forests (Sharifi 2004) and high ecological connectivity value forests (Ferretti and Pomarico 2013).

Conservation of forests by HANPP analysis can also be a powerful tool for measuring food security, as it could provide basic research evidence for land and habitat suitability analysis; it was used for example by Catullo et al. (2008) and Ferretti and Pomarico (2013). The concept needs to be refined though for use in the tropical forests of Southeast Asia because these tropical forests are heavily influenced by the local rural communities, who utilize them for 'non-timber forest products' (NTFPs). HANPP has also been poorly studied in these tropical forests because of the perception that these areas are under a forest governance policy the National Policy on Biodiversity (MOSTE 1998) for Malaysia and it is assumed that the areas are already "protected".

Remote sensing: Tools for forest conservation

Tropical forests are becoming a critical research area for forest conservation and sustainable forest use (Phua and Minowa 2005; Reza et al. 2013). Study methods should concentrate on high spectral and temporal and also medium resolution satellite data. This is the best choice for observing tropical forests, because access is difficult in mountainous zones at high attitudes or on steep slopes; in these areas, human impact assessment is impossible or too costly to assess using on the ground methods.

Mapping rapid land cover changes requires high temporal satellite data such as unrestricted MODIS image. Much of the current land cover mapping by the Forestry Department of Peninsular Malaysia and other researchers focuses on a small scale using high resolution image data, and some have also restricted their focus to develop mapping methods by employing high resolution data (Jusoff 2009). More recently, however studies have demonstrated methods for mapping tropical forest areas and agricultural lands using medium resolution data (Senf et al. 2013; Sheldon et al. 2012).In this context, MODIS imaging is a good source of data for monitoring both land cover and climate changes (e.g., drought, flooding, wind damage); its capabilities have been recognised and verified in tropical applications (Galvão et al. 2011; Ladle et al. 2010; Luus and Kelly 2008; Xiao et al. 2006). It also has the advantages of ease of interpretation, low costand global coverage (Wang et al. 2009). Many researchers have employed MODIS image for mapping forests and vegetation (Li et al. 2012; Sheldon et al. 2012). Heavy rainfall or cloudy conditions, however can compromise MODIS data; hence it is necessary at times to supplement it with data from higher resolution sensors, such as ALOS PALSAR and IKONOS which these satellite have proven useful in several studies (Dong et al. 2013; Sheldon et al. 2012).

On the other hand, remote sensing data from conventional satellites such as NOAA AVHRRare inadequate for studying canopy water stress, whereas MODIS sensors have suitable spectral configurations for this task (Fensholt et al. 2004). MODIS is capable of supplying important spectral properties, derived from shortwave infrared wavelengths, for canopy water content studies (Cheng et al. 2006; Xiao et al. 2006; Xie et al. 2010; Zhang et al. 2006). Various studies have employed MODIS Channel 5 (1230-1250 nm) and Channel 6 (1628-1652 nm) data, and have shown a correlation with water stress (Fensholt and Proud 2012; Galvão et al. 2011; Propastin et al. 2012) that was earlier verified by (Gao 1996). Figure 3 is a sustainability triangle adapted from Mata-lima et al. (2012), depicted inter-relation between economic, social, enviornmental and technology available to achieve sustainability in the ecosystems.

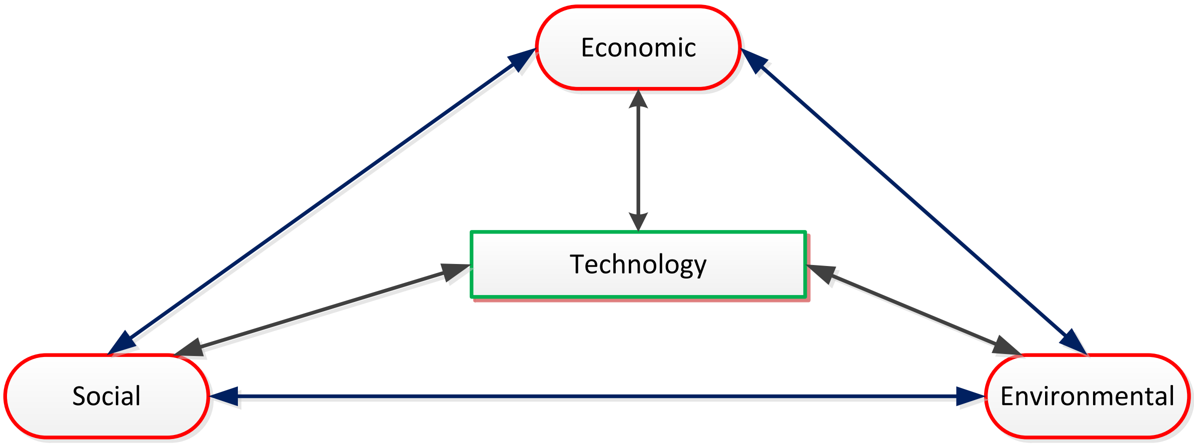


Figure 3. Sustainability approach addressed in a study by Mata-lima and Alvino-borba (2012).

Yet another cost effective way of mapping, monitoring and assessing natural resources is employing Geographical Information Systems (GIS) (Macary et al. 2014; Valente and Vettorazzi 2008; Yates and Chen 2014) at regular spatial resolution (GEC 2010). Finally, the use of tools for mapping, monitoring and assessing the areas are examined. Thus, it is studied the feasibility of remote sensing medium resolution of MODIS for balancing between economics benefits and forests conservation.

Objectives of thesis

The aims of this thesis are:

i. To assess the performance of MODIS imaging for mapping different land uses/covers in the Pasoh Forest Reserve, Peninsular Malaysia using unsupervised classification methods (*Chapter 1*).

ii. To develop a classification system for drought assessment for the Malaysia Southwest Monsoon season, in a drought-prone area using satellite image data from MODIS (*Chapter 2*).

iii. To assess human disturbance impacts on NPP and to develop maps of human appropriation of NPP using human activity criteria (*Chapter 3).*

iv. To compare human population growth impacts on two tropical forests, one in Malaysia and one in Thailand (*Chapter 4*).

~ Chapters~

Chapter

1

Capability of Integrated MODIS Imagery and ALOS for oil palm, rubber and forest area mapping in tropical forest regions

Parts of this chapter have been published in: Sheriza M. R., Arnaldo Marin, N. A. Ainuddin, Helmi Zulhaidi, M. S., Hazandy, A. H. (2014). Capability of Integrated MODIS Imagery and ALOS for Oil Palm, Rubber and Forest Areas Mapping in Tropical Forest Regions. *Sensors* 14: 8259-8282.

Abstract

Various classification methods have been applied for low resolution of the entire Earth's surface from recorded satellite images, but insufficient study has determined which method, for which satellite data, is economically viable for tropical forest land use mapping. This study employed Iterative Self Organizing Data Analysis Techniques (ISODATA) and K-Means classification techniques to classified Moderate Resolution Imaging Spectroradiometer (MODIS) Surface Reflectance satellite image into forests, oil palm groves, rubber plantations, mixed horticulture, mixed oil palm and rubber; and mixed forest and rubber.

Even though frequent cloud cover has been a challenge for mapping tropical forests, our MODIS land use classification map found that 2008 ISODATA-1 performed well with overall accuracy of 94%, with the highest Producer's Accuracy of Forest with 86%, and were consistent with MODIS Land Cover 2008 (MCD12Q1), respectively.

The MODIS land use classification from our study was able to distinguish young oil palm groves from open areas, rubber and mature oil palm plantations, on the *Advanced Land Observing Satellite (*ALOS) map, whereas rubber was more easily distinguished from an open area than from mixed rubber and forest. This study provides insight on the potential for integrating regional databases and temporal MODIS data, in order to map land use in tropical forest regions.

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1. Introduction

The natural land cover of the Peninsula of Malaysia is primarily evergreen forests, including mountain, hill, and lowland tropical forests, along with peat swamps and mangrove forests in the lake and river regions. The most significant land use change in the peninsula has been the clearing of forests for agricultural purposes and mining activities, as well as for the establishment of settlements along the coastal and riverine areas (Cleary and Goh 2000). The conversion of natural forest into agricultural uses such as for oil palm, rubber, coconut, pineapple, mixed horticulture, market gardening and floral farms, has been reflected in regional land use maps of the peninsula. By the 1960s, the Malaysian Agricultural Department had successfully produced the first land use classification maps for the West of Malaysia, with the cooperation of the Canadian Government. To date, the maps have been updated every two years based on soil surveys, satellite image interpretation, digitizing and ground verification through the utilization of satellite imagery such as aerial photos, Landsat Thematic Mapper (TM) and System Probatoire d'Observation de la Terre (SPOT). Utilization of high resolution satellite such as SPOT proved reputable in previous studies, since satellite imagery has been used for decades in many areas such as evergreen tropical forest and riparian studies (Kamp et al. 2013; Zhang and Zhang 2007). The process, however, is very expensive, requiring extensive human labour to interpret the results, maintain the software and monitor the equipment (Dong et al. 2013). Consequently, although land use maps for Peninsular Malaysia are available in digital format to the related government agencies, private or non-governmental sectors, non-profit making nature society, environmental public researchers and scientists have not been able to acquire these data because of the high cost.

The classification of satellite imagery for land cover mapping requires the extensive skills of an experienced analyst (Aitkenhead and Aalders 2011). When such skills were not available, land cover classification maps have been developed through ground surveys and base maps such as digital topographic maps, recent land use maps and soil suitability agricultural maps; these techniques have been increasing the accuracy of land cover classification maps (Reichenbach and Geng 2003). Updating or replacing these maps with a large amount of remotely sensed data remains a very challenging task (Franklin and Wulder

2002). Yet both the private sector, governmental and non-governmental agencies are now depending on satellite applications for mapping their land uses. For example, the United States Geological Survey's Gap Analysis Program, which started in 1998 (Scott and Jennings 1998), and the National Land Use Change Program of China (Zhang and Zhang 2007), rely on such data.

The 10th Conference of the Parties for the Convention on Biological Diversity, held in Japan, was aimed at achieving the Aichi Biodiversity Targets, whose goal is to at least halve and where feasible, bring close to zero the rate of loss of natural habitats, including forests, and to establish a conservation target of 17% of terrestrial and inland water areas and 10% of marine and coastal areas. One of the most crucial sectors where Earth Observation (EO) can assist in such land use and land cover mapping is by enabling the mapping of large inaccessible areas. Hence EO is playing a major role in providing essential tools to support national and international monitoring systems (Clerici et al. 2012).The objective of this study was to provide techniques for mapping land uses such as evergreen forests, oil palm and rubber farming, and other land use types.

The rubber industry in particular is being given special attention, as it has great economic potential and provides income for over 400,000 small landholders. The area planted in oil palm has expanded year by year. In 1998 it was planted with 109,446 ha; this was increased to 123,343 ha in 2000 and to 134,427 ha in 2001. The area reached a maximum of 171,647 ha in 2008 but was reduced to 166,501 ha in the next year, and has continued to fall, to 164,362 ha in 2010 (MPOC 2010). The rubber plantation scenario presents a different pattern, as reported by the report. Rubber was planted in 1,430,680 ha in 2000, 1,325,600 ha in 2003, and 1,263,590 ha in 2006, and consistently dropped from 2007 to 2010 (1,248,040 to 1,020,380 ha) (Figure 1). In addition, the National Key Economic Area (NKEAs) of Malaysia report identified oil palm and rubber as priority areas for contributing most of Malaysia's economic performance by 2020 (MPOC 2011).

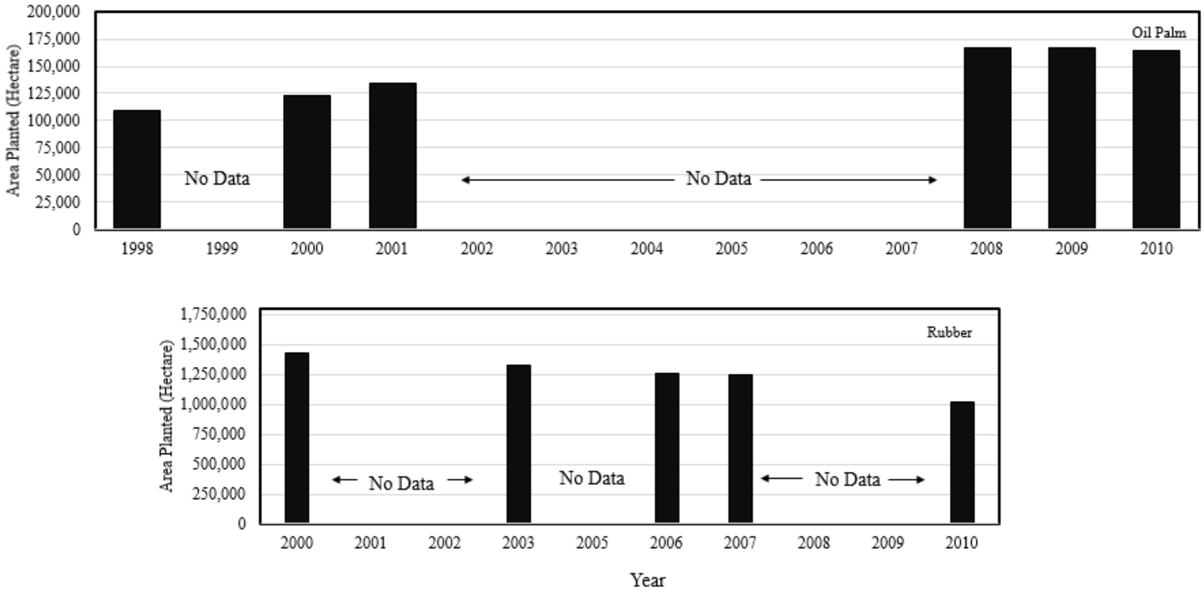

Figure 1. Graphs of area planted with oil palm and rubber from 1998 to 2010.

With the increasing global demand for oil palms (at least before 2008) and rubber products, it is necessary to develop and update land use maps for improving our understanding of land use changes, with minimal labour and equipment cost. Furthermore, such maps provide information not only on existing land use types such as tropical evergreen forests, oil palm and rubber, but also on other agricultural uses such as pineapple, cocoa, mixed horticulture and other crops.

2. Material and Methods

Study Area

Negeri Sembilan is located in the western part of the Peninsula of Malaysia. Research was conducted in an area of slightly more than 1,000 km^2 centred on the Pasoh Forest Reserve (PFR). The PFR is located at 2°58'N, 102°18'E (Figure 2). It is connected to urban areas by the Kajang-Seremban Highway (E21), road number 86 and N23; travel time is about 2 hours and 15 minutes from the Federal Territory of Kuala Lumpur. The PFR is covered with primary lowland mixed dipterocarp forest (tropical evergreen broadleaf forest) that includes various species of Shorea and Dipterocarps (Kosugi et al. 2008). There are numerous types of vegetation in the area surrounding the forest reserve. The oil palm plantations of Felda

Pasoh Dua known as PFR Corridor are dominant, covering the southern region and Felda Pasoh Empat in the northern part of the area. At the other site of the PFR is Felda Lui Barat, which is planted with both oil palm and rubber. Mean temperature recorded is 26.3°C measured for 2002–2005. Recent annual precipitation is 1,702 mm measured for 2000–2011 (MMD 2008; NIES 2011; UKM 2011). Historically, most of the surrounding area has been natural forests, but human exploitation has led to a significant decrease in these primary forests, as they are turned into oil palm plantations (Manokaran 1990), with a total area of 568,561 ha planted in the peninsula by 1975 and dramatically increased for more than 1 million ha by 20 years.

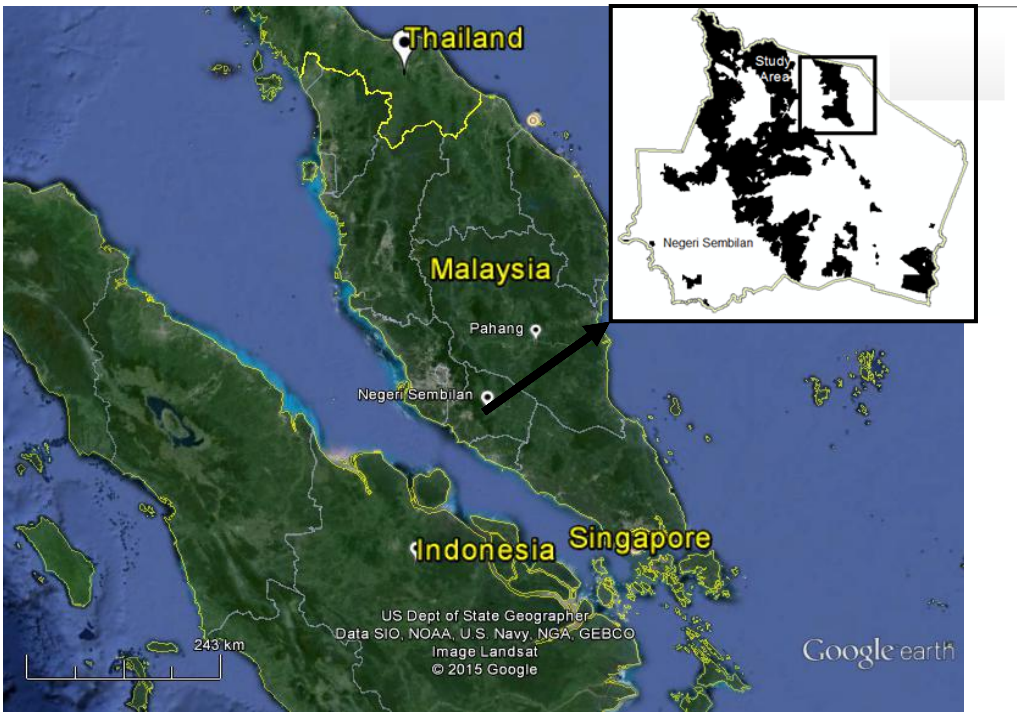

Figure 2. Location of the study area. Source: Google Earth (2015).

The objective of this study was to provide techniques for mapping land uses such as evergreen forests, oil palm and rubber farming, and other land use types. Negeri Sembilan, the location for the permanent research plot of Pasoh Forest Reserve in Southeast Asia, was chosen as the central point of the study area. The plot was used for intensive biomass and productivity research from 1971–1973, under the International Biological Programme (IBP), Universiti Malaya (UM) and the UNESCO Biosphere Program (MAB), and the joint Rainforest Research Project of Universiti Malaya and the University of Aberdeen, UK. The Negeri Sembilan region is a critical area for both oil palm and rubber production, and was chosen as a focus of the Malaysia Government's Economic Transfer Programme.

MODIS Data, Pre-Processing and Enhancement

To carry out the objectives of this study, MODIS Surface Reflectance series data (MOD09A1) acquired in 2000, 2005 and 2008 were used. MODIS Land Cover products (MCD12Q1) was taken in 2001, 2005 and 2008 and ALOS was taken in 2008 (Table 1). The 500 m MOD09A1 series data of 2000, 2005 and 2008, which could potentially be used for land use mapping (Braswell et al. 2003),was been inter-calibrated with other data such as *National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (NOAA AVHRR)* and linked to field census data such as in Huete et al. (2002).

Table 1. Data used in the study.

No.	Data	Resolution (meter)	Year	Source
1.	MODIS Surface Reflectance series data (MOD09A1)	500 m	2000, 2005, 2008	LP DAAC (2011)
2.	MODIS Land Cover products (MCD12Q1)	500 m	2001, 2005, 2008	LP DAAC (2011)
3.	ALOS *AVNIR-2*	10 m	2008	Imaging Cooperation

Images were selected based on scale, availability of the image data, cost, time constraint and atmospheric correction (Lu and Weng 2007). The MOD09A1 500 m resolution was chosen because it's covers the whole study area with one scene, hence, reducing times and cost for mosaicking the imageries. The images were collected based on the availability of the image with minimum cloud cover, which could decrease precision during image interpretation and classification. The high temporal resolution promotes good quality imagery with limited cloud contamination (Wang et al. 2009). Unfortunately, good quality satellite data is often particularly difficult to obtain in tropical forest areas due to lower seasonality and heavy cloud cover conditions (Huete et al. 2008). We have downloaded more than fifty images for those years and reanalysed them with band matching for filtering a high quality image. Finally, with these disadvantages only one individual image were identified for each year for further processed. Higher frequencies of bright pixels were detected on forested areas, because clouds are generally bright in the visible spectrum and cold in the infrared spectrum. Therefore, to overcome these disadvantages cloud removal analysis were conducted using density slice and masking procedure techniques in Exelis Visual Information Solution (ENVI).

In this study, cloud detection procedure were conducted based on comparison with Present Land Use map of Negeri Sembilan 2004 and the images in visible and infrared bands (focusing in band 1, band 2 and band 6), where cloud cover is the unwanted information in optical images. Furthermore, image enhancement were conducted using band combination techniques of: (i) 6, 4, 3; (ii) 1, 2, 3; (iii) 1, 3, 4; (iv) 5, 3, 4; (v) 3, 1, 2; and (vi) 2, 6, 1. The images were also enhanced using histogram equalization for further image interpretation (Tseng et al. 2008). MOD09A1 of 2000 and 2005 image were validated with Present Land Use map of Negeri Sembilan 2004. The land use map is updated every two years and reproduced with recent SPOT image and JUPEM (Malaysian Survey and Mapping Department), Topography Map Series 7030, which further verified with ground survey by land surveyor of Malaysian Agricultural Department. First, the map was geo-corrected using Topography Map Seremban 1996 Series 7030 and resample to 500 m pixel sizes as the same size of MOD09A1 data. The map was subset into an area of interest by using an areas similar with MOD09A1 data.

MOD12Q1 500 m resolution was chosen based on availability of the image that was first produced from 2001. Therefore, we chose MCD12Q1 2001 data to compare with our land use classification from MOD09A1 2000 data. The MCD12Q1 2005 and 2008 were fortunately available for our study. ALOS had to order from our satellite data vendor, Satellite Imaging Corporation (SIC), therefore much time consuming waiting for choosing the recent data, suitable image with minimal cloud cover, acquiring, pre-processing and mapping. We found ALOS 2008 was the best image data available for the study area.

The study was conducted in four parts: (1) creating a MOD09A1 500 m land use classification map, employing unsupervised ISODATA and K-Means classification techniques; (2) creating an ALOS 10 m land cover types map from reclassification, proximity analysis and spatial analyst; (3) creating an elevation map from NFI-4 data; and (4) comparing the MODIS land use classification map with ground verification survey, NFI-4 data, Topographic data 1997, MCD12Q1, ALOS land cover type and elevation.

ALOS AVNIR-2 Data and Processing

The ALOS is ALOS AVNIR-2 or *Advanced Land Observing Satellite* of Advanced Visible and Near Infrared Radiometer type 2 with 10 m resolution. The ALOS 2008 image was enhanced utilizing histogram equalization that was found to be effective at improving image interpretation for land uses such as rubber, oil palm plantations and forested areas (Tseng et al. 2008).

Image Classification and Unsupervised Classification (ISODATA and K-Means)

Although many computer-aided techniques have been developed for land cover classification, the skills and experience of an analyst are still very important to the success of the image classification (Aitkenhead and Aalders 2011; Lu and Wong 2008). We chose ISODATA because our study area consisted a less complex land cover types, consisting forested areas and agricultural plantation mostly an oil palm or rubber—which are widespread in the peninsula. ISODATA is a suitable technique to be applied in forested areas with presence of agricultural plantations because most of forested areas which have been previously logged several years ago may have excellent ancillary data. Data such as land use maps, national land cover maps and as well as a good local knowledge of the terrain, vegetation and soil of an area are essential databases for logging managers. Therefore, the data is possibly to be acquired and employed in ISODATA classification for this area or other similar background area.

K-Means was chosen because the study area consisted with forested areas within lowland and hilly dipterocarp and also non-dipterocarp, peat swamp and mangrove forest. Most of forest and land managers in tropical forest were updated with new technology of land mapping. This is because they should facilitate ecological and monitoring systems with the aim of providing useful guidance on forest information included forests dynamics, regeneration, *etc.* (Secretariat of the Convention on Biological Diversity 2009). Therefore, with this current situation most of the information databases required for the classification are highly available. Because the K-means clustering technique is simple, where K is the desired number of clusters to be input, highly available database number increased the number of K. The classification adopted in this study is therefore applicable to the background of the study area.We therefore chose to adopt unsupervised classification, to overcome the challenges of mapping land use in a tropical region using mediumresolution satellite imagery.

Mapping Land Use Classification

Mapping MODIS

The initial observations were conducted on a topographic map of Seremban and Kuala Pilah 1996; and Present Land Use maps of Negeri Sembilan from 1996 and 2004 as a base map for the classification. The land use map was produced by the Malaysian Agricultural Department whose study found that the land use map was a good background to present the land use classification map for the 2000–2008 MODIS data sets, since there had been no conversions of forest land to oil palm plantations at the border of PFR and Pahang since 1997. The maps were registered using Rectified Skewed Orthomorgraphic (RSO) coordinate format, the format that has been utilized by Malaysian government agencies such as the Malaysian Forestry Department in registering their map for further image processing, analysis, spatial applications and also for decision making, for example forest fire risk assessment and forest resource updating.

Furthermore, the maps were rectified based on Nearest Neighbor, 1st Order Polynomial with pixel size of 500 m and were projected to WGS 84, UTM Zone 48 N. Geo-correction was based on four points: (i) an area at the boundary of Negeri Sembilan/Pahang;

(ii) an area bordering the oil palm plantation and PFR, of which the nearest point indicated in Google Earth is Kampung Lui; (iii) PFR, which is the nearest point to Felda Pasoh Dua; and (iv) PFR and an area bordering a rubber plantation in the southern part of PFR; in this study we used Google Earth images to locate points for image registration for this point (Dong et al. 2013).

Unsupervised classification of ISODATA Gamma (ISODATA-1), ISODATA Kuan (ISODATA-2), K-Means Gamma (K-Means-1) and K-Means Kuan (K-Means-2) were employed in the study area as depicted in Table 2. The ISODATA was determined using maximum likelihood decision rule to calculate class mean that are evenly distributed in the data space and then iteratively clusters the remaining pixels, using minimum distance techniques (Melesse et al. 2007; Tou and Gonzales 1974). The K-Means was conducted using the Erdas Imagine 9.1 software. Parameters incorporated in the analysis for ISODATA were reported as the following: number of classes at minimum 5 and maximum 10; minimum pixel in classes, 1; minimum class distance, 5; and minimum merge pairs, 2. Finally, the clusters were classified in terms of the ground conditions they represented, identified from the ground survey and land use maps of 1997 and 2004 (Justice and Townshend 1982). The parameter for K-Means arranged was the number of classes at minimum 5. The Gamma and Kuan applied in the study following the methodology from Tung et al. (1998), tested for pixels filtering at 3 × 3 and 5 × 5 pixels window. After preliminary classification, 5 × 5 pixels window classifications were and applied to all the images.

Mapping ALOS

ALOS was subset to approximately 41 km^2, or 3.7% of the whole 1,000 km^2, at the west side of the study area. Prior to that, ALOS land cover types were derived from unsupervised classification. First the image had been classified into five land covers and were reclassified into four types because we are interested in assessing accuracy for the massive pixel size of MODIS, though, only the open areas, forests, oil palm and rubber plantations were considered in clustering; the others were merged and grouped as unclassified. Overall techniques employed to derive final map of ALOS incorporated of reclassification, proximity analysis and spatial analyst of majority filtering by using ARC GIS 10.0 as reported in Table 3.

Table 2. Description of the classification label assigned.

Methodology	Description of Filtering (5 × 5) pixels
ISODATA Gamma	ISODATA-1
ISODATA Kuan	ISODATA-2
K-Means Gamma	K-Means-1
K-Means Kuan	K-Means-2

We used ground verification survey, NFI-4 and Topographic data 1997, MOD12Q1, ALOS land cover type and elevation to evaluate the accuracy of the MODIS land use classification, since accuracy assessment is a critical step in analysing any map created from remotely sensed data (Wang et al. 2009). Standard assessment of accuracy included Producer's, User's and Overall Accuracy were employed for accuracy assessment (Ayhan and Kansu 2010; DeAlwis et al. 2007; Wessels 2004). The accuracy data were derived from error matrices table to find the reliability and accuracy of the maps produced (Manandhar et al. 2009). The accuracy is a direct interpretation of percentage of cases correctly classified (Gómez and Montero 2011). Producer's Accuracy indicates the probability of a reference pixel being correctly classified. User's Accuracy is where if the total number of corrected pixels in a category is divided by the total number of pixels that were classified in the category (Congalton 1991). Overall Accuracy is the simplest and one of the most popular accuracy measures computed as conducted by Ayhan and Kansu (2010).

Table 3. ALOS land cover types development techniques.

Methodology	Parameters
Reclassification	Natural Breaks
Proximity analysis	Buffering features at 500 m
Spatial Analyst with Majority Filter	Aggregate Cell Factor is ''10–20'' Boundary Clean is ''Ascending'' Number of Neighbours to use is ''8'' Replacement threshold is ''Half''

Sampling Points and Accuracy Assessment of MODIS Land Use Classification

Comparison with NFI-4 and Topographic Data 1997

We employed stratified random sampling points in order to assess the accuracy for MODIS land use classification. Because of moderate resolution of the MODIS satellite image employed and inaccessibly of the forested areas except for the central point (PFR) areas and agricultural areas limited number of sampling points were qualifying to locate and survey. This is because a low number of points may contribute to errors (Powell et al. 2004). Therefore, to supplement this, we used NFI-4 data to input more points which generated a total of 4,791 points on the MODIS land use classification.

The points generated were for four different categories such as forests, oil palm, rubberand mixed horticulture. We used the NFI-4 data because it was produced for long-term Malaysian forest inventory resources database (2000–2010), which also incorporated SPOT image of 2010 for delineation of forested area (FDPM 2014). Furthermore, Topographic data 1997 (sheet codes 3957b, 3957d, 4056a and 4057c in CAD format); which had been ground proofed by the Malaysian Survey and Mapping Department was used for generation of sampling points. The complete data employed was presented in Table 4.

Subsequently, all the points were ground verified to obtain an error matrix and overall accuracy of the classification. The areas surveyed included oil palm and rubber plantations, forests areas, paddy fields, and housing areas located among crop trees such as langsat (*Langsium domesticum*) trees, mangosteen (*Garcinia mangostana*) and coconut trees (C*ocus nucifera*) (Figures 3). The survey was started on 24 October 2011 and ended at the end of March 2012 with Global Positioning System (GPS) and digital camera as the main information capture tools. In order to conduct further comparison, percentages of land use classes were also derived.

Comparison with MCD12Q1

This study extracted three data sets: MODIS 2000 ISODATA-2, MODIS 2005 K-Means-1 and MODIS 2008 ISODATA-1 for further development of accuracy assessment with MCD12Q1 data sets as a result of a successful classification of those pixels into a land use classification. The land use classification of MODIS 2000, 2005 and 2008 have overall accuracy of 85%, 65% and 94%, respectively.

A comparison between the land use classification and MCD12Q1 for all data sets was conducted, and an error matrix was generated to evaluate the consistency of the land cover classification results (Dong et al. 2013). MCD12Q1 data sets were regrouped into forest and non-forest based on NFI-4 data. In this study, sample points of land use classification from MOD09A1 which covered as at least 95% pure on MCD12Q1 were assigned to the dominant cover ("forest or non-forest"), while points of our land use classification from MOD09A1 that were below 95% on MOD12Q1 were also assigned as ("forest or non-forest") class (Figure 4).

Table 4. Data employed in the study for an accuracy assessment.

Map	Source	Produced/Published, Year
Present Land use—Negeri Sembilan 1997 and 2004, Scale: 1:150,000	Malaysian Agricultural Department, Putrajaya	Malaysian Agricultural Department, Putrajaya/Soil Resource Conservation and Management Division, Malaysian Agricultural Department, 1997 and 2004
Topographic map—Seremban 1996 (Sheet 3856), Scale: 1:50,000 Topographic map—Kuala Pilah (Sheet 3956) Scale: 1:50,000 Topographic Sheet Code (3957b, 3957d, 4056a, 4057c) (CAD format), Scale: 1:250,000	Universiti Putra Malaysia	JUPEM/Director of National Mapping, 1996 JUPEM/Director of National Mapping
NFI-4—2000–2010	Peninsular Malaysian Forestry Department	Peninsular Malaysian Forestry Department, 2000–2010

Note: JUPEM (Malaysian Survey and Mapping Department).

Previously, the sampling points on MCD12Q1 were buffered at 500 m, extracted and overlaid on the MODIS land use classification. The objective was to link with MCD12Q1 data to improve the purity level of the classification and to assess accuracy as modified by (Wessels 2004) such as sites that were at least 70% pure were assigned to the dominant cover type, while mixed sites (e.g., 67% conifer and 35% herbaceous) were classified as mixed coniferous/herbaceous. The objective of the appointment of purity was to avoid confusion during the evaluation of an accuracy of the points reaching the designated threshold.

Validation of ALOS Land Cover Types

In addition, sample images from Google Earth in 2008 were used as reference to the ALOS land cover types accuracy assessment. We matched and validated rubber and urban areas with Google Earth images of Thailand which were the areas studied by (Li et al. 2012; Tan et al. 2012). An area from a non-traditional rubber plantation planted on 10,000 ha to 50,000 ha in Kuan Wan, Thailand which is near the border of Cambodia was used in the study. In addition, rubber estates in Kemayan, Negeri Sembilan and an open area in several areas in Penang Island of the peninsula were also incorporated in the study. Land Surface Temperature (LST) product derived from Landsat TM in a study conducted by Tan et al. (2012) were used to compare with urban areas, since, LST measure temperatures from land surface. The surface temperature (T_s) is related to percentage of green cover, hence, the lower the green cover the higher the surface temperature.

Figure 3. Ground proofing photos of (**a**) a housing area in the rubber and oil palm estate which also contained langsat (*Langsium domesticum*) trees, mangosteen (*Garcinia mangostana*) and rubber; (**b**) abandoned paddy field; (**c**) Rubber trees; (**d**) Oil Palm trees; (**e**) Bamboo trees (*Bamboo* spp.) and finally (**f**) Banana trees (*Musa* spp.) with other local fruits trees.

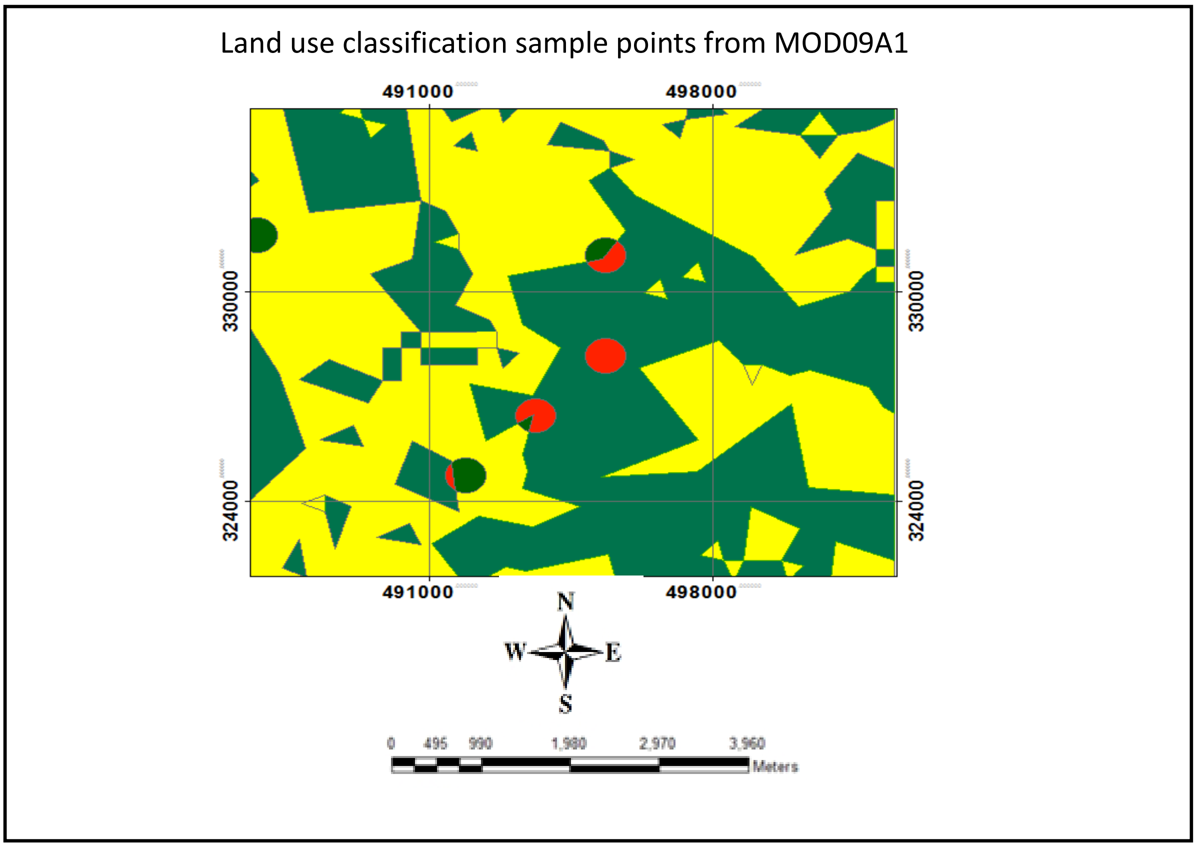

Figure 4. Land use classification sample points from MOD09A1, which are covered by at least 95% pure on MCD12Q1 were assigned to the dominant cover ("forest or non-forest")-red colour, while points of land use classification sample points from MOD09A1 that were below 95% were assigned as ("forest or non-forest") class.

Comparison with ALOS Land Covers map

Once a classification map is developed in this way, it needs to be validated against known data. Researchers have been validating their maps with available global satellite data land cover products such as the MODIS Land Cover Type product (MLC) (Friedl et al. 2010); Landsat-based National Land Cover datasets—for example, the IKONOS-derived forest map (Sheldon et al. 2012), China's database (NLCD) (Peng et al. 2002) and Google Earth (Li and Fox 2012), which has a high horizontal potential accuracy (Potere 2008). Mapping forests with ALOS PALSAR 50-m data, for example, was successfully used to differentiate between primary forest and newly deforested areas in the Brazilian Amazon (Almeida-Filho, Shimabukuro, 2009). However, we might have needed more ALOS data to represent our area, which significantly increased time and cost. Therefore, a combination of MODIS land use classification and highly satellite resolution data was the most feasible method of land use mapping in our tropical forest. The MODIS land use classification of 2008 ISODATA-1 (our highest overall accuracy) was overlaid to compared and assess spatial distribution of the land use classification on higher resolution satellite image as a sample from all the maps.

Elevation Map

The elevation map was derived from following standard geo-statistical procedure of kriging interpolation analysis conducted in the ARC GIS 10.0. Elevation play a huge role in differentiating in soil and light resources hence appears related to stature of the forest (Ediriweera et al. 2008). A relevant study by Aiba et al. (2005) on species richness of different elevational of Mount Kinabalu in Borneo tropical rainforests found species pool among forests was one of the causal interpretation among dynamics, productivity and species richness of the study. Study by Ashton et al. (2001) has revealed rainforests from lower slopes up to 300 m elevation comprise the mixed dipterocarps community. In this sense, we sought to examine the distribution of forest clusters, again with the land use classification of MODIS 2008 (ISODATA-1) (our highest accuracy) with elevation as a sample. In addition, the NFI-4 data was overlaid with elevation map to further evaluate and validated the spatial distribution of land use classification (only for forest class).

3. Results and Discussion

MODIS Land Use Classification

Overall classification methods within an overall accuracy of 57% to 94% and percentage of the clusters area are given in Table 5 and the results of the accuracies were depicted in Table 6. The estimation of 10% incorporated mixed land uses indicated insufficient components or character of MODIS pixels to be classified into oil palm or rubber crops. The areas for MODIS 2005 were: 2% forest; 57% mixed forest and rubber; 39% oil palm; 2% mixed horticulture, indicating overlapping or misclassification of forest and rubber. The areas for MODIS 2008 were: 44% forest; 23% oil palm; 33% rubber, giving a better representation of the whole study area. Estimations of area percentage of MODIS land use classification for data sets were different among the ISODATA and K-Means methods. The areas of land use classification are: 87% forest; 10% mixed oil palm and rubber; 3% mixed horticulture (MODIS 2000) (Table 5).

As seen in Table 6 Forest was classified in all the data set maps excluding those for ISODATA-1 from MODIS 2005.The unclassified Forest from MODIS 2005 shows that forest areas in the data were underestimated in the southern part of the study area, as thin clouds over the forest were misclassified as crops. In Table 6 the Producer's Accuracy for the Forest was highest in data sets from MODIS 2000 for K-Means-2 (87%) and lowest in data sets MODIS 2005 (71%) for K-Means-1. User's Accuracy for the Forest was highest in data set MODIS 2000 and MODIS 2005 for K-Means-2 and K-Means-1 (100%).

Table 5. Overall land use/land cover produced with 57%–94% overall accuracy.

MODIS Land use classification Map	**Classification with Overall Accuracy (57%–94%)**	**Land Use/Land Cover Classes, Area (%)**
MODIS 2000	ISODATA-2	Forest (87), Mixed Oil Palm and Rubber (10); Mixed Horticulture (3)
	K-Means-2	Forest (2), Mixed Oil Palm Rubber Oil Palm (79), Mixed Horticulture (19)
MODIS 2005	ISODATA-1	Mixed Oil palm and Rubber (12); Oil Palm (76), Mixed Horticulture (12)
	K-Means-1	Forest (4), Mixed Forest and Rubber (57); Oil Palm, Mixed Horticulture (39)
MODIS 2008	ISODATA-1	Forest (44), Oil Palm (23), Rubber (33)
	ISODATA-2	Forest (39), Oil Palm (16), Rubber (45)
ALOS	Reclassified, Proximity analysis and Spatial Analyst	Open areas, Forests, Oil Palm, Rubber, Unclassified (Area not tested)

User's Accuracy for the Forest was lowest in data set MODIS 2008 (90%) for both ISODATA-1 and ISODATA-2. Table 6 also depicted the highest overall accuracy was 94% for the data set MODIS 2008 for ISODATA-1, while the lowest overall accuracy was 57% for MODIS 2005, ISODATA-1. MODIS 2005 land use map had lower accuracy than 2000 because the image consisted with thin cloud cover over the forest areas. This is because tropical forest areas are a difficult site to obtain good quality satellite data due to heavy cloud cover conditions (Huete et al. 2008). Although, the image was improved by atmospheric correction and cloud screening by MODIS science team (Zhao et al. 2005) the image still influenced by minor cloud contamination.

Table 6. Data employed in the study for an accuracy assessment.

Land Use Map	Classification	Land use types	Producer´s Accuracy	User´s Accuracy	Overall Accuracy
MODIS 2000	ISODATA-2	Forest	60	90	85
		Mixed Oil Palm and Rubber	53	53	
		Mixed Horticulture	0	33	
	K-Means-2	Forest	87	100	67
		Mixed Oil Palm and Rubber	53	45	
		Oil Palm	50	50	
MODIS 2005	ISODATA-1	Mixed Oil Palm and Rubber	55	50	57
		Oil Palm	50	67	
		Mixed Horticulture	50	33	
	K-Means-1	Forest	71	100	65
		Mixed Forest and Rubber	67	74	
		Oil Palm	63	83	
		Mixed Horticulture	63	33	
MODIS 2008	ISODATA-1	Forest	78	90	94
		Oil Palm	80	94	
		Rubber	45	29	
	ISODATA-2	Forest	86	90	76
		Oil Palm	76	94	
		Rubber	67	47	

Oil palm had the highest Producer's and User's Accuracy of 80% and 94%, respectively, in data sets from MODIS 2008 for ISODATA-1, where components of oil palm were also detected in every dataset map. However, oil palm was misclassified as Mixed Oil palm and Rubber in datasets from MODIS 2000 for ISODATA-2 and in the datasets map from MODIS 2005 for ISODATA-1. Species such as *Calopogonium mucunoides, C. caeruleum, Centrosema pubescens* and *Pueraria phaseoloides* are legumes used as cover crops for oil palms for soil erosion control during the 8–10 months of land clearing (Wahab 1991). In general, oil palm showed strong performance for accuracies in both data sets from MODIS 2008 for ISODATA-1 and ISODATA-2.

Heterogeneity of evergreen tropical forests with agricultural land was not acknowledged among the MODIS 2000 and 2005 dataset maps as reported in the results; however, this was relevant to MODIS 2008 for ISODATA-1 and ISODATA-2. An example of MODIS 2008 employing ISODATA-1 and ISODATA-2 is given in Figure 5. In general, Forest performed highly, as highlighted by a User's Accuracy of 90% and Producer's Accuracy of 86% from the MODIS 2008 dataset for ISODATA-2.

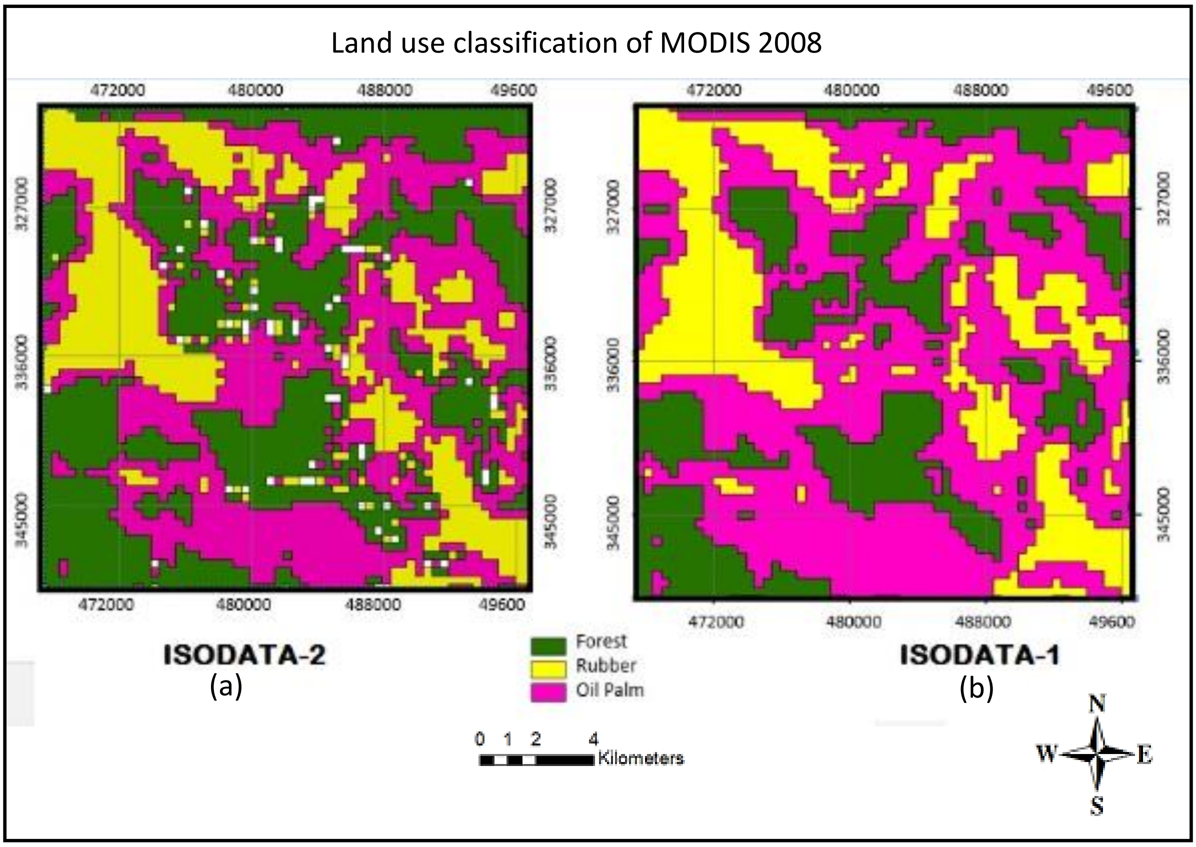

Figure 5. An example of land use classification of MODIS 2008. (**a**) ISODATA-2 (overall accuracy = 76%) and (**b**) ISODATA-1 (overall accuracy = 94%), that showed better accuracy.

In this study, rubber trees (Rubber) in the plantation were misclassified into the more dominant evergreen forest. Multispectral reflectance of the trees leading to the misclassification led to over-estimation of the rubber area (Li and Fox 2012; Ozdogan 2010). Overall, ISODATA and Gamma (with filtering window 5 × 5) classification were very successful at classifying MODIS pixels into forest and non-forest, although the MODIS 2005 data showed low overall accuracy and Forest percentage and also completely failed to discriminate the forest classification in ISODATA-1.

Finally, the study found ISODATA revealed its capability at classifying homogeneity areas although overlapping occurred in MODIS 2005 ISODATA-1 (mixed oil palm and rubber classes). Again, misclassification may have been caused by thin or small areas of cloud cover, which occurred in some places in the study area. Generally, most clouds occurred in tropical forests with frequent rainfall during the time the images were sensed.

A study on the Bukit Soeharto evergreen tropical forest on the east coast of Kalimantan (Indonesia) had similar problems in obtaining good-quality satellite data due to a lower seasonality and heavy cloud-cover conditions (Huete et al. 2008; Luus and Kelly 2008; Sheldon et al. 2012). We also highlighted that the loss of a large portion of forest classification in the MODIS 2005 for ISODATA-1 was not due to deforestation or human physical contact, but was a result of misclassification caused by the persistence of clouds in the image. ISODATA alone achieved 85%–94% overall accuracy, indicating that ISODATA classification was successful at classifying coarse-resolution pixels such as MODIS images. Finally, we found that the overall accuracy of the 2008 data sets ISODATA-1 was more than acceptable as compared to the control data and presented as the best land use classification in the study.

To explore the potential of MODIS image in the study, we found that an assortment of multi-temporal data effectively contributed to higher overall accuracy in the study. The MODIS 2000, MODIS 2005 and MODIS 2008 data represented a phenology of rubber in the study area, and since rubber is sensitive to temperature change, it has different phonological characteristics. The MODIS Enhance Vegetation Index (EVI) satellite phenology map was depicted for vegetation activity in Dong et al. (2013). However, we found the map too coarse to be spotted and compared with our study map. Our desire in employing the data in the study is to present a more understandable MODIS capability in the classification of land use in tropical forest regions.

Validation of ALOS Land Covers Map with Google Earth image

ALOS produced five land cover types, namely Open areas, Forests, Oil Palm, Rubber and Unclassified land cover (Figure 6). Oil palm areas were also consistent with Google Earth image which showed a comparable oil palm plantation adjacent to Kemayan, Negeri Sembilan. Open area which was identified to the same extent of higher reflectance after comparison with areas in Penang Island at a central point of 100°15'E 5°20'N (e.g, Batu Maung, Bayan Lepas, Air Itam, George Town and Gelugor. The study found that both open areas and urban areas had higher reflectance, indicated by optimum Land Surface Temperature (LST) image in a study conducted by Tan et al. (2012). The results showed good agreement of ALOS with Google Earth that confirmed the capability of ALOS image to further compare with MODIS map.

Comparison of MODIS Land Use Classification ISODATA-1 and ALOS Map

Clusters of MODIS 2008 data such as Forest, Rubber and Oil Palm overlaid on the ALOS map showed various proportions (Figure 6) that showed the classification consisted with ALOS land cover types. Visually, young oil palm groves could be distinguished from open areas or rubber on the ALOS, whereas rubber was more easily distinguished from an open area than from mixed rubber and forest. Mapping MODIS land use, combined with unsupervised classification of low and higher satellite resolution, compromise a low-cost land-use mapping production process and the data analysis can be rapidly performed.

Comparison of MODIS Land Use Classification and MCD12Q1

The accuracy results are given in Tables 7 and 8. The overall best accuracy for purity > 95%, was 92%, which was the highest in the MODIS 2005 K-Means-1. Overall, the highest Producer's Accuracy for forests was 73%; conversely, forest was better in User's Accuracy for the data sets of MODIS 2000 ISODATA-2 and MODIS 2008 ISODATA-1 which indicated higher success for user interpretation (100%) for both data. Meanwhile, the Producer's Accuracy was 100% (for MODIS 2000 and 2005) of non-forest, which separated the area very well and was expected to derive a higher User's Accuracy, of more than 80%; however it was low in 2008. The regrouping of pixels of the MCD12Q1 data sets led to a higher Producer's Accuracy in the non-forest components.

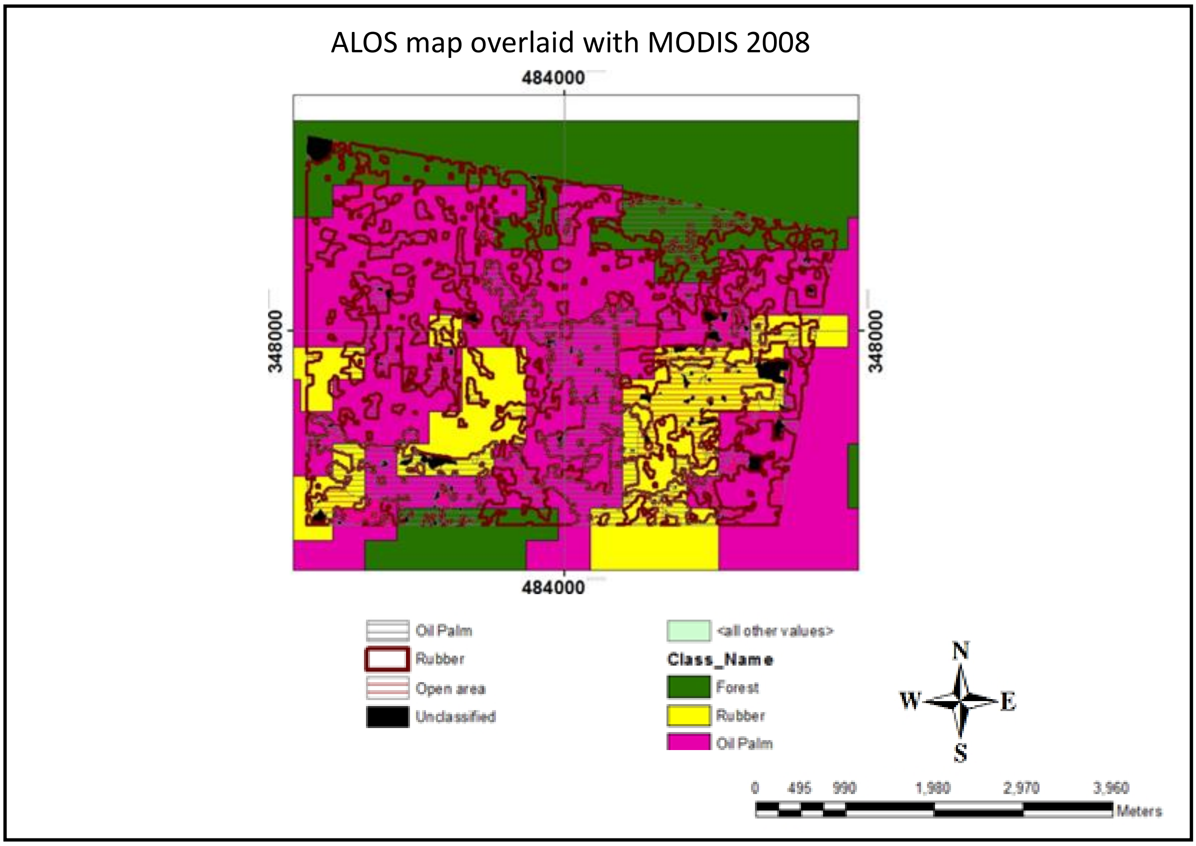

Figure 6. ALOS map overlaid with MODIS 2008 land use classification.

Low overall accuracy for purity <95% averaged 55%. Forest had low Producer's Accuracy from MODIS 2000, MODIS 2005 and MODIS 2008 of 60%, 44%, and 24%, respectively. However, it achieved a good agreement with User's Accuracy for data sets from MODIS 2005 (90%), which again showed that the MCD12Q1 2005 was a very high-quality global land cover map derived from MODIS satellite imagery, which also showed in accuracy for purity of >95%.

As expected, visual interpretation of the comparison found that the PFR polygon delineated a good shape of forest reserved in the MCD12Q1 data, where most the sampling points for forest were distributed as observed in the map. This indicated a good agreement between the two products (Wessels 2004).

Table 7. An accuracy assessment between land use classification and MOD12Q1data sets (sampling points >95% purity).

MODIS 2000 ISODATA-2	**Forest**	**Non-Forest**	**Total**	**UA (%)**
Forest	20	0	20	100
Non-Forest	8	33	41	80
Total	28	33	61	
PA (%)	71	100		87
MODIS 2005 K-Means-1	Forest	Non-Forest	Total	UA (%)
Forest	20	0	20	100
Non-Forest	8	36	41	88
Total	28	36	61	
PA (%)	71	100		92
MODIS 2008 ISODATA-1	Forest	Non-Forest	Total	UA (%)
Forest	11	9	20	55
Non-Forest	4	37	41	61
Total	15	46	61	
PA (%)	73	80		79

Note: PA=Producer's Accuracy; UA =User's Accuracy.

Table 8. An accuracy assessment between land use classification and MOD12Q1 data sets (sampling points <95% purity).

MODIS 2000 ISODATA-2	**Forest**	**Non-Forest**	**Total**	**UA (%)**
Forest	12	8	20	60
Non-Forest	20	21	41	51
Total	32	29	61	
PA (%)	60	72		54
MODIS 2005 K-Means-1	Forest	Non-Forest	Total	UA (%)
Forest	18	2	20	90
Non-Forest	23	18	41	44
Total	41	20	61	
PA (%)	44	90		59
MODIS 2008 ISODATA-1	Forest	Non-Forest	Total	UA (%)
Forest	4	16	20	20
Non-Forest	13	24	41	68
Total	17	44	61	
PA (%)	24	64		52

Note: PA=Producer's Accuracy; UA =User's Accuracy.

Visually, we also found that MCD12Q1 2001 and 2008 data sets inadequately presented at least the heterogeneity of oil palm or rubber in the study area. We had limited ability to identify the growth stage of the oil palm and rubber trees from our MODIS land use classification, as our sampling points were not located according to different ages or maturity of the trees. Thus, we expect some misclassification of rubber plantations and forests, due to the homogeneity of forest trees, bushes, scrub and shrubs within rubber trees. The survey found that the rubber trees were mature, but that the land was also occupied by fallow vegetation.

Comparison of MODIS Land Use Classifications with Elevation map

The elevation ranged from approximately 23 m to 236 m is overlaid with MODIS 2008 ISODATA-1 land use map (Figure 7). The map showed the forests are concentrated mainly in the higher and moderate elevations, with 49 m–76 m at the highest levels, although PFR is located at a lower elevation: 75 m–103 m, which is consistent to a study by Hirata et al. (2008) and agreed with Ediriweera et al. (2008). The study found significant benefits in applying elevation map to the land use classification, hence, enhanced better understanding of mixed dipterocarpaceae species distribution due to different elevation. It also had a good agreement for forest clusters and the oil Palm was mainly distributed at a level similar to Forest: 103 m to 129 m, and Rubber was distributed much lower, at 23 m–49 m. Moreover, NFI-4 of forest class was observed to be consisted with the elevation, with distributed of mixed dipterocarpaceae at the highest elevation in the study area.

4. Conclusions

This study evaluated the application potential of ISODATA and K-Means (Gamma and Kuan) classification for delineation and land use mapping of evergreen tropical forests, oil palm and rubber plantations and other land uses in tropical zones. The study first constructed the accuracy assessment from our sampling methods. The most successful maps, ranging from 65% to 94% of overall accuracy, were then extracted for further comparisons. MODIS MCD12Q1 map from the years of 2000, 2005 and 2008 were employed for accuracy assessment with the MODIS study map products. Finally, we overlaid and compared the maps with NFI-4 data; topographic data 1997, ALOS land cover map and elevation map. The study revealed the advantages of using unsupervised ISODATA classification.

ALOS map overlaid with MODIS 2008 land use classification and NFI-4 data

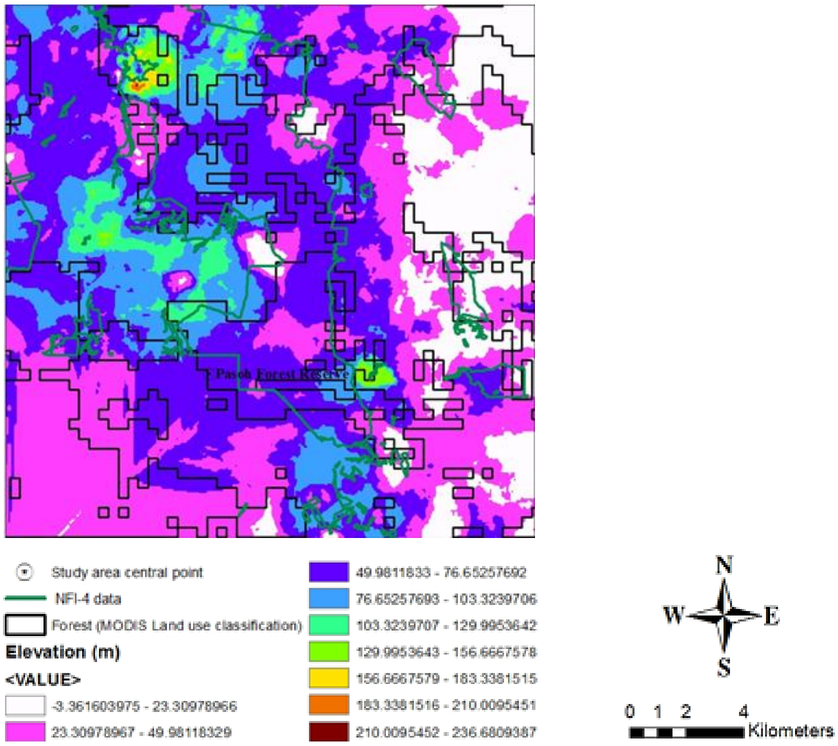

Figure 7. ALOS map overlaid with MODIS 2008 land use classification and NFI-4 data.

This study recommends that future works be concentrated on matching regional or local vegetation densities information (surveys) to compare with the vegetation density from MODIS satellite data such as EVI and Normalized Difference Vegetation Index (NDVI) (Clerici et al. 2012; Huete et al. 2008; Huete et al. 2002). Generally, NDVI have different values in evergreen tropical forest, both young and mature rubber plantings, and open areas in young oil palm plantations (Razali et al. 2010). By taking into account the vegetation indices, the map can be enhanced to show conditions as recent as the past 8 days, which can then be analysed for environmental stresses such as soil moisture stress and can also be used for forest fire risk assessment (Fensholt 2003), as it can even assist in distinguishing fuel types. For example, *Imperata* grassland present in an oil palm growing region is a flammable material, and has a higher combustion rate that can express the proportion of biomass likely to be consumed by fire (Germer and Sauerborn. 2008).

The oil palm classification in this land use classification map is also valuable for providing information about natural pasture in the area, and which vegetation can be utilized for forage for livestock production (Wahab 1991), especially since the areas between the rows in young oil palm groves are usually covered with vegetation comprising legumes, grasses, broadleaf species and ferns. Consequently we also suggest that oil palm, which is classified by employing low to moderate resolution imagery, should be recognized as mixed oil palm and other vegetation. We also recommend the (Huete et al. 2008) phenology vegetation activity map as a good foundation for phenology reference for future study in tropical forest land use classifications.

Sustainable Forest Management (SFM) in Malaysia is a dynamic and evolving concept aimed to maintain and enhance economic, social and environmental value of all type of forests for the benefits of present and future generations (Secretariat of the Convention on Biological Diversity 2009). Robust economic development will remain in the medium-term as reported in 2013 particularly in Southeast Asia (surrounded by tropical evergreen broadleaf forest) (International Energy Agency 2013), leaved those countries facing upcoming limited or cutting down expending allocation to certain governmental sectors. With constraints allocation of funds from government and private sectors to achieve the aims, SFM would be not meaningful.

MODIS imaging showed capability to provide economically viable updated imageries and integrated land use mapping. MODIS imaging with integrated land use mapping, highlighted by using higher resolution of ALOS imagery, could assist forest managers to achieve SFM aims through increased frequency of land use mapping within the management areas with minimum labour and equipment cost. This is because MODIS enables deriving data at no cost, requiring a very low human labour cost with additional powerful computers. Moreover, land use mapping and GIS application unit at Forestry

Departments could enhance their work through sustaining and updating their land use maps as a database which can be used by other governmental sectors.

With this study, we hope that an exploration of the development of land use maps for tropical forests will continue and will increase the usefulness of EO data in the future. This study revealed that there is insufficient information for a crop data base for the study area and for the peninsula as a whole, a situation that might be corrected with the application of MODIS imaging. For example, site suitability, soil suitability class, and agro-climatic region maps produced by the Malaysian Agricultural Department, do not include information on crop growth. But with a frequent data collection cycle (1–2 days) in 36 spectral imaging, maps could be produced for input and update to such a database. Furthermore, more rapid processing and analysis from higher-resolution remote sensing could lower the cost for image pre-processing.

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Chapter

2

Monitoring vegetation drought using MODIS remote sensing indices for natural forest and plantation areas

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Abstract

Natural forest, oil palm and rubber plantations are economically and environmentally important for Peninsular Malaysia. The present study analysed four years of Moderate Resolution Imaging Spectroradiometer (MODIS) surface reflectance data to develop spectral indices of vegetation, water availability and moisture stress for the study area. The indices, the Normalized Difference Vegetation Index, the Normalized Difference Water Index and the Moisture Stress Index were applied to the three different habitats to monitor drought and develop a Malaysia Southwest Monsoon (M–SWM) classification. By integrating indicators of the Southwest Monsoon, the Standard Precipitation Index, mean precipitation and temperature and spectral indices correlation analysis, M–SWM classification showed greater sensitivity to drought conditions than any of the individual indicators alone. The results also found that July is the driest month; it was the only period classified as "Very Dry" based on the M–SWM.

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1. Introduction

The Southwest Monsoon season (SWM) is a dry period for Peninsular Malaysia and particularly extreme for the states on the western coast of the peninsula. This dry periods often results in drought, which has significant adverse effects on environmental, agricultural and socioeconomic conditions (Bhuiyan et al. 2006). A report by the Climate Change Knowledge Portal (2013), compiling more than 100 years of data covering a period of 1900–2009, showed a consistent decrease in mean precipitation for June and July. Drought has led to reductions in both crop production and the quality of human life (Wan Zin et al. 2013).

The natural forest cover in the study area is evergreen tropical forest with a dominance of Dipterocarpaceae family species in the upper layer, a pattern not found in any other tropical forest in the world (Corlett 2014). These trees play a huge role in sequestering carbon from the atmosphere, as recently reported in many studies (Bonan 2008; Girardin et al. 2014; Joseph et al. 2012). However, an increase in the frequency of dry spells in Peninsular Malaysia has placed the forest in a drought risk situation. In 2005, Malaysia, Indonesia, and Thailand collectively produced 69% of the world's natural rubber.

A recent study found that this proportion has now increased to about 97% (Li and Fox 2012), indicating that the revenue from rubber plantations is critical to the economies of these Southeast Asian countries. Rubber (*Hevea brasiliensis*) and oil palm (*Elaeis guineensis*) are tropical tree crops grown primarily in large estates in the region, and predictable seasonality is critical to the trees' survival (Panuju and Trisasongko 2012).

In general, rubber is planted in two distinctive seasons and is sensitive to temperature change (Dong et al. 2013; Huete et al. 2008). Good water management is essential, because drought can harm flower production and hence reduce crop yield (Corley and Tinker 2003). A minimum of 2000 mm of annual precipitation is required for optimal production in a rubber plantation (Rantala 2006). Because the rubber industry is of great economic value to the region and provides income for over 400,000 small land owners, rubber plantations need to be properly managed. In addition to rubber, the government of

Malaysia is committed to supporting oil palm cultivation, to achieve sustainability and maintain a predominant market share. Oil palm residues is highly beneficial for supplying fibre sources for wood-based industry and at the same time pre-treatment could enhance its properties to the required standard (INTROP 2010). Besides, global demand for edible oils and animal protein tremendously increase area under oil palm cultivation (Teoh 2002).

A recent study found that variability in either rainfall or temperature, or both, has a negative impact on palm oil revenue (Zainal et al. 2012). After the 1998 drought episode in the peninsula, a Standard Operating Procedure was developed to support the National Drought Management Policy in response to severe drought in the region and in Malaysia as a whole. The Standard Precipitation Index (SPI) and rainfall anomalies were employed to assess drought by assigning risk criteria to the region (Sani et al. 2012).

Satellite data have been used to detect damage to forest caused both by natural processes and by human interference (Fuller et al. 2002). Various mathematical combinations of spectral channels in satellite images have been used as sensitive indicators of the presence, condition and vigour of green vegetation. Vegetation indices normalize internal and external responses to detection signals (e.g., sun angle, topographic variation, plant textures and soil conditions) and thus enhance the sensitivity of the signals for measuring forest biophysical properties and their changes (Jensen 2000). The Normalized Difference Vegetation Index (NDVI) is commonly used to express this information. Satellite data analyses have verified the relationship between NDVI and vegetation productivity, because there is a link between the index and both the fraction of absorbed active radiation (fAPAR) and the absorbed active radiation (APAR), which decrease along with NDVI (Li et al. 2012). Indeed, Propastin et al. (2012) found that increased leaf production enhances the absorption of radiation by vegetation and causes an increase in fAPAR, which is reflected in higher productivity. NDVI has shown excellent sensitivity to green biomass in young and growing vegetation in tropical forests. Furthermore, it measures the changes in chlorophyll content via absorption of visible red radiation in satellite images and in spongy mesophyll via reflected near–infrared (NIR) radiation within the vegetation canopy (Gu et al. 2007). Hence, the NDVI signal is sensitive to chlorophyll and photosynthetic vegetation (Hill et al.

2013) and therefore useful for detecting biomass reduction in tropical forests as a consequence of drought stress.

The Moisture Stress Index (MSI) has been applied to assess canopy water content. MSI has been shown to have a strong negative correlation with water parameters such as Equivalent Water Thickness (EWT) in subtropical secondary forests (Wang et al. 2009). The Normalized Difference Water Index (NDWI), however, is the most useful tool for detecting forest die–back and recovery as a result of severe drought (Fensholt et al. 2004; Gu et al. 2007). Moreover, in a forest-fire study (Wang et al. 2009), NDWI showed a stronger significant correlation with the water concentration index and a better relationship with fuel moisture content (FMC) than did the MSI.

The objective of this study was to develop a classification system for drought assessment in a drought-prone area using satellite image data from MODIS. The variables selected included all the critical drought-measuring parameters that could be integrated into the model: (1) the SWM, (2) standardized precipitation as defined by the SPI, (3) mean monthly precipitation, (4) mean monthly temperature and (5) the MODIS satellite indices of NDVI, NDWI and MSI.

2. Drought classification system

A drought classification system is commonly used in a huge country such as the United States of America. Many drought classification schemes, such as the Standard Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI) and the Keetch-Byram Drought Index (KBDI), have been developed in order to describe various levels of drought.

The SPI is a powerful and flexible index, yet is easy to calculate (World Meteorological Organization, 2015) because it is based exclusively on precipitation data. The more complex PDSI (Smakhtin and Highes, 2004), which represents soil moisture variations over a region, requires more input data and calculation effort. A study by Kogan (1995) suggested that PDIS is more useful when employed at the global scale. The KBDI is an index for determining forest fire potential; it has been used as a National Forest Fire Danger Point

Forecasting Tool in United States Forest Service wilderness areas. A study conducted in Malaysia by Ainuddin and Ampun (2008) found a positive correlation of the index with fire frequency.

The SPI has been widely used by Khan and Gadiwala (2013) employed it for assessing drought levels in Pakistan for the period 1951 to 2010. SPI was also utilized for drought-prone areas in India, such as Gujarat and Orissa (Patel et al., 2009). Since the beginning of the 1998 El Niño episode in the Malaysian peninsula, a Standard Operating Procedure has been developed to support a National Drought Management Policy in response to drought severity in the region and in Malaysia as a whole, using the SPI and rainfall anomalies to assess drought by assigning risk criteria across regions (Sani et al. 2012). A drought rating can be an additional indicator for monitoring drought–prone areas. The drought monitoring system used for this study is shown as a map that identifies general drought areas, labelling drought conditions by intensity (The National Drought Mitigation Center, 2015).

3. Methodology

Study area

The central point of the study area is located at 2°58'N, 102°18'E in the Pasoh Forest Reserve (PFR), Negeri Sembilan. The annual precipitation is 1702 mm, as measured between 2000 and 2011 by the National Institute for Environmental Studies, Japan (NIES 2011). During the SWM season, the area had the lowest rainfall in the Negeri Sembilan region for 2000–2007, while the monthly mean temperature during the dry monsoon season was 26.3°C for 2002–2011. The research was conducted in three different habitats: evergreen tropical forest (referred to as natural forest), and oil palm and rubber plantations (Figure 1).

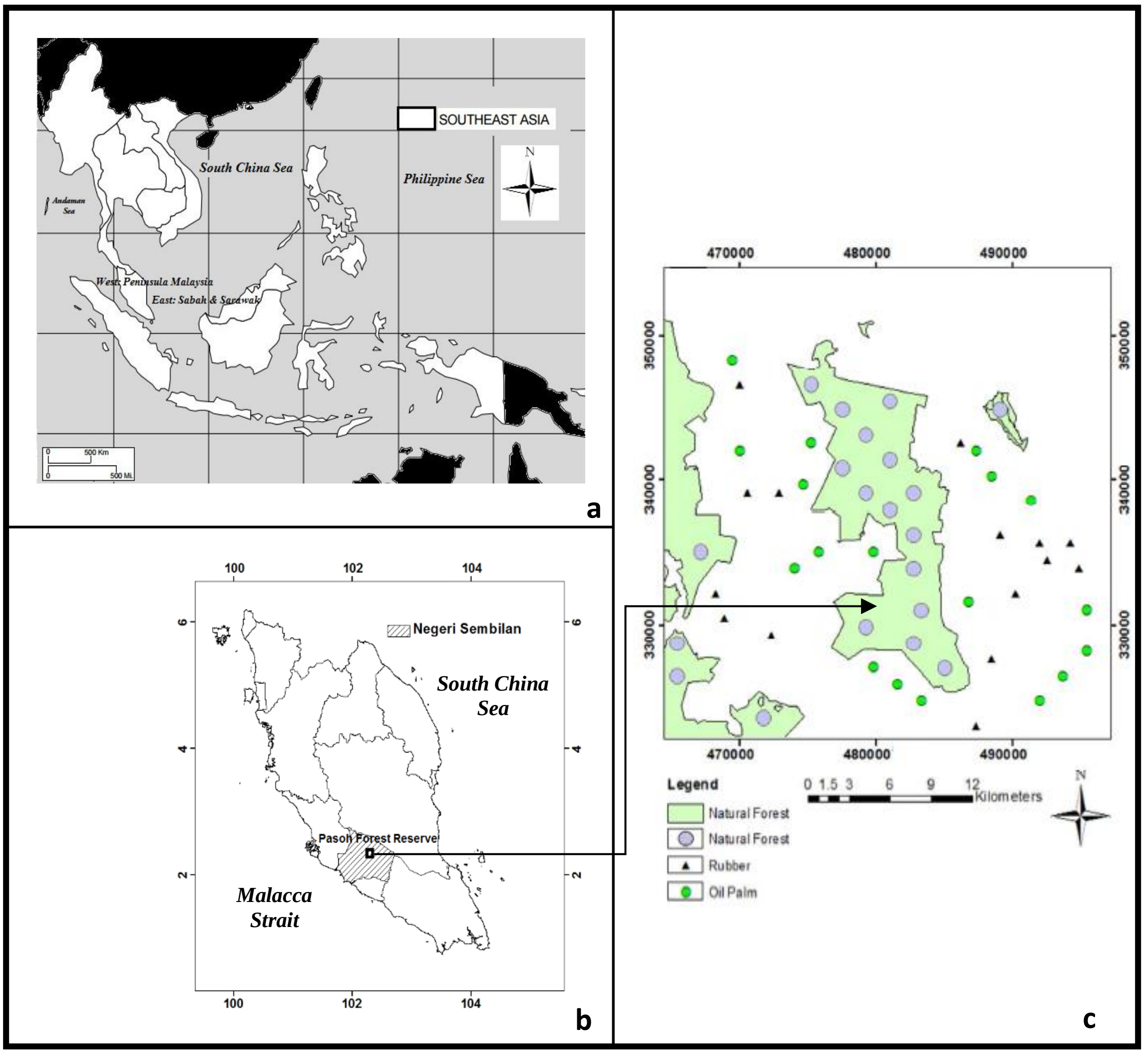

Figure 1. Study area: (a) Southeast Asia (blank) (b) Peninsular Malaysia and (c) the Pasoh Forest Reserve, showing areas of natural forest, oil palm and rubber plantation habitats.

Since the 1998 El Niño, prolonged dry conditions have become a recurrent phenomenon on the peninsula (Wan Zin et al. 2011). The El Niño event recurred in 2003 and again in 2005. A report by the Department of Irrigation and Drainage (2005) showed a huge reduction in precipitation during the June 2005 dry season. The deficiencies, ranging from 18% to 44%, occurred from the west coast to the middle mainland regions (DID 2005). The study area experienced a similar reduction in precipitation during the El Niño, in a drought-prone area of the Regent estate. An isohyetal contour map showed that the area experienced its lowest annual rainfall in 2002, perhaps because of its proximity to the drought-prone area (Razali et al. 2010).

Satellite Data

The present study was based on one of the MODIS satellite products, known as MOD09A1 (Surface Reflectance 8–day L3 Global), at 500m resolution, for 2000–2011. MOD09A1 is one of the inputs for the MODIS satellite used to produce other MODIS land data such as MOD12 and MOD13. MOD12 is a land cover and MOD13 is a vegetation indices products. The data were derived at 8–day intervals and contained seven spectral bands (Xiong et al. 2006). The spectral band on the MODIS is suitable for obtaining a vegetation signal as well as moisture and water stress indexes, by employing band information of near–infrared, red, green and shortwave infrared reflectance bands.

The satellite product is suitable for studying the drought situation in tropical forests because the MODIS satellite was built with special characteristics in its instruments and its spacecraft components, for thermal sensitivity and mechanical isolation structure (Xiong et al. 2006). The data for this study were collected from the Land Process Distributed Active Archive Centre (LP DAAC 2011), the most convenient data archive platform available for browsing, data quality checking and data organizing.

Image pre-processing

The images were collected on minimum cloud-cover days, because cloud cover contaminates information in optical images (Tseng et al. 2008) and can interfere with interpretation, thus reducing precision. Cloud detection procedures were conducted by image enhancement using the band combination method: (i) 1, 4, 3 (true colours); (ii) 7, 2, 1 and (iii) 2, 6, 1 (Huete et al. 2008; Tseng et al. 2008) to identify isolated clouds. A reflectance value of > 0.2 was used to eliminate contaminated pixels from all the images. Density slices were taken and a masking procedure was followed, using Exelis Visual Information Solution (ENVI) slice tools to remove the clouds. MODIS images with high visibility are often particularly difficult to obtain in tropical forest areas because of heavy cloud-cover conditions.

To increase precision during sampling, we downloaded more than fifty images for the years in question and reanalysed them with band matching to obtain high-quality images. Finally, despite the inconvenience of isolated cloud cover we successfully obtained four years of MODIS data representing several seasons (Table 1).

Spectral indices

For satellite indices, we used NDVI, NDWI and MSI as the vegetation, water and moisture-stress indices. See Table 2 for descriptions of the indices utilised and the precise bands used for their formulation. where ρ_{Red}, ρ_{NIR}, ρ_{Green}, and ρ_{SWIR3} are the reflectance values for MODIS at bands 1 (645-670 nm), 2 (841-876 nm), 4 (545-565 nm) and 7 (2105-2155 nm), respectively.

Table 1. MODIS data used for the study.

Season	Time frame of MODIS images	Label
Wet	September 2000	S2000
Dry	July 2000, May 2009, May 2011, August 2005	J2000, M2009, M2011, A2005
Drought Year	March 2005	M2005

Table 2. Spectral reflectance indices and MODIS bands used in this study.

Index	Formulation	Source
NDVI	$\frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$	Rouse (1973)
NDWI	$\frac{\rho_{NIR} - \rho_{SWIR3}}{\rho_{NIR} + \rho_{SWIR3}}$	Gao (1996)
MSI	$\frac{\rho_{Green}}{\rho_{NIR}}$	Hunt and Rock (1985)

These indices have been used extensively in recent studies, particularly for tropical forests (Asner and Alencar 2010; Panuju and Trisasongko 2012). The indices have a native scaling of -1 to +1. Linear regression was performed for each of the satellite images for the three habitats. The correlation coefficients were obtained at a 0.01 level of significance to examine the correlations between NDVI and NDWI; and between NDVI and MSI (Rocha and Shaver 2009).

A study by Gu et al. (2007) showed that during dry periods vegetation had a greater loss of water content than during green periods, as is depicted in vegetation indices such as NDVI. Here, we assumed that the NDVI was correlated with variations in photosynthetic activity (Pettorelli et al. 2005), whereas NDWI measured sensitivity to changes in the liquid water content (Gao 1996). MSI is negatively correlated with water content, so that a reduction in vegetation canopy water content suggests an increase in MSI. To develop a complete drought classification index we created a drought rating and categorization scheme from the results of the linear regression model, for input to the M-SWM index, in order to determine the driest conditions that may possibly occur in the habitat.

The NDVI, NDWI and MSI indices were analysed with the Principal Coordinates Analysis (PCO) of Euclidean distance, which allowed the most relevant dry-period patterns to be observed. PCO was performed using Primer 6 and PERMANOVA plus (Anderson et al. 2008; Clarke and Gorley 2006). This flexible ordination method was chosen because it can be based on any resemblance matrix, projecting the points onto axes that minimize residual variations in the space to which the resemblance measure is applied.

Sampling of the habitats

Habitat samples of natural forest, oil palm and rubber plantation areas were extracted from the MODIS satellite images. A total of 18 samples were collected for the entire habitat area and used for satellite indices correlation analysis. Sampling within each set of habitat points was structured to characterize the vegetation within an approximate 500m x 500m-pixel-sized area. The natural forest samples were located in the PFR in Compartments 22 and 23, an inland regenerating evergreen tropical forest. The forest is adjacent to an oil palm plantation area, according to the Present Land Use map of Negeri Sembilan 2004 (Figure 1). Points were first identified on pre–processed image, then validated with higher-resolution 10m satellite images from the Advanced Land Observing Satellite, Advanced Visible and Near Infrared (ALOS AVNIR), the National Forest Inventory Series 4 and land use maps (FDPM 2004; DOA 2004). The points were then transferred to a handheld global positioning system (GPS) with a spatial accuracy of ±15 m, verified and finally registered back to the image for further analysis. The point locations were modified according to the suitability of the area. An example of the points is shown in Table 3.

Table 3. Example of sample point locations for the habitat sampling.

No.	Point coordinate	Habitat
1	102.28, 3.13	Natural forest
2	102.35, 3.07	Oil palm
3	102.27, 2.99	Rubber

Oil palm and rubber samples were collected based on ground point data taken at two plantations: Felda Pasoh Estate and Felda Pasoh Dua. The samples were first identified with reference to non-traditional rubber plantation patterns in Kuan Wan, Thailand (Li and Fox 2012) and on Hainan Island (Dong et al. 2013). The verification showed that rubber trees in the plantation grow alongside fallow shrubs and grassland. The samples included trees in three phases of their life cycle: (1) young immature (0-3 years); (2) young mature (4-8 years); and (3) mature (over 8 years). The samples were validated using Google Earth images from a study conducted by (Li and Fox 2012).

Malaysia Southwest Monsoon (M–SWM) index

A similar qualitative model developed using the SPI and Palmer Drought Severity Index was used for drought categorization and rating based on all the M-SWM index variables (Gu et al. 2007) (Table 4). We assigned the MODIS images to different SWM categories based on information from several studies. Two studies, by Yasuda et al. (2003) and Okuda et al. (2004), showed distinct rainfall peaks in April-May and November-December, while less precipitation was observed in the May-August period, known as the SWM (Jamaludin et al. 2010). Cruz et al. (2013), defined SWM as the period from June to

September, based on the prevailing flow at the surface, analyzed using ERA-40 datasets from (Kallberg et al. 2007).

Precipitation is one of the most important aspects of monsoon climatology (Ranatunge et al. 2003). In the study, data for precipitation and temperature were obtained from the (NIES 2011). We calculated monthly mean precipitation for March to September, 2000-2011 as in Figure 2, to determine the best dates for collecting MODIS satellite images.

Precipitation conditions and ratings were assigned based on precipitation data recorded at 41 rainfall stations over the entire Malaysian Peninsula during the April-June drought season 2005 (DID 2005). Monthly mean temperature was also calculated for input to the M-SWM calculation. The SPI data were retrieved from http://iridl.ldeo.columbia.edu, which contained data for the study area.

The satellite indices coefficient of correlation was assigned to four drought-rating categories. The M–SWM was then defined by accumulating the rating scores and simplifying them into one index. In summary, the index was calculated according to Equation (1):

$$M - SWM = MOD_{i=1-3} + SPI_{j=1-7} + P_{k=1-3} + T_{l=1-3} + SI_{m=1-4} \quad (1)$$

where M-SWM is the Malaysia Southwest Monsoon index developed for the study and the subscripts *i, j, k, l,* and *m* indicate the variables for the index: MODIS Image (MOD), Standard Precipitation Index (SPI), monthly mean precipitation (P), monthly mean temperature (T), and satellite indices (SI). Using this equation, an accumulation index of 16-20 was classified as ‘Very Dry’ (VD); a range of 11-15 as ‘Mid Dry’ (MD); 6-10 and 1-5 as ‘Low Dry’ (LD) and ‘Wet’ (W), respectively. A complete flowchart of the index development process is presented in Figure 3.Finally, to measure the relationships between the M–SWM index and the satellite indices; a correlation analysis was conducted for the study.

Table 4. Drought categorization for M–SWM index.

Variable	Condition	Categorization	Rating
	S2000	Wet	1
MOD_i	M2009, M2011, J2000, A2005	Dry	2
	M2005	Drought Year	3
	> 3.0 – 3.0	Extremely wet	1
	3.0 – 2.0	Moderately wet	2
	2.0 – 1.0	Near normal	3
SPI_j	1.0 – 0	Normal	4
	0 – -1.0	Moderately dry	5
	-1.0 – -2.0	Severely dry	6
	-2.0 – -3.0	Extremely dry	7
	130 – 195 mm	Wet	1
	65 – 130 mm	Dry	2
P_k	0 – 65 mm	Drought Year	3
	23 – 24 ºC	Wet	1
	24 – 25 ºC	Normal	2
T_l	25 – 26 ºC	Drought Year	3
	R^2 < 0.6 (NDVI vs NDWI, MSI)	Not Dry	1
	R^2 > 0.6 (NDVI vs NDWI) but R^2 < 0.6 (NDVI vs MSI):	Dry	2
SI_m	R^2 > 0.6 (NDVI vs NDWI, MSI) but (NDVI vs MSI) weaker than NDWI correlation	Moderately Dry	3
	R^2 > 0.6 (NDVI vs NDWI, MSI)	Extremely Dry	4

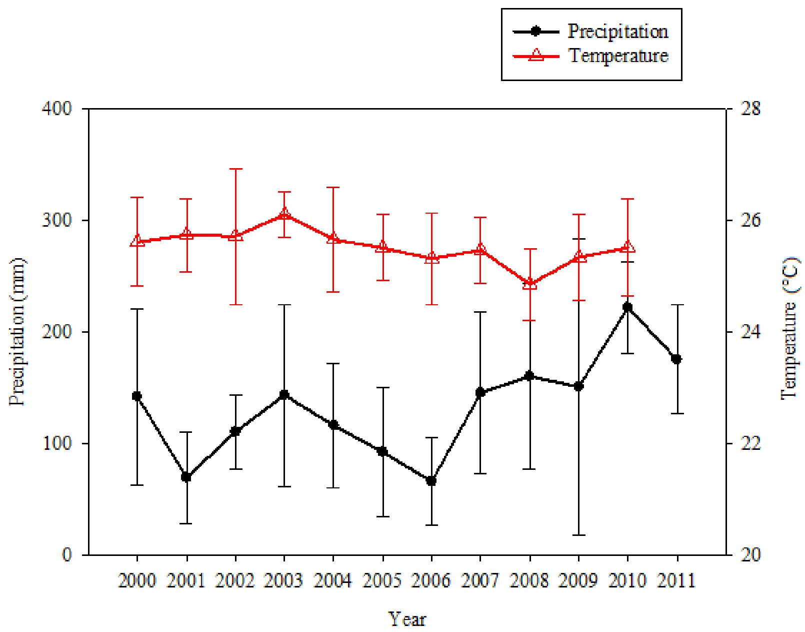

Figure 2. Monthly mean recorded precipitation and temperature for March to September, 2000- 2011, for the study area.

4. Results

M-SWM index

An index of the M–SWM was developed and is presented in Table 5. As can be seen from the table, three of the six images analyzed in the study were associated with the drought rating index range 11-15, categorized as MD. The J2000 image was categorized as VD, with the highest drought-rating index of 16. The images of M2005 and A2005 were classified as MD, with a drought index of 14. The M2009 image was also classified as MD with a drought index of 13. The images of M2011 and S2000 were classified as LD with drought-rating indexes in the 6-10 range.

MODIS Image (MOD_i)

Based on the SWM information from several studies, MODIS images were assigned to the SWM ratings (Table 5). The M2005 image was assigned to Drought Year, with a drought-rating score of 3, meaning that M2005 was the highest drought rating in the study. The J2000, A2005, M2009 and M2011 images were all categorized as Dry, with a score of 2. Only one image, S2000, was categorized as Wet, with a score of 1.

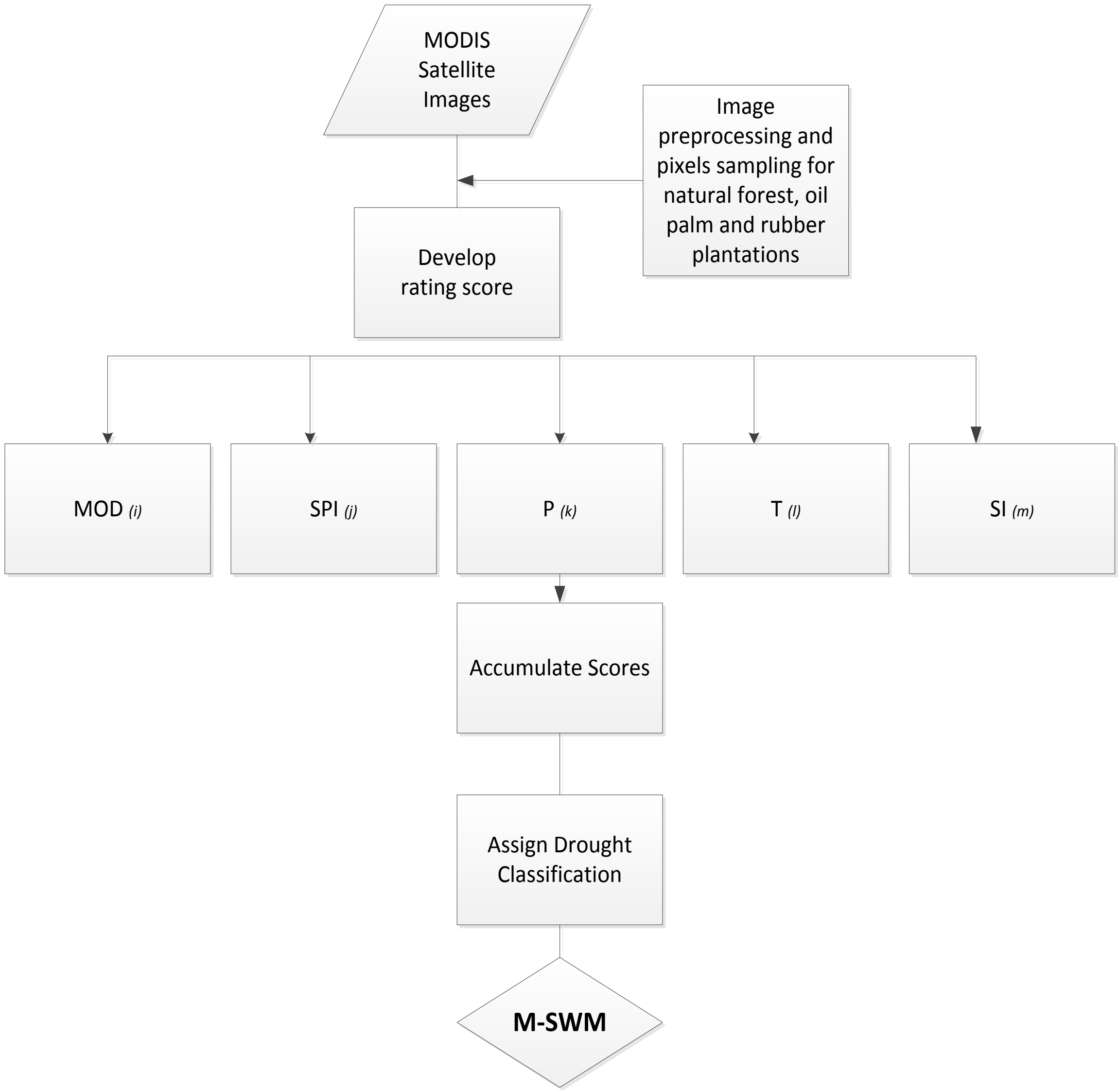

Figure 3.Flowchart of the M–SWM index processing.

Table 5. Results for the M–SWM index.

MODIS Image	***MOD$_i$***	***SPI$_j$***	***P$_k$***	***T$_l$***	***SI$_{(m)}$***	**Rating Total**	**Classification**
	Rating						
July 2000 (J2000)	2	4	3	3	4	16	VD
March 2005 (M2005)	3	4	2	2	3	14	MD
August 2005 (A2005)	2	3	3	3	3	14	MD
May 2009 (M2009)	2	5	1	3	2	13	MD
May 2011 (M2011)	2	4	1	1	1	9	LD
September 2000 (S2000)	1	3	1	2	1	8	LD

Note: VD: Very Dry; MD: Mid Dry; LD: Low Dry

SPI (SPI_j)

The highest rating score for SPI was for M2009, with a score of 5, which was categorized as Moderately Dry. The Normal condition was reflected in the J2000, M2005 and M2011 images, with a rating score of 4. The A2005 and S2000 images showed the smallest SPI rating score of 3—Near Normal.

Precipitation (P_k)

The J2000 and A2005 images indicated clearly dry conditions with a rating score of 3 and a Drought Year categorization. M2005 showed a clear difference from the other images, with rating score of 2, categorized as Dry. As anticipated, M2009, M2011 and S2000 had a rating score of 1, in the Wet category—lower than the M2005 image.

Temperature (T_l)

The coolest area under the M–SWM classification was M2011, with the lowest rating score of 1, while the warmest were J2000, A2005 and M2009, with the highest rating score of 3. The normal rating score in the study occurred in M2005 and S2000, with a rating score of 2.

Satellite Indices (SI_m)

The strongest correlation for the satellite indices was for J2000 (NDVI vs. NDWI, r^2=0.99and NDVI vs. MSI, r^2=0.96) giving the highest rating score of 4, which was classified as Extreme Dry. The weakest correlation was seen for S2000 (NDVI vs. NDWI, r^2= 0.24 and NDVI vs. MSI, r^2= -0.00 (Table 6).

Table 6. Correlation coefficients for spectral indices.

MODIS Images	Correlation (r^2) NDVI vs NDWI	NDVI vs MSI
J2000	0.99	–0.96
M2005	0.99	–0.61
A2005	0.99	–0.68
M2009	0.95	–0.12
M2011	0.16	–0.40
S2000	0.24	–0.00

M-SWM index and satellite indices correlation analysis

The relationship between the M–SWM index and the satellite indices is plotted in Figure 4 (a) to (c). The relationships varied widely among the three habitats. In general, the relationships of the indices with NDVI showed an r^2ranging from 0.24 to 0.60, with a significant correlation only in the natural forest r^2=0.60 However, the relationship of the index with NDWI showed insignificant correlation for all the habitats. The highest significant correlation, between the index and MSI relationships, occurred for the rubber plantations, r^2=0.73.

PCO Analysis

The PCO scores plotted for NDVI, NDWI and MSI indices are presented in Figure 5. The plot shows the J2000 samples of natural forest, oil palm and rubber separated from the other sample periods, indicating their dissimilarity, which is driven by the higher values of NDVI and NDWI. In the PCO analyses, the first two principal coordinates explained 83.7% and 9.4% of the variance, respectively.

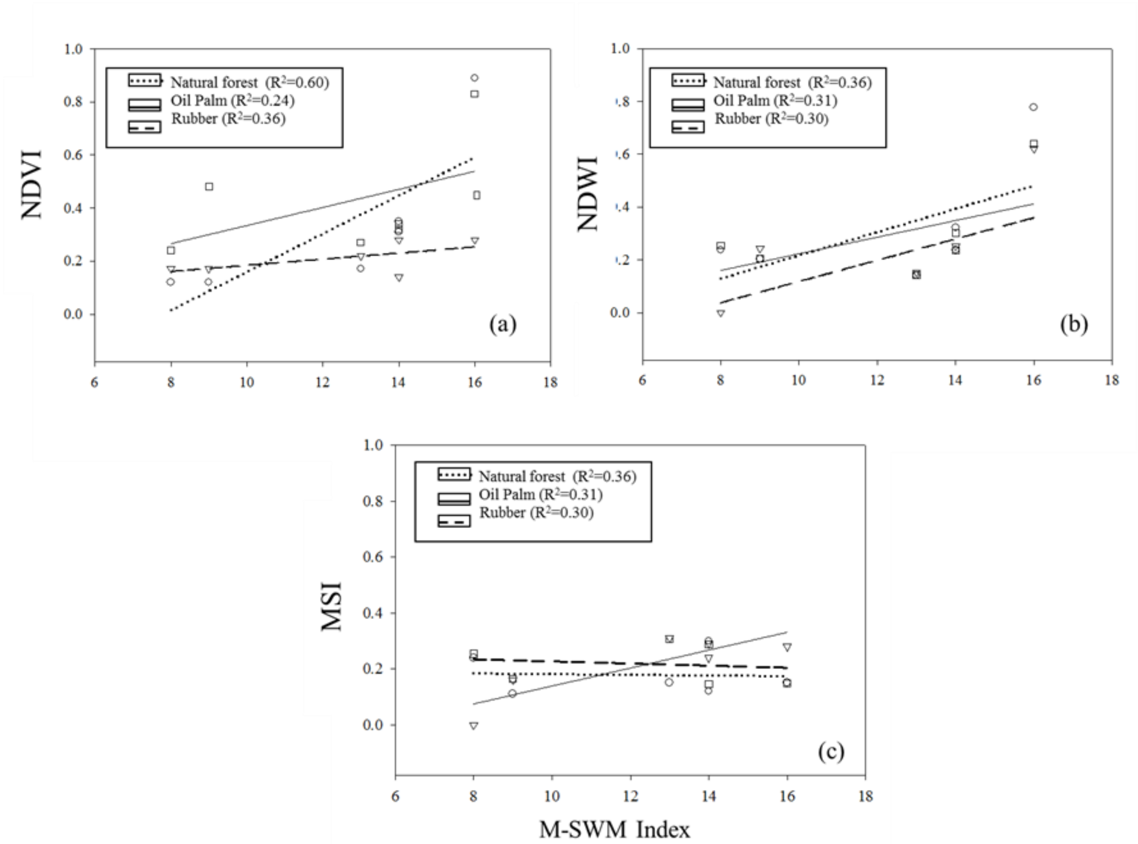

Figure 4. Correlation results for M–SWM index with satellite indices for the three habitats studied: (a) NDVI, (b) NDWI and (c) MSI.

5. Discussion

Because the impact of drought is usually first apparent in agricultural areas (Bhuiyan et al. 2006), using an area such as oil palm and rubber plantations to develop a key indicator for drought classification makes sense both scientifically and economically. The variables integrated into the M–SWM index resulted in an indicator that successfully classifies levels of drought conditions using climatology and satellite indices of MODIS data.

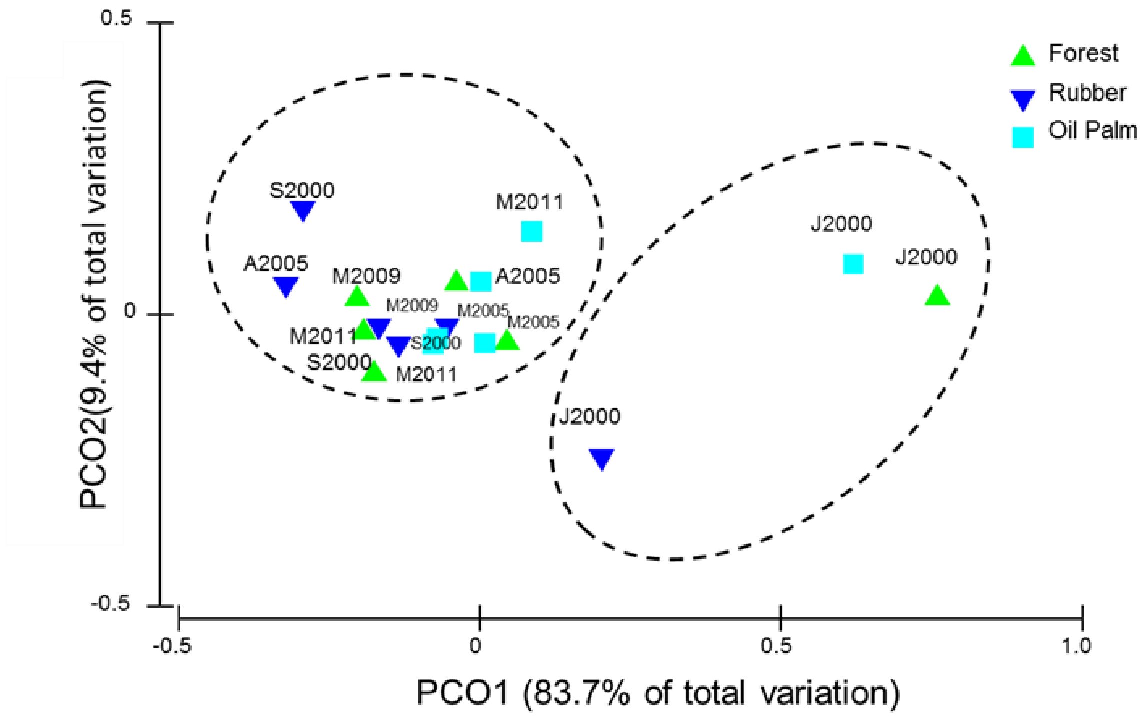

Figure 5. PCO computed on Euclidean distance between NDVI, NDWI and MSI indices. PCO1 and PCO2 are the first and second principal coordinates, respectively. The proportional variance explained by the principal coordinate is given in parentheses.

A similar study from seasonal tropical forests (Asner et al. 2004), reported a close categorization of the dry category employed in this study, with the Amazon forests. Another study (Gu et al. 2007) found that a categorization assigned over the three different habitats (natural forest, oil palm and rubber plantations) can be accomplished using MODIS images. SPI was used here in combination with other inputs to the M–SWM in order to produce a more balanced view, since an SPI-based drought index would indicate a clear separation between drought and non-drought years but would ignore intermediate gradations. Some authors (Almedeij 2014; Caccamo et al. 2011; Sani et al. 2012), however, have used the SPI alone to assess and monitor drought conditions in their regions.

Precipitation data used for drought index development showed a good agreement with other studies conducted in tropical regions during the drought season. Climate–induced mortality events have occurred in various climates, wherever vegetation includes tropical rainforests with mean precipitation > 3000 mm/year (Allen et al. 2010). Conversely, another author (Mohamed et al. 2004) found a direct and immediate enhancement of vegetation production following a positive precipitation anomaly. Meanwhile, the other major climate parameter in the study, the temperature plays an important role in forest areas that depend on high precipitation. In our case, nearby water-dependent agricultural land may increase water stress for the forest in the presence of warmer temperatures during the drought season, by increasing agricultural irrigation.

There was also a strong correlation between NDVI and NDWI, as well as between NDVI and MSI, for the J2000 data which is the only Very Dry period in the study, with an M–SWM rating index of 16. The increasing NDVI values manifest as a “green–up” in the absence of precipitation, during the more severe drought periods. Earlier, Huete et al. (2006) found a similar widespread greening in the dry season along the climate transect spanning central and eastern Amazon rainforests. This effect can be attributed to the deeper root systems that trees in the studied habitats have developed, which gives them access to water resources during the monsoon drought periods. Two other studies, (Breshears and Barnes 1999; Rich et al. 2008), found that woody plants pursue a more gradual and steady growth trajectory, and are hence less reliant on precipitation input than is herbaceous vegetation.

Another plausible explanation of these high NDVI values may be changes in epiphylls (micro epiphytes colonizing leaf surfaces). Epiphylls decrease the NIR reflectance as well as the NDVI (Toomey et al. 2009). On the other hand, Roberts et al. (1998) found that dry-season leaf flush replacement of aging or epiphyll-covered foliage produces an increase in the NIR reflectance, and much smaller modifications in red reflectance. Thus, the dry season leaf flush may potentially increase the NDVI of a tropical forest because this index is positively and strongly correlated with the NIR reflectance. A recent study from seasonal evergreen forest sites (Galvão et al. 2011) detected an increase in canopy foliage during the dry season.

The PCO score plots showed a separation of the J2000 data from the other sample periods, which could be attributed to increasing NDVI and NWDI values during more severe drought periods. In fact, during the start of the dry season, June to July, the most vigorous rubber trees succeeded in regenerating part of their canopy (Guyot et al. 2001).

In addition, Restrepo-Coupea et al. (2013) hypothesized that the seasonality of canopy photosynthetic capacity in tropical forests arises when the limiting resources for leaf growth are seasonal. Other potential causes of the greening have also been identified, such as diurnal variability in leaf water (Frolking et al. 2011) or leaf chemistry and structure. The production of new leaves should occur during the season of maximal irradiance, which occurs during the dry season in our study area. This hypothesis agrees with our results because of the similar responses of natural forest, oil palm and rubber plantation habitats. This study also suggests that severe drought can even occur during the wet season of March-April (M2005).

The M–SWM index could be an important tool for detecting and monitoring drought in an area such as Malaysia and other locations with similar characteristics. Therefore, the index can be a better tool for monitoring drought than any individual index alone. Such findings, however, should be accompanied by weather warning advisories derived from knowledge of within–season rainfall characteristics such as length of growing season, for effective agricultural planning.

6. Conclusion

A drought classification system of M–SWM was produced for the study area. Although the classification was associated with low satellite and M–SWM index correlation, the developed index still proved useful in classifying levels of drought conditions. It can be concluded that this model performed adequately in classifying the months subject to higher drought ratings. The results also classified July as the driest month, based on the M–SWM.

The study demonstrated that the integration of SWM, SPI, mean precipitation and temperature and spectral indices correlation analysis is effective in increasing the model sensitivity. The integration of the climatological and satellite remote sensing indices in this study made it possible to create an effective drought assessment tool for this study area, which could assist the Malaysian Meteorological Department in classifying months with the probability of extreme dryness. The results of this study can be used to support governmental policies for responding to climate change, particularly to more extreme drought seasons.

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Chapter

3

Mapping human impact on Net Primary Productivity Using MODIS Data, for developing better forest management policy

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Abstract

Tropical forests support core biological, hydrological and socioeconomic functions essential to life on earth. An assessment based on the Human Appropriation of Net Primary Production (HANPP) could help reduce exploitation of these forests, increasing their adaptive capacity and lessening their vulnerability to losses of Net Primary Productivity (NPP). Here we apply HANPP to the study area, based on Land Use Impact variability between the forest and contiguous roads and plantations by application of Geographical Information Systems of Protected Area Tools. We used the human activity index and biomass extraction from forest to study the effects of population pressure. The final land use impact map showed that the largest area of forest land (37%) is now in urban and agricultural use, and that these areas are located within 0–3 km of the forest land.NPP with human intervention showed, total NPP of the forest decreased by 7.4%, from 104.4 $gCm^{-2}month^{-1}$ to 96.6 $gCm^{-2}month^{-1}$. This study developed a new HANPP model and enhanced the usefulness of HANPP indicators by demonstrating the impact of human activity inside the forest. Because NPP changes most in higher–productivity areas, suitable policies should be enforced to avoid further human interference in the area.

1. Introduction

Tropical forests are essential for sustaining hydrological, climatic and biogeochemical cycles (Huete et al. 2008). They also provide resources for fulfilling human biological and social needs in the form of, for example, fresh clean water, food and recreational areas. However, a rising human population, along with economic and social development, is causing increased demand for food, fibre and energy, resulting in the expansion of land dedicated for both agriculture and urbanization, including both buildings and infrastructure. Exactly how the human system affects the environment, though, is determined by factors such as the social and economic situation of individual households and communities, their geographical locations and cultural backgrounds (Seppala et al. 2009).

Malaysia is projected to increase its population by 13.3%, to 32.4 million people, by 2020, and another 19.1%, to 38.6 million, by 2040 (World Population Review 2014). This rapid population increase will require extensive new housingconstruction, with consequent pressure on forest biomass resources. This pressure, combined with inadequate policy enforcement in forested areas, could result in serious disturbance to forest ecosystems. In addition, the trend toward developing renewable energy resources in order to reduce greenhouse gas (GHG) emissions is leading to an increase in the use of biofuels, putting further pressure on forest biomass and not only in Malaysia. Elsewhere, in the tropical forests of Africa, for example, where about half of the 2.6 billion people live without access to electricity, most of the population relies on the traditional use of biomass for cooking. Such increased direct use of biomass will contribute to an estimated 20% rise in energy–related CO_2 emissions by year 2035 (International Energy Agency 2013).

Net Primary Productivity (NPP) is the amount of biomass produced by green vegetation, which provides the chemical energy driving most biotic processes on earth (Krausmann et al. 2008; Potter et al. 2013). Meanwhile, Human Appropriation of Net Primary Production (HANPP) is an indicator used for measuring human impact on NPP, including (1) the human impact of land use changes (NPP_{LC}) (land conversion) and (2) the harvesting and destruction of forests (NPP_h) (Haberl et al. 2011). A study by Krausmann et al. (2008) provided an extensive analysis of the effects of timber extraction, by merging used and unused timber in order to estimate the removal and use of biomass from forest, known as Total Biomass Appropriation (TBA).

Rapid social and climate change, however, has made it difficult to determine how human and natural systems interrelate, and little effort has been put into such studies (Su et al. 2012). Nevertheless, the introduction of human dimension measurement, the Human Development Index (HDI), introduced by the United Nations Development Program (UNDP), has resulted in further studies in the field of human–environmental inter-relations. Moreover, since the concept of HANPP was first introduced, researchers have begun mapping HANPP variability using Geographical Information System (GIS) technology. A study by Etter et al. (2011) developed maps based on integrating multi–biophysical variability, land use type and intensity for human footprint assessment.

Recent studies found proximity analysis to be useful for assessing human influence on ecosystem services in China (Su et al. 2012; Yang et al. 2014; Zhou et al. 2015). Elsewhere, the human impact on NPP has received a great deal of attention in drier areas of the world, such as in the semi–arid regions of Spain (Schwarzlmüller 2009). Comparatively little study has been conducted in tropical forest areas, although some studies include tropical forests in a more global overview (Erb et al. 2009; Krausmann et al. 2008).

Therefore, given this background there is an urgent need for assessing and developing maps of human impacts on NPP incorporating human activity and network influences, to estimate HANPP in tropical forest areas. The objective of the present study was to develop a method that calculates HANPP and to map HANPP for the study area using a MODIS (Moderate Resolution Imaging Spectroradiometer) satellite image.

2. NPP and Human disturbance

The calculation of NPP from remote sensing images is usually based on the analysis of low–resolution, high–spectral satellite images, such as these provided by MODIS (Anaya et al. 2009; Hazarika et al. 2005; Landmann and Dubovyk 2014; Liu et al. 2014). MODIS has an excellent spectral range and is suitable for this application in tropical forests (Biudes et al. 2014). The MODIS product, MOD09A1 (Surface Reflectance 8–day L3 Global), at 500-metre resolution has become a standard for forest canopy and area study in tropical forests (Joseph et al. 2012; Xiao et al. 2005) and elsewhere (Kimball et al. 2006). Other satellites such as SPOT (Satellite Pour l'Observation de la Terre), NOAA AVHRR (*National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer*) and Landsat ETM+ (Enhanced Thematic Mapper Plus) with lower spectral ranges are not suitable for this type of application.

Spectrally, the main advantage of MOD09A1 is the large number of spectral bands, including red and infrared bands, which make it ideal for quantifying NPP on the land surface. In particular, MOD09A1 is operates with 36 spectral bands with wavelengths from 0.41 to 14.4 µm (Xiong et al. 2009). Band infrared and red in MODIS is usually best for studying vegetation dynamics, as demonstrated by recent studies (Fabricante et al. 2009; Rulinda et al. 2012). Many studies used MODIS to derive vegetation index the Normalized Difference Vegetation Index (NDVI) by using a band combination of near infrared and red, as demonstrated by various studies in the Sahelian region, the Mediterranean Basin and Austria, respectively (Clerici et al. 2012; Fensholt and Sandholt 2003; Matsushita et al. 2007) which further used NDVI for NPP modelling (Donmez et al. 2011; Handcock and Csillag 2004). MOD09A1 data provide an appropriate way to derive NDVI and are also valid for estimating NPP due to 8–day and 16–day data availability.

HANPP is an indicator of changes in the availability of energy in tropical ecosystems induced by land use (Harberl et. 2004; Krausmann et al. 2008). This type of cartography helps identify of the land degradation and land conversion. In addition to the use of remote sensing in estimating NPP, the use of GIS has made it possible to combine several human influence parameters in order to produce HANPP for specific areas. The main factors included in the development of HANPP in this study are the human activity index, and the influenced human population and roads or settlements (Su et al. 2012). In particular, the use of proximity analysis has made it possible to produce HANPP modelling for example, distances to roads, buildings settlements and towns (Etter et al. 2011; Su et al. 2012). Vu et al. (2014) assessed human–induced biomass productivity decline using physical accessibility to land, such as proximity to roads and towns that assist in the social–ecological development of agricultural and forested zones in Vietnam.

Moreover, a study by Lele et al. (2010) incorporated population density to analyse forest change in Cauvery Basin in India. Few studies include the biomass extraction indicator in their HANPP model, although Krausmann et al. (2008) and Schwarzlmüller (2009) applied the indicator in their studies.

Large–scale timber extraction, agricultural expansion and infrastructure development are recognised as the major drivers of tropical deforestation (Geist and Lambin 2002). For example, infrastructure developed at forest plantations, perennial crops and annual intensive agriculture play a major role in assessing ecosystem and landscape responses to human disturbance (Etter et al. 2011). Meanwhile, Zhou et al. (2014) in a human contribution and climate study in northwest China, combined actual NPP, potential NPP and a dynamic desertification model to quantify the relatives influence of human activity and climate for each region.

HANPP with its different categories is important for ranking NPP, which can decrease in the face of human activities. A study by Wrbka et al. (2004) scaled HANPP to categorize the study area at different land altitudes in Austria. Researchers set great value by the HANPP map because the indicators can be used to bring ecological constraints and their potential implication for human well–being to the attention of a wider audience such as policy makers both, private and government sectors (Haberl et al. 2004). These indicators, have been identified as being useful to combat biomass productivity degradation (Vu et al.

2014). Policy makers often need information about areas of severe degradation in order to prioritize national budgets and plan strategic interventions (Le et al. 2012).

For example, the National Biodiversity Policy 1998 (NRE 1998), which was formulated to protect Malaysia's flora and fauna, will become more significant in the coming years only if it takes a broader approach, taking into consideration on all forest user sectors, for example, local peoples, aboriginal inhabitants, tourists, business and policy makers. In addition, Qasim et al. (2013) has identified institutional factors and policies as underlying factors for biomass removal from forest. The analysis showed the ineffectiveness of forest management systems such as the Forest Policy of North West Frontier Province in Swat, Pakistan, where rules in the policy are almost totally ignored. This is because the forest area is harvested at a higher rate than the government records. There are no doubts that HANPP is important for policy development. However, Haberl et al. (2004) found the HANPP concept too incomplete to provide specific and comprehensive policy guidance.

3. METHODS AND DATA

Study area

Located in Southeast Asia region, in the western part of the Peninsula Malaysia, the Pasoh Forest Reserve (PFR) (2°58'N, 102°18'E) is covered with lowland mixed dipterocarp forest, generally known as tropical evergreen broadleaf forest (Fig. 1). The area includes various species of Shorea and Dipterocarps (Kosugi et al. 2008). The PFR is generally characterized by the peninsular climate—warm, with an annual mean temperature of 26.3°C (measured in 2002–2005). Land uses in this area consist of rubber and oil palm plantations. From 1975 to 1995 the area dedicated to oil palms grew for 568,561 ha to 1 million ha, all converted from natural forest (Wahid et al. 2002).

The population in this area is projected to rise from 0.83 to 1.03 million people, at approximately 1.7% per annum, between now and 2040. Since the 2000s, the number of pave roads in all the states of the Peninsula Malaysia has increased dramatically (64,404;

92,438 and 108,301 km in 2000 to 2009 and 2011, respectively) (Department of Statistics Malaysia 2012).

Quantification of Net Primary Productivity

NPP is usually calculated based on the Light Use Efficiency (LUE) model with the assumption that rates of primary productivity are proportional to the rates of solar radiation absorbed by vegetation (Potter et al. 2012; Sakamoto et al. 2011). In our work, we calculated NPP using the MOD09A1 product at 500 m resolution, inter–calibrating the data with other data from *NOAA AVHRR* and to field census data as in Huete et al. (2002).

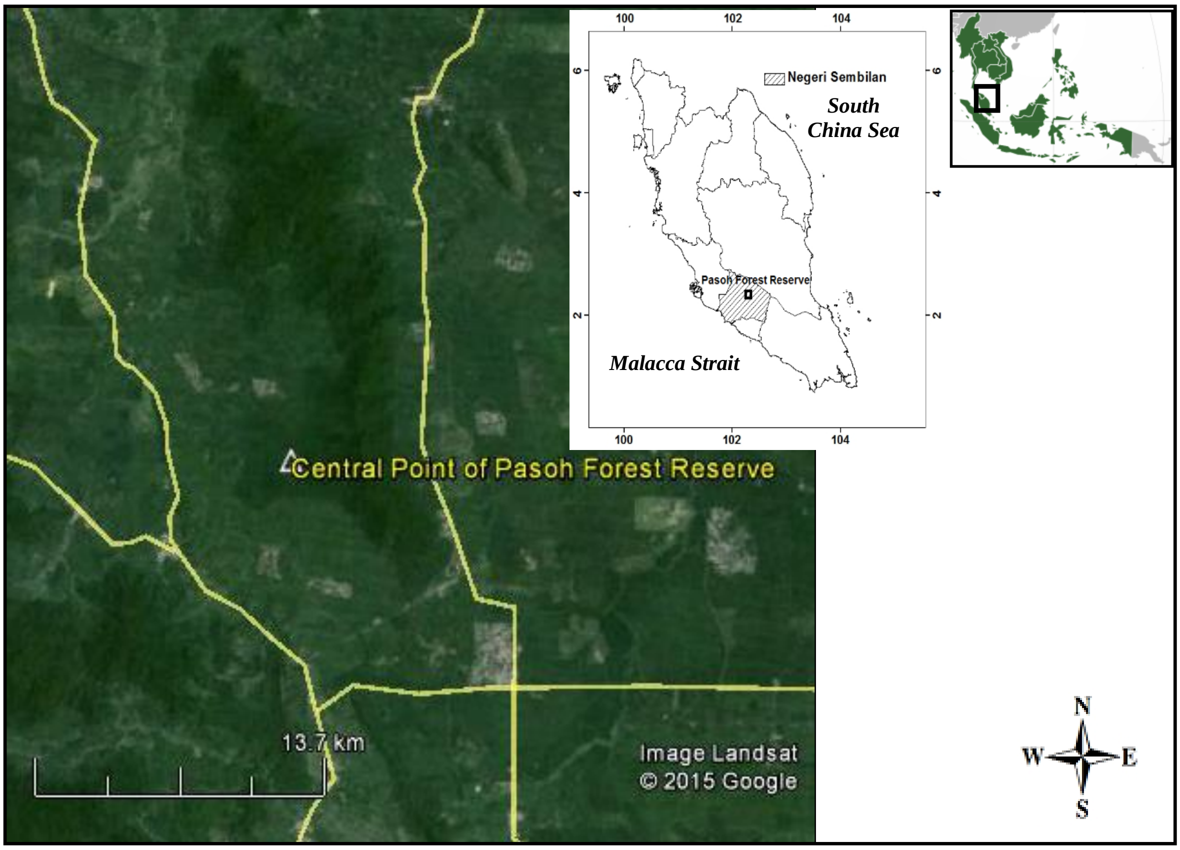


Figure 1. Study area with central point.

The MODIS satellite instruments were built with special attention paid to the structure's thermal sensitivity and the mechanical isolation of the instruments and spacecraft components. This makes MODIS suitable for multipurpose forest canopy and surface studies (Biudes et al. 2014; Fensholt and Sandholt 2003). The MOD09A1 500 m resolution was chosen because it covers the whole study area with one scene, including the time needed for image pre-processing. The resolution is suited to the context of tropical forest, as previously found in a study conducted in French Guiana (Pennec et al. 2011).

We estimated the NPP for 2000 because the year was "normal" with no drought events reported and based on the limited availability of MODIS data. In tropical forest areas, good–quality satellite data are often particularly difficult to obtain due to heavy cloud cover conditions (Huete et al. 2008). To carry out the objective, one of the MOD09A1 image acquired in 2000 was used for the study area. Other MODIS images, for example 2005, provided lower NDVI values due to reduce of water availability, which alters vegetation greenness (Caccamo et al. 2011). Similarly, Nepstad et al. (2004), who investigated the response of Amazon forest to drought, found that severe moisture deficits in tree stem–wood can decrease annual carbon storage. In addition, Malaysia experienced a severe drought in 2005 that affected the vegetation growth of agricultural industry crops (DID 2005).

First, a cloud removal analysis was conducted using masking procedure techniques in Exelis Visual Information Solution (ENVI). The forest study area was demarcated by employing the National Forest Inventory Series 4 for Malaysia forest using "forest reserve boundary" layer obtained from Forestry Department of Peninsula Malaysia. In this study, GPP was estimated using the following equation (Xiao et al. 2004):

$$GPP = fAPAR \times PAR = \varepsilon \times APAR \quad (1)$$

Where, the LUE (ε) equation highlights an important element of the radiation regime for tree growth: (i) incoming photosynthetically active radiation (PAR) ($gMJ^{-1}m^{-2}$) and (ii) the fraction of PAR intercepted by foliage (Fraction of photosynthetically active radiation or fAPAR). PAR was derived from a reduction of 50% of solar radiation collected from Pasoh Forest Reserve climatological station. We obtained the absorbed fraction of photosynthetically active radiation (APAR) (gMJ^{-1}) by multiplying the two most important elements of radiation, fAPAR and PAR (Coops et al. 2010). In this study, LUE was calculated as (Handcock and Csillag 2004):

$$LUE = 0.8932 + TMonth + 0.0015\,(PRECIPMonth) - 0.002\,(GDD) \quad (2)$$

Where, the LUE (gMJ^{-1}) equation was derived using a study by Band et al. (1999). T_{Month} is the monthly temperature in Celsius (^{o}C); $PRECIP_{Month}$ is the monthly precipitation in millimetres (mm) and GDD is the average number of growing degree days. GDD was based on literature on the growth of tropical forests (1%), and was set to 1 based on a study conducted in several tropical forests, where growth of the aboveground biomass was about 1% to 2% (Clark et al. 2001).

The fAPAR was calculated based on a study by (Goward et al. 1994). In this work, fAPAR was calculated as:

$$fAPAR = 1.21\ \times NDVI\ -\ 0.04 \quad (3)$$

Equation 3 was applied to the study area which shares many climatic characteristics with the Mixed Plains ecozone in Ontario, Canada (long growing season and warm summers and abundant precipitation throughout the year). A study by Rasib et al. (2008) used Equation 3 to derive fAPAR in a similar study area. Elsewhere, in another study based on MODIS images, As-syakur et al. (2010) assessed the NPP for Southeast Asian countries with a closely related equation: fAPAR = 1.075 x NDVI–0.08. Similarly a study in a similar area conducted by a group of NPP researchers used the equation: fAPAR = 1.24 x NDVI–0.168 (Faidi et al. 2010).

The NDVI was calculated as (Rouse et al. 1973):

$$NDVI = \frac{(\rho_{857} - \rho_{645})}{(\rho_{857} + \rho_{645})} \quad (4)$$

Where, ρ_{645} and ρ_{857} are the reflectance of MODIS images at 645 nm (red band) and 857 nm (infrared band), respectively. The NPP ($gCm^{-2}month^{-1}$) was therefore estimated by reducing the Gross Primary Productivity (GPP) by 50%. This percentage was based on a study by Rasib et al. (2008) conducted in a similar area, and chosen after an extensive literature survey. The NDVI of MODIS was used to calculate fAPAR because it is related to vegetation development, vigor and biomass (Prince and Goward 2011; Rulinda et al. 2012). In this study, we classify NPP based on Natural Breaks (Jenks optimization) applied in ArcMap. A study by Potter et al. (2013) used this approach to divide NPP into low, moderate and high production forest categories in tropical forest of Southeast Asia. The method minimized the average deviation of each class, while maximizing each class's deviation from the means of the other groups (Jenks 1967). The quantitative classification applied to the NPP values is intentionally based on assignment of NPP range, namely highest range as "very high" and the lowest range as "very low".

Quantification of Human influence

Land Use Impact (LUI)

Man is the dominant factor in determining the extent of the world's forests through forest clearing (UNDP 2013). Human influence on forests can be measured using HANPP, which links: (1) the alteration of NPP through human–induced land use or land cover changes and (2) the extraction and destruction of forest biomass by human activities (Erb et al. 2009; Kastner 2009).

To determine this impact, we first assessed land use changes, assigning to human access points, as defined by (1) distance to roads, (2) distance to urban buildings, (3) distance to rubber plantations, and (4) distance to oil palm plantations (Table 1). Agricultural expansion, infrastructure development and wood extraction are the obvious impact factors for land use changes (Qasim et al. 2013). The above criteria were selected and represented in point format. The data were digitized by Malaysian Survey and Mapping Department based on the location of urban buildings (JUPEM 2000).

All datasets were placed into the same 500 m grid buffered using the Multiple Ring Buffer tool in ArcMap in ArcGIS 10.0. The distances were set to 500 m in the dialog tools.

The data was classified into six levels of human-influenced, for every 500 m, from the value 1 (indicating very low human impact) to 6 (indicating very high human impact on the forest area), as shown in Table 1. Among these 4 land use impacts, urban building was difficult features to quantify and so we limited the distance buffer to a maximum of 2500 m, and a score value of 5. After weighting all the layers, we classified the values using the qualitative model developed by Mansor et al. (2004) and Razali et al. (2010), using the term of "low", "moderate", "high", "very high" and "extreme" disturbance. Finally, we calculate area percentage for each of the classification.

Table 1. Land Use Impact variables used in the study.

Variable/type of measurement	Distance (m)	Score
	0–500	6
(a) Distance to roads/line	500–1000	5
(b) Distance to urban buildings (settlements, shops)/points*)	1000–1500	4
(c) Distance to rubber plantation/points	1500–2000	3
(d) Distance to oil palm plantation/points	2000–2500	2
	2500–3000	1

Note:* Maximum distance buffer; 2500 m, and Maximum score 5.

In addition, we incorporated roads in the model because roads are important factors in reducing of the total area of an ecosystem, reducing in forest productivity by converting forest into an artificial surface (Valente and Vettorazzi 2008). Roads can be helpful in serving to society, but a threat to the forest. Many areas are deforested at lower altitude in Tarai, Pakistan, which has been mainly attributed to their accessibility by roads (Bhattarai et al. 2009). Urban buildings are an additional factor in modelling HANPP. Study by Mon et al. (2012) conducted in Myanmar, found that a 1 km increase in the distance to the nearest town decreased the probability of deforestation by approximately 6%. Moreover, they reported that cultivated land or areas of permanent agricultural expansion in low lying areas is one of the factors contributed to forest degradation, thus decreasing NPP.

Human Activity Index (HAI)

Secondly, we developed HAI index incorporating four human behaviour parameters that modify the environment. The index was based on the year 2000, because of the availability of MODIS satellite data. The equation was adapted from a method implemented in China, with the human population given a scale factor of 0.3 and road influence a scale factor of 0.2 (Su et al. 2012). The equation developed for HAI is as follows:

$$HAI = P(0.3) + R(0.2) + HDI + TBA \tag{5}$$

Where, *P*, *R*, *HDI* and *TBA* are the total human population of the area, road influence, the Human Development Index and Total Biomass Appropriation, respectively. Total population is recognized as structure and dynamic factors (Vu et al. 2014). Based on the Present Land Use map of Negeri Sembilan 2004 from the Department of Agriculture Malaysia, we identified all the paved roads as 'county and township roads', thereby quantifying the influence as 500 as shown in Table 2. The extent to which each road type corresponded to human influenced was based on a dimensionless value. The weight was ranked on a scale of 0–1200 (Hu et al. 2007). After that, based on the influence value we derived the rate of human influence by using roads to the forest area by assigning scores, 1 indicating low human influence and 7 very high human influences. HDI was used as a measurement index for assessing progress in three basic dimensions of human development—namely, a long and healthy life, access to education, and a decent standard of living for all countries in the world (UNDP 2013). The index is measured on a yearly basis and each country is given a rank compared to all other countries.

Table 2. Road network influence and classification (Hu et al. 2007).

Road rank	Influence [a]	Score [b]
High–grade highway	12000	7
National highway	10000	6
Railway	10000	5
Provincial highway	800	4
County and township road [c]	500	3
Cart road	300	2
Dirt road	200	1

[a] Defined as a dimensionless value by Hu et al. (2007).
[b] Developed in this study.
[c] Road identified for this study.

TBA represented the total amount of biomass harvested from the forest (Erb et al. 2009), for example, the extraction of forest products by local people for food, hand crafts, tools, fuel, grazing of livestock, etc. The TBA is very important for forest-dependent poverty-stricken populations, for example in Africa. The community is already vulnerable to climate change, which has forced them deeper into the forest to find marketable forest products, a situation exacerbated by lower government support and subsidies. The following formula was use to derive the TBA:

$$TBA = \frac{(Used\ Extraction) + (Unused\ extraction)}{Population} \quad \text{(Krausmann et al. 2008)} \qquad (6)$$

Most importantly, the TBA calculated for this study encompassed the most critical forest-related elements, (1) wood removal (used extraction, UE), and (2) unused below-ground and felling losses in the forests (unused extraction). The TBA elements in 2000 were summed and finally divided by the number of population living in Negeri Sembilan. The data was entered into Microsoft Excel and calculated based on data provided by the Institute of Social Ecology, Vienna (Krausmann et al. 2008). In this way, the biomass consumed per-capita in Negeri Sembilan for the year 2000 is derived for the study.

HANPP using Environment Risk Surface of PAT tool

In this calculation ArcGIS 10.0 was used to perform all the analysis. To analyse forest areas we extracted forest pixels from the National Forest Inventory Series 4 for Malaysia forest using "forest reserve boundary" polygon obtained from the Forestry Department of Peninsula Malaysia using Extract tools. The LUI was weighted using the linear decay function by applying the Environmental Risk Surface model provided by Protected Area Tools (PAT) in ArcGIS 10.0. The equation developed for HANPP was:

$$HANPP = LUI + HAI \qquad (1)$$

Where, LUI and HAI are Land Use Impact and Human Activity Index, respectively. This model consisted of *intensity value* and *influence distance* elements to calculate LUI values. The *intensity value* represents the relative level of threat that the risk element poses to the forest, which in this study was the distances from roads (*e.g.,* 0–500 m). It is important to remember that the distances generated do not represent an absolute measure of human impact on NPP but it could be a guide. The *influence distance* of each variable was assigned to determine spatial extent of the activity in the forest, representing the maximum distance at which the element has a negative impact on forest NPP, which in this study was 3000 m. The buffer effected increased with distance from the centre of the area (*e.g.,* oil palm) where the targeted element is located. At the same time, the *intensity value* diminishes gradually, which is known as the *distance decay* or decay function. Therefore, the impact on the forest gradually decreases away from the area studied (McPherson et al. 2008) (Table 3). After that, the accumulated values were weighted and incorporated with the HAI values to develop a single layer using Map Algebra tools. Then HANPP classification was made by grouping the HANPP values of the integrated layers based on the degree that each is considered to be a threat to the forest.

A similar qualitative model to that developed by Mansor et al. (2004) and Razali et al. (2010), combined with the Natural Breaks classification approach, was used in this study, using the classification terms "low", "moderate", "high", "very high" and "extreme" rather than the numbers 1 through 5. In this way, the range 19.2–27.2 was classified as "extreme"; range 15.2–19.2 as "very high"; range 12.2–15.2, 8.2–12.2 and 5.2–8.2 as "high", "moderate" and "low", respectively. The percentage for each of the classifications was also measured. Furthermore, we calculated the NPP value of human influence by subtracting HANPP from NPP. In addition, to analyse spatial difference in NPP (modifying by HANPP), the NPP map was also subtracted from the HANPP one. Finally, we conducted a correlation analysis of NPP pixels with the HANPP for the study area. We separated the analysis into: (1) "very high" and (2) "high", "moderate", "low" and "very low" classes.

Data sources

The MOD09A1 data acquired in 2000 was retrieved from the website of the United States Geological Survey (https://lpdaac.usgs.gov/data_access) and the NPP values were derived from these data. Human population data for Malaysia and Negeri Sembilan for 2000 were obtained from the Department of Statistics Malaysia (http://statistics.gov.my).

Land use map data were digitized by the Malaysian Survey and Mapping Department (JUPEM 2000). The data used in this study corresponded to the period 2000–2008, and were obtained from the Sultan Abdul Samad Library of Universiti Putra Malaysia, Serdang, Selangor. The data, taken in CAD format, contained four series of 3957b, 3957d, 4056a, and 4057c. We assumed that the land taken for urbanization grew at an average rate of 2.8% from 2000 to 2010, as reported by the Federal Department of Town and County Planning (FDTCP 2003). Similarly, Jaafar (2004), who investigated the trends of urbanization in Malaysia, assumed that the average growth rate of urbanization was 2.2–2.9% between 1980 and 2000. According to the report, such changes were only associated to the growth of isolated and small towns, which excluded conversion of forest land to agriculture.

The HDI of Malaysia for 2000 was taken from UNDP (http://hdr.undp.org/eng/countries) from the Global Pattern of Socioeconomic Biomass flows for the year 2000, provided by the Institute of Social Ecology, Vienna (Krausmann et al. 2008).

MODIS image pre-processing and classification

Isolated clouds identified based on a comparison with the Present Land Use map of Negeri Sembilan acquired in 2004 by focusing on visible and infrared bands during the procedure (band 1, band 2 and band 6). Moreover, we conducted image enhancement using band combination techniques: (i) 1, 4, 3 (true colours), (ii) 7, 2, 1 and (iii) 2, 6, 1 for our image to further detect contaminated areas. Later, we used blue band reflectance to eliminate the contaminated pixels. Pixels with reflectance values of > 0.2 were eliminated from the image using a masking procedure (Xiao et al. 2005). Using the land use map that depicted forest polygon, bands combinations and single blue band we focused on forest area to further validate the masked areas. This is because in moist tropical forests areas satellite remote sensing images is frequently associated with cloudiness problem. In addition, the image was enhanced using histogram equalization for further image interpretation and classification into forested areas (Tseng et al. 2008). Iterative Self-Organizing Data Analysis Techniques (ISODATA) were used to classify the image into forested areas (Razali et al. 2014).

4. Results

Land Use Impact (LUI)

LUI distances for all the variables ranged from 0 to 3000 m, in 500 m increments, indicating the distance from the point or layer to the forested area, using 1 as the lowest influence value and 6 as the highest in LUI, except for urban buildings, where the lowest value was 5 (Fig 2a-e). Road buffer is the land nearest and contiguous to the forest area, excluding other buffer layers. The maximum accumulation of the index was 23 (Table 3).

Table 3. Human land use impact from LUI variables applied in Protected Area Tools. Grey is high land use impact and dark is low land use impact.

Distance decay →

Intensity Value

Variable	Buffer distance (m)					
	0–500	500–1000	1000–1500	1500–2000	2000–2500	2500–3000
Road	**6**	5	4	3	2	**1**
Urban	x	**5**	4	3	2	1
Rubber plantation	**6**	5	4	3	2	1
Oil Palm plantation	**6**	5	4	3	2	1
Total Influence Values	**23**	Other Weighting Values				**1**
Human Impact to forest NPP	**Very high land use impact** →				**Very low land use impact**	

The LUI map shows values from 1 to 23, with 1 indicating the lowest and 23 the highest land use impact on the NPP of the forest. As can be seen from Fig. 2e, the LUI was classified into "low", "moderate", "high", "very high" and "extreme". The area outside the buffer area, for which there were no data, was calculated as 0.

The LUI that were generally concentrated at the edge of the forest, with values greater than 10 are "very high" and "extreme" classes. The LUI values that were located in the middle towards the southern edge of the forest, are the values of 1 to 10 ("low" to "high"); these were located 3000 m or more from roads, urban buildings, rubber plantation and the oil palms buffer. LUI values of 7–10 classified as "high" occupied the largest part of the forest—37%, followed by values of 14–23 classified as "extreme" occupied the smallest area—8%. LUI values of 1–2 and 2–7 for "low" and "moderate" classes covered 11% and 25% of the study area, respectively. Meanwhile, the LUI values of 10–14 for "low" class covered another 10% of the area (Fig. 2e).

Human Activity Index (HAI)

The population in 2000 for Negeri Sembilan was used as representative for the study area, encompassing 0.83 million people, or 3.7% of the 22.0 million population of Malaysia. TBA per capita for 2000 for Negeri Sembilan was 1.66 metric tonnes per year (t/cap/year). The HDI utilized in this study was 0.712 for Malaysia as a whole and the final value of the HAI index for the study area was 4.221.

Human Appropriation of Net Primary Production (HANPP)

The HANPP index is classified into five classifications based on Natural Breaks, with 5.2 indicating the lowest and 27.2 as the extreme value. The final HANPP map is shown in Fig. 3. In this study, the HANPP "extreme" covered 13% of the forested area, found primarily along the edge of the forest. The range "very high" covered 22%, very similar to the "high" class at 23%. Moreover, "moderate" and "low" covered 33% and 9%, consequently "low" was characterized as the smallest proportion, 9%, situated in the southern part close to the area outside the buffer zone. In the study, LUI classified as "low" and "high" covered an area of 11% and 37%, respectively, while HANPP used 9% and 23% for the same classification.

Based on the results, these classifications recorded decrement of their coverage at 2% and 14%. In other hand, "moderate", "very high" and" extreme" recorded increment of 4%–8% of the forest area. Therefore, authorities should introduce new guidelines and policies by assigning specific HANPP classifications for each of the forest areas.

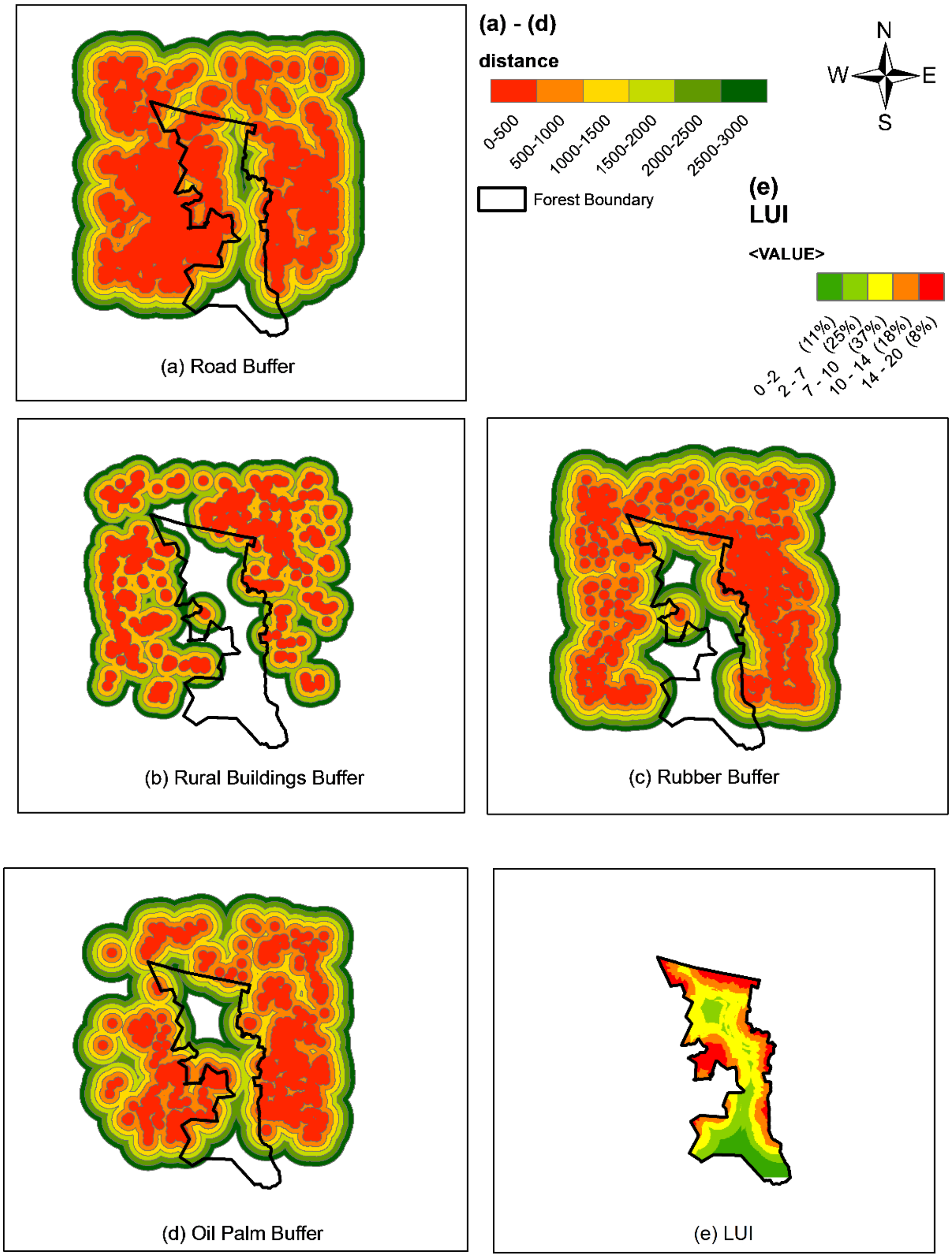


Figure2.(a-d) LUI variables buffered and (e) final accumulation of LUI.

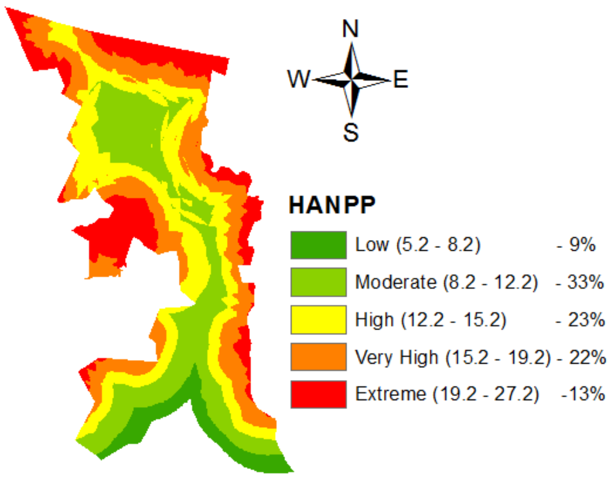


Figure 3. HANPP map with values, classification and percentage of occurrence.

Net Primary Productivity (NPP)

Using the Natural Breaks classifier, five NPP classes were derived: "very low", "low""moderate", "high" and "very high". After alteration by the HANPP index which is finally known as NPP with human intervention, the NPP is decreased for "very high" area, nevertheless increased for the other areas. Detail of the classification and results for NPP alteration are shown in Table 4 and Fig. 4.

Table 4.NPP and NPP with human intervention.

		NPP Coverage (%)		
Classification	NPP ($gCm^{-2}month^{-1}$)	NPP	Human intervention	Alteration
Very High	202.2–213.5	54.7	1.1	– 53.6
High	192.1–202.2	18.4	31.5	+ 13.1
Moderate	180.3–192.1	17.8	39.3	+ 21.5
Low	162.1–180.3	6.8	21.8	+ 15.0
Very Low	133.4–162.9	2.3	5.3	+ 3.0
Unclassified (new classification)	< 133.4	–	1.0	–

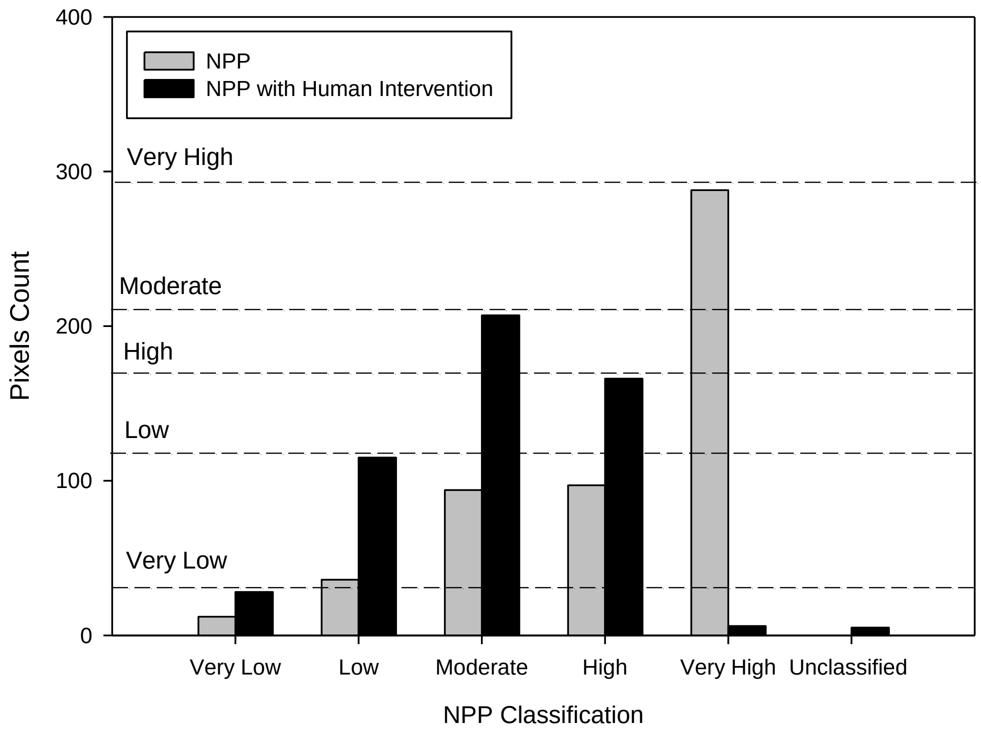


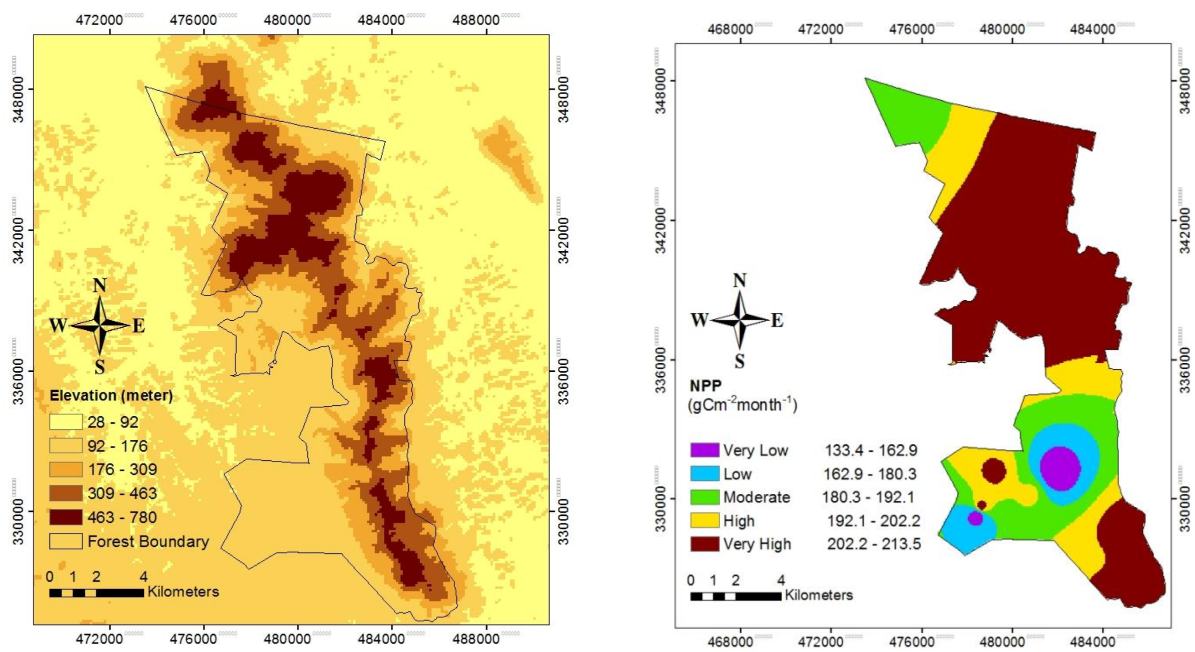
Figure4. Pixel counts in NPP and NPP with human intervention.

Meanwhile, the elevation and the results of the NPP maps are shown in Fig. 5a and 5b. The "very low", "low""moderate" and "high" were very closely located; however, "very high" NPP values were dispersed over a much higher gradient, and the values decreased as the gradient declined from north to south-west, from 463–780 to 92–176 metre above sea level shown in the NPP map.

Figure 6 shows the NPP with human intervention map that permitted interpretation of the impact of human influence on NPP for the study area. The main impact of human intervention was located in the forest with "very high" NPP, which was transformed to "moderate" and "high". The "very high" NPP was reduced in testimonial area (1.1%) located on the decreasing level of altitude at about 92–176 meter above sea level. The results showed the areas shifted further southward in the NPP with human intervention map. Overall, NPP is seen to be changing in high productivity areas.

Moreover, the map showed the new NPP classification (unclassified) substitute in the centre of the "very low" area (1.0%). As anticipated, "low" used additional areas in the northwest replaced "high" and "moderate"; and "low" circulated within the "very low" at the lower altitude, that similarly occurred for both occasion.

The correlation analysis showed no significant correlation between NPP pixels and the HANPP index for this study, R^2 = 0.0039: "very high" pixels and R^2=0.0027: "high", "moderate", "low" and "very low" pixels respectively. Therefore, these results demonstrate a poor relation between NPP and HANPP index. This is because the NPP calculated in the study is depending on climate impacts such as water stress, meanwhile HANPP index is expressed as the value that relying to the rate of human accessibility to the forests (ie. distance to roads).



(a) (b)

Figure 5. Elevation of the study area derived from Digital Elevation Model (DEM) provided by Shuttle Radar Topography Mission (SRTM), 300 m. The data was collected from CGIAR Consortium for Spatial-Information (CGISR-CSI) (a) and NPP classification (b).

The map suggests that a forest conservation strategy needs to be implemented to restrict access to high potential human impact areas such as those containing roads to preserve NPP for the area. The global impact in the studied area showed that the total calculated NPP decreased by 7.4%, from 104.4 $gCm^{-2}month^{-1}$ to 96.6 $gCm^{-2}month^{-1}$.

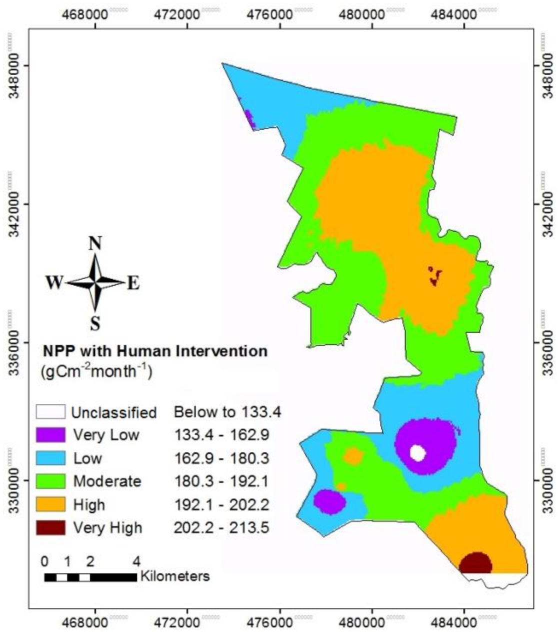


Figure 6. NPP with human intervention after application of HANPP index for the study area.

5. Discussion

Past studies have used various variables for assessing HANPP; for example, socioeconomic factors, including human population pressure (Kastner 2009), human activities (i.e. road construction, soil removal) combined with human population pressure (Su et al. 2012), and land–use changes (Schwarzlmüller 2009). In our study, roads presented the major human impact, with numerous roads connecting the forest and the human community within the 0 to greater than 3000 m range. Heavily used roads may trigger land use changes in an area. For example, roads may be built to initiate deforestation and forest fragmentation may occur if a forest is exposed to long-term human pressure (Qasim et al. 2013).

The present study found that LUI variables demonstrated the impact of human activities in the study area. The LUI map showed 37% of the forest to be classified as "high" LUI, implying that urbanization and agricultural use covered much of the forest. The LUI input to the HANPP (roads, agricultural land and urban sectors) can be used to manage forest areas, a finding that agricultural managers and urban planners can use in planning development projects.

The lowest human impact on the forest area of LUI variables is from urban buildings; most of them are widely scattered outside the forest and hence have only a slight impact on the forest area, at least as predicted from this model. The distance of the urban buildings from forests create large gaps, providing spaces for the forest to persist without human interference. Furthermore, roads leading to these buildings from forests tend to be short, so that the forest has more opportunity to thrive without human interference.

The HANPP model with exploration of TBA and HDI to develop the HAI showed proportionately to the LUI results. Nevertheless, comparison of the HANPP with the LUI map, reveals a major different in "high" areas, representing 14% of the area. This showed that including TBA and HDI in the HANPP improves human disturbance analysis in the study area. TBA is a global average measurement for used and unused biomass in the forest by all the human population in a given area and year (t/cap/year) (Krausmann et al. 2008): for example, timber removed from forests by legal loggers (used) and biomass left after logging activities (unused), such as buttresses, damaged trunks and other logging residues.

In this study, the area percentage obtained from HANPP classification (Fig. 3) agreed with suggestion in a study by Haberl et al. (2004), which reported an HANPP threshold of 20%. As anticipated in Fig. 3, "extreme" HANPP occupied only 13% of the forested areas so, if we assign "extreme" HANPP as our "sustainability threshold", our HANPP estimation is below that which represents a risk of destruction. A sustainability threshold is a physical indicator of environmental stress that has been suggested for inclusion in assessment of environmental stress (Srebotnjak et al. 2010).

The HAI index is predicted to rise with the projected increase in Malaysia's population from 28.6 to 38.6 million inhabitants, between now and 2040. TBA per capita, by contrast, is expected to decrease with the increase in population. There will be exceptions, though: for example, development factors such as the construction of highgrade highways for a new city in the buffer zone in the study area could increase TBA. Such increases, however, could be balanced with the introduction or improved of economic policies. For example, New Economic Policy of Malaysia implemented in 2012, aims to narrow income gaps, thereby improving livelihoods, life expectancies, economic prospects, and access to health services and quality education. However, the removal or drastic reduction in government subsidies for fertilizer, for example, could influence the sustainability of paddy production, because farmers will not be able to buy their own fertilizer (Ramli et al. 2012).

Therefore, this study enhanced the HANPP model by mapping human activity inside the forest, and by including further variables of the human dimension. The LUI and HANPP map of "extreme" areas seems valid, as found in the other studies: the forest pixels located closest to villages were predicted to have a lower basal area than pixels at greater distances from the villages and the roads (Ingram et al. 2005). This is most likely due to the ease of access to these locations particularly, at the edge of the forest that closest to villages or settlements. Thus, the HANPP model seems valid for application in tropical forest with similar forests types to that of the study area.

Lack of awareness and inadequate enforcement of policies designed to protect restricted areas may expose forests to biodiversity loss and hence reduce their productivity. In Indonesia, for example, the main driving forces of forest loss in provincial areas are poorly controlled infrastructure development, mining, and conversion to crop plantations (Potter et al. 2013). Although these activities are legal, they should be shifted from high productivity areas to lower productivity areas, as depicted in Fig. 5b. Appropriate policies need to be developed and enforced, to avoid further negative human impact on the high productivity areas.

By deriving NPP using the integrated MODIS NPP model, this study closely reflects the findings of a similar study performed in this forest, utilizing the Global Production Efficiency

Model (GLO-PEM) (Faidi et al. 2010). Furthermore, because MODIS produces a high temporal frequency satellite image, and is freely available, this cost effective method can be further used within topical forests. MODIS has in fact proved useful in assessing inter annual variability in productivity for tropical forests (Ichii et al. 2005). A comparison of the NPP at a "very high" area at 500–600 m.a.s.l with the findings of another study shows that the higher the altitude, the lower the human pressure on the forest, thus preserving NPP (Bhattarai et al. 2009).

GIS can provide integrated analysis of spatial data (Shalaby and Tateishi 2007). Weighting variables using the Environmental Risk Surface Generator provided by PAT in ArcGIS 10.0 software can then generate multiple calculations of variables. GIS mapping is highly efficient and enables the higher productivity areas of NPP within forested regions to be highlighted. This tool has enabled researchers to improve their representation of numerical classification ranges into easily interpreted multi coloured maps. HANPP map is useful for forest managers to model human activity for designing policy, particularly in higher productivity areas. More research should be initiated in the higher productivity areas, using biodiversity study techniques currently implemented only in lower productivity areas: for example, a floristic composition of lowland areas (Kochummen 1990); carbon exchange (Kosugi et al. 2008), and assessment of NPP using remote sensing (Cracknell 2010; Faidi et al. 2010). Quantifying and evaluating the spatially explicit impact of human activities on ecosystems can provide an information base to raise awareness and make decisions to protect the environment (Etter et al. 2011).

Finally, the political sector needs to be involved, in order to put scientific principles into practice by enacting and enforcing supporting policies. A number of studies have resulted in the enactment of new ecological conservation policies, such as the "Grain for Green Project (GfG)" for China (Su et al. 2012).

Our study has proved that the HANPP index is an efficient indicator for assessing NPP when both socioeconomic (LUI, HAI) and MODIS data are taken into consideration. This model, using the above variables to assess HANPP for the study area, will be particularly useful because the HDI index is available yearly (UNDP 2013). A study by Hou et al. (2014)

found that HDI is increasingly used to assess a country´s human and economic development for setting human population goals or designing and evaluating policies.

6. Conclusions

A HANPP map was produced for the study area. Although the HANPP map showed that most of the area that it classified as "low", "moderate", "very high" and "extreme" was proportionately to LUI results, the HANPP model still proved useful for forest management. It can be concluded that HANPP can be assessed using proximity analysis in GIS and employing the variables presented here. Our findings suggest that maps are the best medium for representing HANPP classifications, and that MODIS satellite images are capable of providing economically viable NPP data to be used in the model. The integration of MODIS high spectral data and GIS techniques in this study made it possible to create an effective HANPP model and to develop a detailed HANPP map for the study area.

This study found that the most important approach is to maintain and provide policy enforcement in areas with higher NPP. The highest area is safe from human intervention because it is far from urbanization and agricultural land. Globally, including in Peninsular Malaysia with its increasing population, forested land is seen as an alternative source for resource development. This integration of spatial variables, therefore, is especially significant and useful for interrelated human environment research.

7. References

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Chapter 4

Impacto del cultivo de palma aceitera en bosques tropicales en el contexto del crecimiento poblacional humano

Parts of this chapter have been send for publication: Integrated Environmental Assessment and Management

Abstract

Human impacts on tropical forests from deforestation and over consumption of forest products directly affect global ecosystems. This study presents calculations of net primary productivity available from tropical forests based on current and future population growth. Human appropriation of forests through the direct use of forest products, as well as through agricultural development, results in deforestation and also generates agrochemical pollution. This research generated spatial change impact maps of tropical forests, showing the locations that create the most demand for energy, the most extractable forest products, and the most polluted areas, along with estimates of anticipated changes in both forest and agricultural land in two tropical forest regions. The analysis reveals that in Malaysia the greatest degree of change impact (high change) between now and 2045 would be in 2% of the virgin forest area, and that 'intermediate' change will result from an increase in oil palm plantations and rapid population growth. In Thailand, however, with its current and anticipated low population growth, forests will experience 'intermediate' change from an increase in oil palm plantations, due primarily to resultant improvements in standard of living and increased forest products consumption, but there will be little change in agricultural land. Both countries, however, will experience increased agrochemical pollution unless measures are introduced to limit it.

1. Introducción

La rápida conversión de los bosques a tierra agrícola (ej. plantaciones para caucho y aceite de palma) ha supuesto un gran impacto ambiental, especialmente in áreas próximas a poblamientos humanos donde los bosques experimentan una rápida destrucción (Fitzherbert et al. 2008; Wicke et al. 2011).

El crecimiento de la población y la alta vulnerabilidad al cambio climático son uno de los factores que más contribuyen a la degradación ambiental de los bosques. Esta situación es especialmente preocupante en los países en desarrollo donde estos dos factores tendrán una mayor intensidad (Jiang and Hardee 2009; Population Action International 2011). El crecimiento medio de la población en países en desarrollo es 2,5% (Population Action International 2011), disminuyendo la posibilidad de mantener la disponibilidad de recursos forestales per cápita.

Hoy en día en el sureste asiático, la emigración internacional, las guerras civiles (Institute of Peace and Conflicts Studies 2015) y los niveles crecientes de pobreza (Kaur 2009) son los principales factores que condicionan el crecimiento poblacional. El crecimiento poblacional dispara cambios en el comportamiento de consumo y afecta a los niveles de emisión atmosférica. Las poblaciones humanas que viven en o alrededor de los bosques utilizan directamente madera y otros productos, los cuales son conocidos como non-timber forest products (NTFPs), para cubrir sus necesidades inmediatas de combustible y material de construcción (Kusmana 2011). La modernización ha traído modificaciones adicionales, como cambio en la dieta que incluye más alimentos procesados, incremento de la demanda de aceite de palma, el cual constituye un alimento de primera necesidad (Sayer et al. 2012). El crecimiento poblacional también influye en las políticas gubernamentales, tales como un rendimiento sostenible de la economía (MPOC 2011), lo cual requiere un incremento en la producción de alimento y la transformación de tierras a usos agrícolas (Wicke et al. 2011). Se ha estimado que al menos 10 millones de ha de bosque han sido reemplazadas por plantaciones de palma aceitera y caucho durante el período 1995-2011 en Malasia and Tailandia sólo (The Thai Rubber Association 2015; Manokaran 1990; MPOB 2014).

Sobre todo, los impactos humanos en bosque tropicales continúan, con potencialmente nefastas consecuencias para la biodiversidad tropical y el medio ambiente (Gibson et al. 2011; Hartemink 2005). Además, la expansión de las tierras agrícolas ha llevado a niveles más altos de utilización de agroquímicos (Hartemink 2005; Saswattecha et al. 2015). Esos pesticidas, herbicidas y fertilizantes inorgánicos también contribuyen al calentamiento global, acidificación, eutrofización y otros impactos ambientales (Saswattecha et al. 2015). Un indicador preciso de los impactos humanos podría proporcionar una referencia importante para monitorizar el progresos hacia la conservación global (Ma et al. 2012) y la evaluación de los beneficios de la biodiversidadpara reducir la degradación del bosque tropical (Burgess et al. 2007; Williams 2013).

2. Malasia y Tailandia

Los bosque tropicales del sureste asiático comprenden una región con alta biodiversidad, mientras que al mismo tiempo están bajo una enorme presión conducida por el crecimiento poblacional y la explotación de los recursos naturales. Malasia mostró un crecimiento anual de la población del 1,8% antes de 2010 (Department of Statistics Malaysia 2012), mientras que otros países vecinos tales como Tailandia muestran un crecimiento muy bajo, proyectado a tan solo 0,3% entre hoy en día y el 2020, lo cual es atribuible a los bajos niveles de fertilidad (UNPFA 2011).

Malasia ha doblado su área de plantación para la obtención de aceite de palma entre 1995 y 2011, de 2,5 a 5,0 millones de ha, según informe de 2015 (see http://www.mpob.gov.my), plantando 1,4 millones de ha de árboles de caucho en el 2000 para ayudar al crecimiento de la economía debido a que el caucho es la mayor exportación agrícola de este país (MPOC 2011). Tailandia, sin embargo, actualmente tiene 3,6 millones de ha de plantación de árboles de caucho, ha sobrepasado a Malasia como el mayor exportador y productor de caucho natural del mundo (see http://thainr.com). Por el contrario, el gobierno tailandés ha incentivado la tala de 350.000 árboles de caucho en un año y su sustitución por plantaciones de palma aceitera (The Wall Street Journal 2014). Mientras es imposible en este punto cuantificar la extensión del bosque que se ha transformado en suelo agrícola, se podría al menos cuantificar el impacto de la transformación.

Para examinar esta cuestión, en este trabajo hemos valorado el impacto del crecimiento poblacional humano, de la extracción de recursos y el uso de agroquímicos en la producción primaria de dos bosques tropicales localizados en Malasia y Tailandia. Este estudio compara estas dos localidades caracterizadas por tasas de crecimiento poblacional altas y bajas.

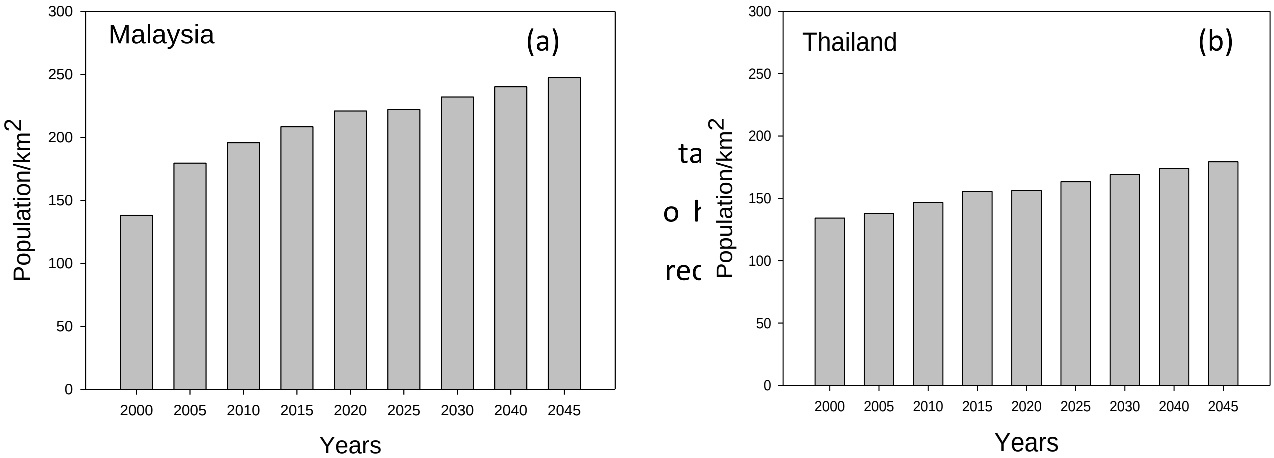

Figura 1. Crecimiento actual and proyectado del crecimiento de la población en (a) Malasia y (b) Tailandia durante el período 2000-2045.

El estudio era realizado en dos bosques tropicales perenes en el sureste asiático localizados en la región en Negeri Sembilan, Malasia peninsular y Nakhon Si Thammarat, Tailandia (Fig. 2). En Malasia se caracterizó el bosque tropical como bosque primario (o virgen) o bosque secundario.

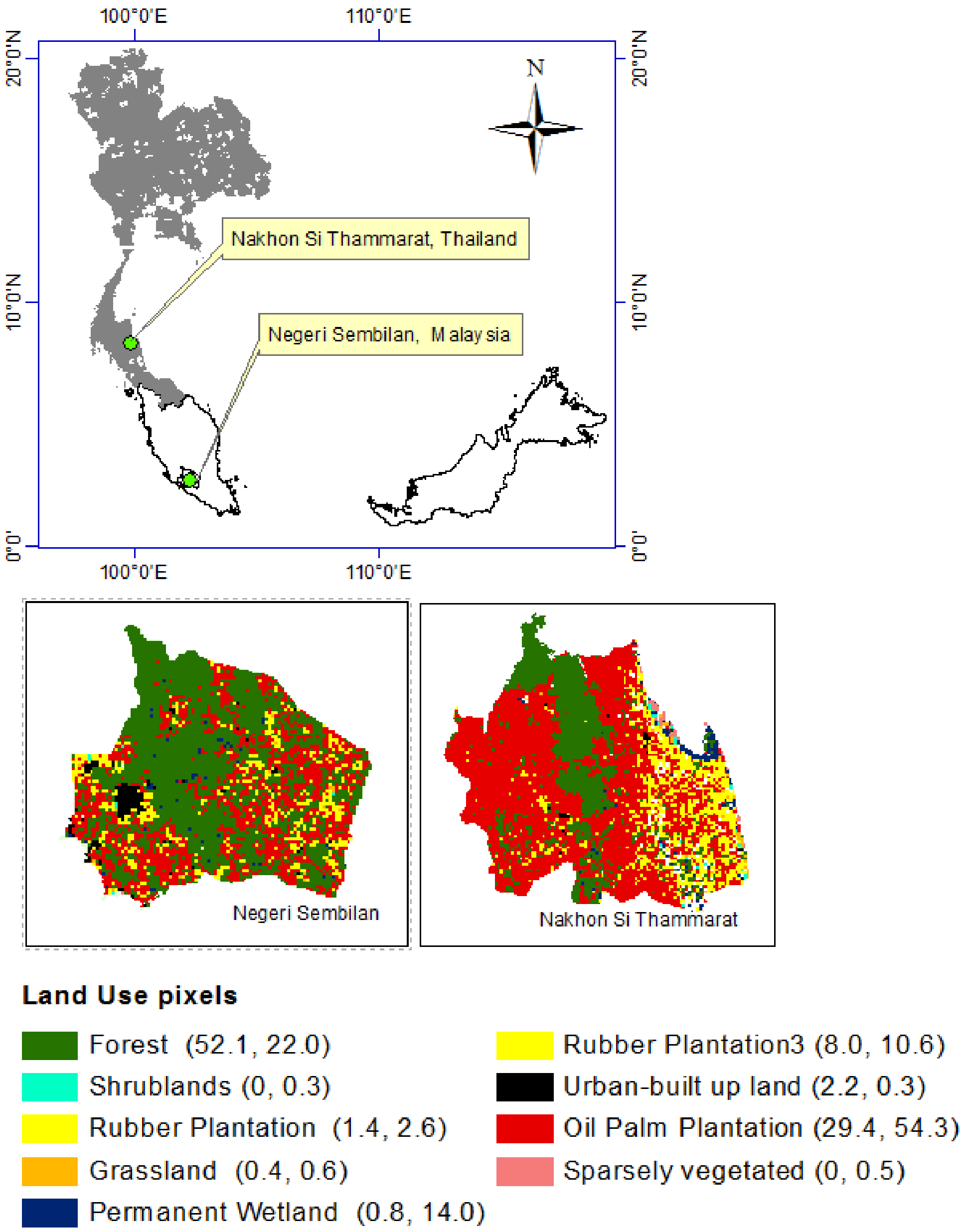

Figura 2. Área de estudio: localización geográfica (arriba) y uso del suelo para cada uno de los píxeles en el área de estudio (abajo). Entre paréntesis se indica la superficie en porcentaje para Malasia y Tailandia respectivamente.

Un bosque secundario es definido como un bosque que ha sido talado y se encuentra recubierto tanto natural como artificialmente. El bosque primario en este estudio era considerado un bosque maduro que ha experimentado poca o ninguna perturbación humano (Gibson et al. 2011). No todos los bosques secundarios proporciona el mismo valor para la sostenibilidad de la biodiversidad biológica o la producción de bienes y servicios como lo hacía el bosque primario que previamente existía en la misma localidad (CBD 2000).

Datos de series temporales de "Gridded Population of the World" (GPWD 2015) eran utilizados para calcular la variación temporal basándose en el método "population multiplier method (PoM)" como es definido a continuación:

$$PoM\ (Y) = \frac{población\ en\ el\ año\ Y}{población\ media\ de\ 2000 - 2030} \quad (1)$$

donde los años (Y) eran 2015 y 2045 en este estudio. Se han incluido tres indicadores críticos para la valoración del impacto humano: "supply" (net primary productivity per capita: gC m^2 yr^{-1} cap), "used" (extraction from forests and plantations: tan ha^{-1} yr^{-1}) and "pollution" (agrochemical use, as a land cover: toxicity pressure indicator), como es expresando en la ecuación:

$$Human\ Impact = supply\ + used\ + pollution \quad (2)$$

Para calcular el impacto humano (human impact) para 2015 y 2045 *(Y),* se ha utilizado la siguiente ecuación:

$$Human\ impact(Y) = \frac{NPP\ mean\ 2000 - 2008}{PoM(Y)} + \ used\ extraction + \ agrochemical\ indicator \ (3)$$

donde NPP 2000-2008 (gC m^2 yr^{-1}) es el valor medio anua en esos ocho años, que proporciona a media de evaluación de los patrones espaciales en productividad así como las variaciones interanuales y las tendencias a largo término en la biosfera (Turner et al 2006), como es representado por los datos de satélite MODIS (MOD17A2) (ver http://lpdaac.usgs.gov) a una resolución pixel de 1 km. Se ha utilizado MODIS Land Cover data (MOD12Q1) basado en la clasificación proporcionada por Friedl et al. (2010) para representar los tipos de cobertura de suelo; estos tipos eran interpretados y validados por Razali et al. (2014). En nuestros cálculos un incremento en el multiplicador de población podría implicar un escalamiento de recursos y demandas en la productividad primaria neta per cápita para agricultura y bosque. Extracción ("used") era calculado basándose en la información de los estudios de Krausmann et al. (2008) y Ngo et al. (2013), según se expresa a continuación:

$$Used\ extraction = \big(Used\ extraction\ x\ population\ (Y)\big) \quad (4)$$

Un estudio de Macary et al. (2014) era utilizado para determinar el indicador de presión de toxicidad del desarrollo (Apéndice 1). Los herbicidas son utilizados principalmente en herbáceas, especialmente *Imperata cylindrica* que está distribuida en las plantaciones de palma aceitera y árbol de caucho, ya que estas herbáceas pueden generar peligro de incendio (Verheye 2010). Una descripción plena de los indicadores de impacto humano se presenta en el Apéndice 2. NPP per cápita era determinado basándose en los histogramas de frecuencia de ArcGIS 10.0 software. Los impactos eran clasificados en tres categorías para incorporarlos en un valor de impacto simple para cada pixel, lo cual a este nivel es más fácil para interpretar por los potenciales usuarios (*ej.*, gestores forestales, políticos e investigadores). Los píxeles eran agregados en rangos para representar el impacto general en los bosques y áreas agrícolas. Finalmente, se valoraba los niveles de cambio del tipo de cobertura de suelo, mostrando dos diferentes niveles de impacto: alto (high) y ningún cambio (no-change).

4. Resultados

El mapa de usos que se muestra en la Figura 2 representa los 9 principales tipos de cobertura de suelo encontrados basándose en los datos de MOD12Q1. En la Figura 3 se muestran imágenes de los usos del suelo, validando la clasificación de la cobertura de suelo frente a los datos del satélite. Un multiplicador de población era medido para determinar la fluctuación de la población para el área de estudio (Fig. 4). Este muestra un tendencia al incremento en Malasia, pero un decrecimiento en Tailandia con una caída próxima al 50% después de 2030. Valores positivos de "used" indican suficiente productividad primaria neta para mantener la población humana, mientras que valores negativos indican deficiente productividad primaria neta para la población, basándose en la relación entre recursos y demanda. Para ambas áreas, los recursos ("used") están declinando, mientras que la demanda esta escalando (Fig. 5). Los resultados para los indicadores simples eran también representados espacialmente (Fig. 6) mostrando variación en cada área de estudio. Los impactos simples mostraban similar presión de agroquímicos para el período 2000 a 2045 debido a que aplicamos las mismas imágenes de cobertura de suelo (del 2000) para ambos años, mientras que la productividad primaria neta si mostraba cambios.

El impacto de los cambios en los dos principales tipos de uso del suelo, forestal y agrícola para el período 2015-2045 ilustra el patrón de distribución para el futuro para la productividad primaria neta, extracción (used) y toxicidad (Fig. 7). Las áreas forestadas di Malasia muestran solo un modesto impacto de cambio comparado a las tierras de cultivo de palma aceitera. Por comparación, los cambios están actualmente afectando los bosques de Tailandia, pero no hay ninguna amenaza inminente para las tierras agrícolas. En resumen, solo un 2% del bosque primario en Malasia experimentarán una alta tasa de cambio, mientras que las tierras agrícolas en este mismo área una alta superficie incurrirá en un cambio intermedio (clases intermedias combinadas: 17% y 76%). En Tailandia solo un 3% de las tierras agrícolas se espera que incurran en una alta tasa de cambio y más importante, la mayoría de las tierras agrícolas (73%) no experimentarán ningún cambio.

Figura 3. Ejemplos de usos del suelo: Bosques, (a) plena cobertura de bosque primario y secundario; Agrícola: (b) plantación de árbol de caucho; (c) plantación del árbol del caucho cerca de caminos; y (d) plantación de palma aceitera.

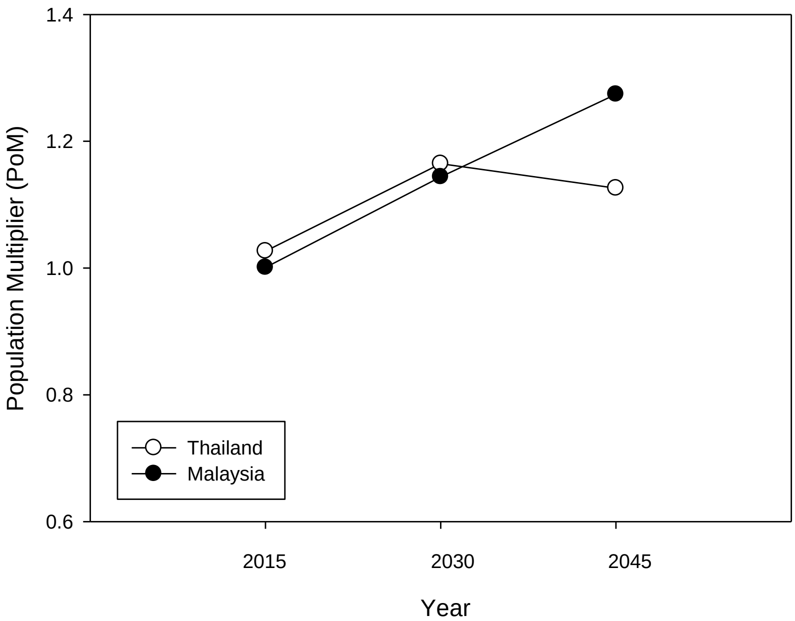

Figura 4. Comparación de multiplicadores de población entre Malasia y Tailandia.

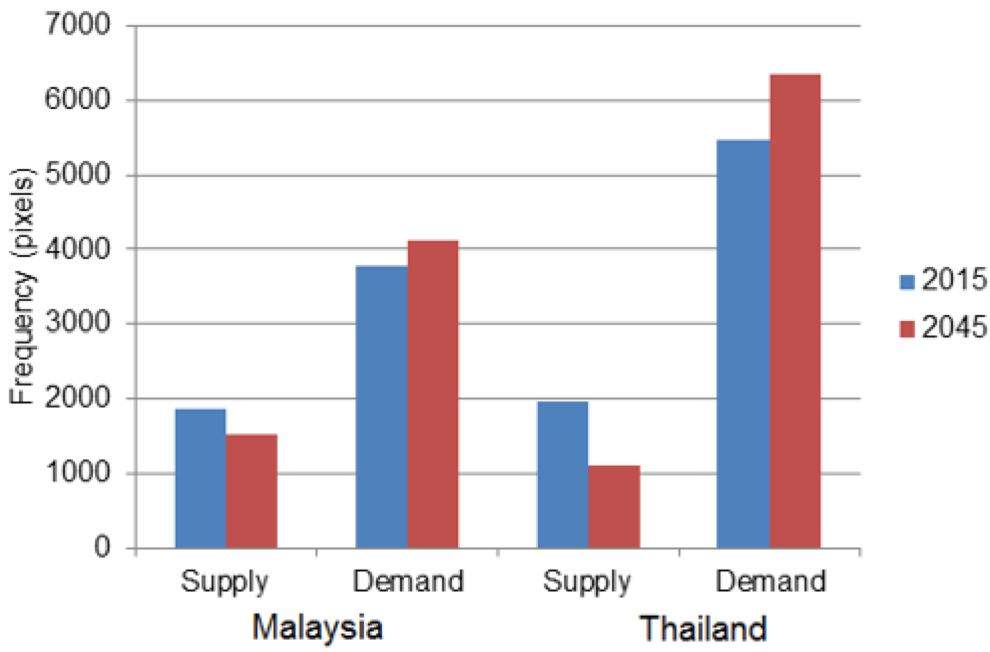

Figura 5. Frecuencia de extracción ("Used) en Malasia y Tailandia mostrando las funciones de suministro y demanda.

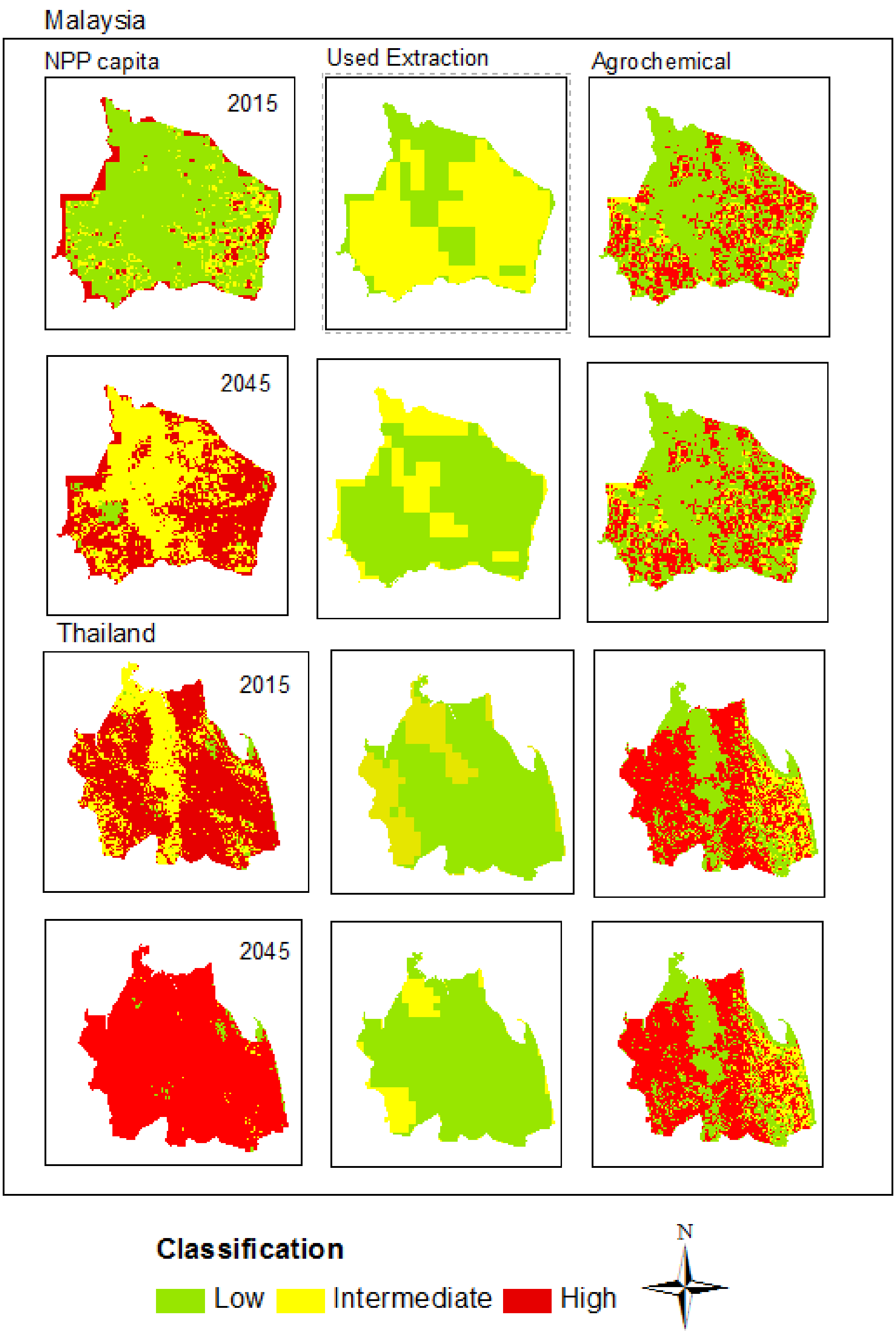

Figura 6. Impacto humano con indicadores simples.

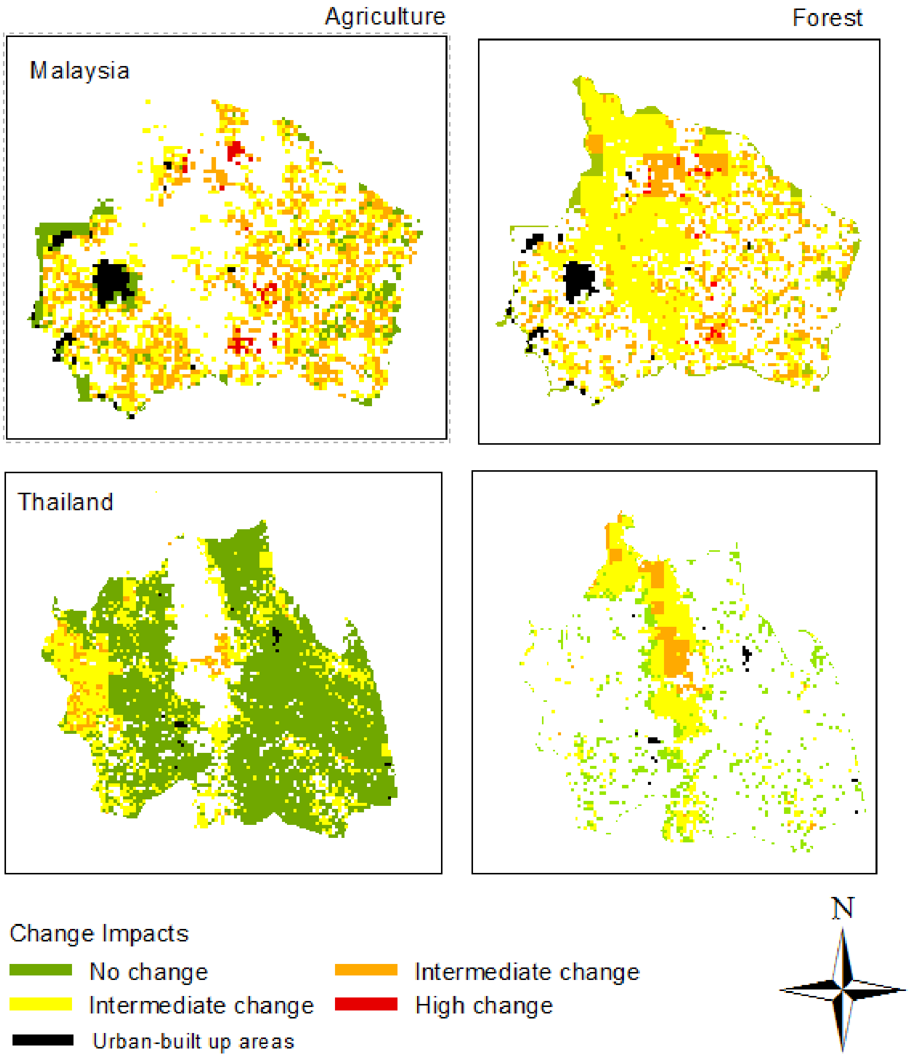

Figura 7. Impactos del cambio humano en el uso del suelo para el período 2015-2045.

5. Discusión

Mientras que el mapa MOD12Q1 con los tipos de usos del suelo en el área estudiada es ciertamente útil para definir como la extracción de recursos está afectando a los cambios de las tierras agrícolas y forestales de Malasia y Tailandia, un indicador complementario muy importante es el crecimiento de la población. La población humana es la fuerza que conduce los cambios y que se encuentra detrás de la extracción y consumo de bienes forestales.

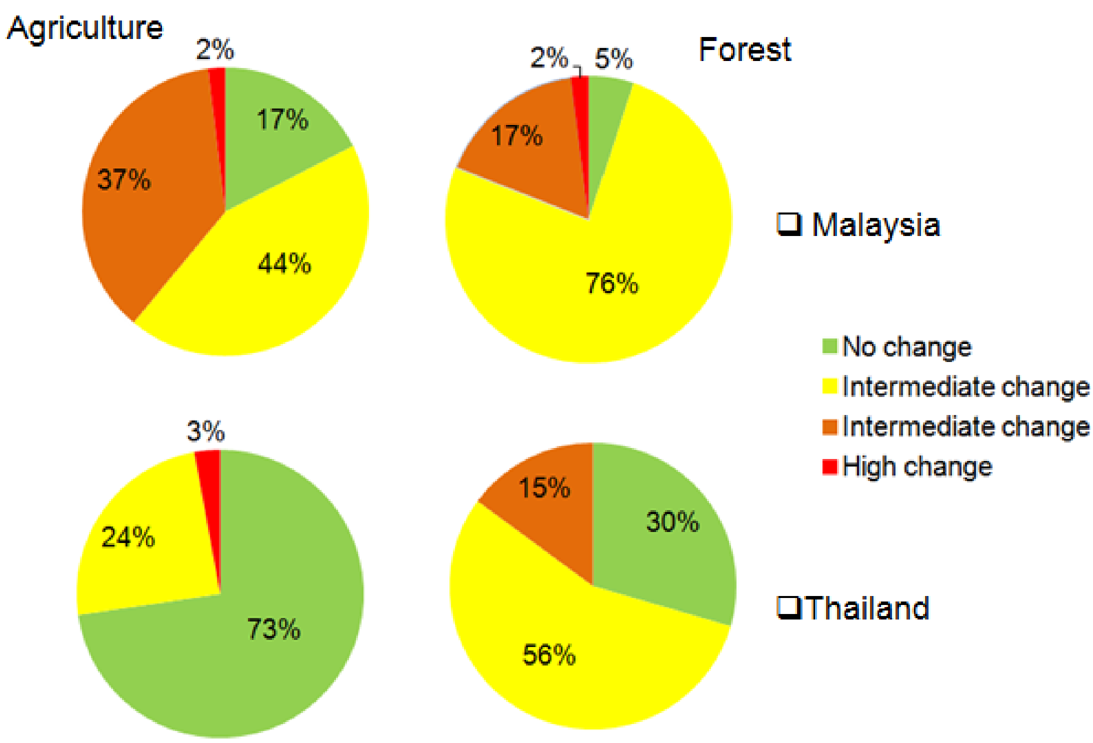

Figura 8. Impactos del cambio asociado al tipo de uso del suelo.

La tendencia positiva del multiplicador de población en Malasia primariamente refleja el rápido incremento de población esperado para 2020, de 150 a 230 persons/km^2 (Fig. 1). Una escalada que ocurrirá antes de la implantación del programa Malasia Vision 2020 (NEAC 2009). Tailandia, mientras tanto está entrando en un nuevo período de crecimiento poblacional lento que se espera persista hasta 2020 (UNFPA 2011).

La principal causa del crecimiento de la población en Malasia es la alta tasa de inmigración. Entre 195 y 2010 esta tasa incrementó de 1 a 5 inmigrantes por cada 1000 residentes. Aunque no tenemos la misma información para Tailandia, en base a datos indirectos podemos decir que este país presentará cero inmigrantes desde la actualidad hasta el 2045 (United Nation 2015). Este crecimiento diferente incrementará el impacto en el bosque primario virgen de Malasia en comparación a Tailandia. Los bosques secundarios serán más importantes para mantener la biodiversidad y para incrementar la productividad primaria neta en un futuro (Gibson et al. 2011; Roy 2001). El patrón de cambio de los impactos humanos es más elevado en las plantaciones de palmera aceitera donde se aplican más agroquímicos por hectárea que en otros tipos de cultivo. Mientras que el papel de las plantaciones de palma aceitera para Malasia es predominante (Fig. 7), en Tailandia ha desarrollado cultivos de caucho principalmente y por lo tanto los niveles de toxicidad son diferentes. También Tailandia está desarrollando plantaciones de palma aceitera y consecuentemente en algunas áreas los residuos tóxicos están incrementando. El cultivo de palma aceitera proporciona más beneficios, lo cual cambia el bienestar de los habitantes incrementando sus entradas y mejorando sus condiciones de vida (Dayang Norwana et al. 2011). Estas mejoras incrementan consecuentemente el consumo de recursos, incrementando la presión en las tierras agrícolas y forestales incluso sin un aumento de la población.

Los gestores forestales debería proteger más intensamente esas áreas y priorizarlas para la conservación de la biodiversidad. En un estudio global de los bosques tropicales realizado por Phalan et al. (2013) describía las medidas que deberían aplicarse para limitar la sobreexplotación e intensificar la protección de los bosques tropicales primarios de la deforestación.

La transición a diferentes tipos de cultivos tiene impactos sociales y ambientales. En un estudio realizado en Sabah (Malasia) Awang Ali et al. (2011) examinó los cambios en el bosque tropical causados por diferentes prácticas empleadas en las granjas. Por ejemplo, estos autores encontraron que el cambio de cultivo de árbol de caucho a palmera aceitera, como el gobierno de Tailandia está promoviendo (The Thai Rubber Association 2015), producirá un alto impacto en las áreas agrícolas próximas a bosques tropicales.

La mejora en la gestión de las plantaciones para la obtención de caucho y aceite de palma deberían estar basadas en el código de conducta de pesticidas (Foo and Hameed 2010) y la utilización de los estándares de sostenibilidad global para la producción de aceite de palma conocido como Roundtable on Sustainable Palm Oil (RSPO) (Saswattecha et al. 2015). Esta mejora podría reducir la cantidad necesaria de pesticidas aplicados. También, sistemas que permitan monitorizar la producción y las entradas a nivel de granja podría resultar un mejor control de la aplicación de pesticidas.

Sobre todo este estudio ha encontrado que futuro crecimiento poblacional en áreas de alto cambio de impacto probablemente empobrecerá y disminuirá los recursos forestales. Las áreas fuertemente impactadas requerirán elevado suministro de productividad primaria neta y bajas cantidades de extracción humana para adquirir un equilibrio en los patrones de consumo y minimizar el impacto humano. Políticas gubernamentales han guiado hacia la sustitución de la producción de caucho por aceite de palma en Malasia podría incrementar la cobertura vegetal, lo cual podría mejorar la biodiversidad y regenerar las áreas degradadas, y además incrementar la producción primaria neta y mantener las cosechas de las plantaciones (Gibson et al. 2011; Meijaard and Sheil 2013). Propuestas para la creación de almazaras para las plantaciones de palmas aceiteras podría ayudar a promover aceite de palma barato, atrayendo a compañías como Ferrero, Mars y Mondelez (Fitzherbert et al. 2008; Nieburg 2013).

De ahí, que los gestores forestales jueguen un papel vital en la protección de los bosques vírgenes y en la restauración de bosques parcialmente talados (bosques primarios) más que en la regeneración de áreas degradadas (ej. incendios forestales, etc.), tal y como ha sugerido Gibson et al. (2011). Los patrones cambiantes del impacto humano tendrán importantes consecuencias para la biodiversidad tropical. Los mapas finales (Fig. 7) ilustran los impactos de la creciente población en la producción primaria neta y bienes de los bosques tropicales. Los resustados de este estudio pueden ayudar a predecir el futuro impacto humano en la biosfera tropical y monitorizar los cambios en esta región a lo largo del tiempo para ayudar a la implantación de posibles medidas gubernamentales que favorezcan la mitigación de los problemas ambientales.

6. Conclusiones

Este estudio muestra que en las futuras plantaciones para obtener aceite de palma habrá mayor impacto en las regiones tropicales. La predicción del crecimiento de la población para los próximos 30 años indica un incremento de la demanda de extracción humana y consecuentemente en el consumo de la productividad primaria neta per cápita. La gestión de medidas forestales juegan un papel fundamental en la salvaguarda de los bosques tropicales.

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Conclusiones Generales

Capítulo 1

1. La cartografía final de usos del suelo obtenido con nuestra metodología muestra una precisión que oscilan entre el 65% y el 90%, demostrando que la cartografía se puede utilizar posteriormente para la comparación con otras informaciones espaciales como National Forest Inventory (Inventario del Bosque Nacional), el mapa topográfico de 1997, la cobertura de tierra de ALOS y los mapas de elevación.

2. La resolución media de imágenes MODIS mostró la capacidad significativa para la clasificación de la cobertura de la tierra en bosques tropicales. Las áreas de cultivo de aceite de palma eran delineadas de forma precisa en los mapas. Esta información pueden permitir la identificación de la naturaleza del pasto en las zonas de forraje y producción ganadera.

3. Las imágenes ALOS de alta resolución es el complemento más importante a las imágenes de media resolución MODIS para el mapeado de la cobertura del suelo. Con estos datos suplementarios, el uso del mapa de la tierra podría desarrollarse en la gestión de los bosques con un mínimo coste de la mano de obra y equipamiento, permitiendo la producción más frecuente y cumpliendo con los objetivos de los gestores forestales para establecer una gestión sostenible.

Capítulo 2

4. Integrando los índices climáticos y de satélite, creamos una herramientas efectiva de valoración de la sequía, para asistir al Departamento Meteorológico de Malasia durante la estacion de sequía con la determinacion de los meses con probabilidad de extrema sequía.

5. Los resultados de este estudio mostró que el criterio usado en el modelo M-SWM, SPI, precipitación media-temperatura y los índices espectrales de análisis de correlación incrementaban la sensibilidad del modelo M-SWM para su empleo en ambientes tropicales. Julio era identificado como el mes más seco utilizando el modelo M-SWM.

6. Este modelo puede ser usado para sostener las políticas gubernamentales para responder al cambio climático, particularmente para las estaciones de sequía más extremas.

Capítulo 3

7. El mapa de HANPP puede ser útil para la gestión de los bosques como ha sido representado en diferentes niveles de intervenciones en el área forestal: baja, moderada, muy alta y extrema.

8. Los resultados subrayan la utilidad de la proximidad del análisis en SIG empleando variables presentes en el estudio. La utilización de mapas que muestren los niveles de intervención HANPP puede ser el medio más sostenible para evaluar las intervenciones humanas asociadas con los paisajes de bosque tropicales.

9. Este trabajo ha demostrado que se puede desarrollar un modelo HANPP detallado utilizando datos espectrales MODIS y técnicas SIG.

Capítulo 4

9. En el futuro, la plantación del aceite de palma tendrá el mayor impacto en las regiones de los bosques tropicales.

10. La predicción del crecimiento de la población en los próximos 30 años indica un aumento de la demanda de extracción del usuario y consecuentemente en el consumo de producción primaria neta per cápita.

11. Las medidas de gestión forestal desempeñan un papel importante en salvaguardar los bosques tropicales.

General Conclusions

Chapter 1

(1) The final land use maps show an overall accuracy ranging from 65% to 94%, demonstrating that the maps can be further utilized for comparisons with other spatial data from the National Forest Inventory, Topographic map of 1997, ALOS land cover and elevation maps.

(2) Medium resolution MODIS images showed significant capability for classifying land cover for tropical forest environments. Oil palm areas were accurately delineated in the maps. These data can provide material for identifying natural pasture in the area for forage and livestock production.

(3) Higher resolution ALOS imagery is the most important supplement to the medium resolution MODIS image, for mapping land cover. With this supplementary data, land use maps can be developed within forest management areas with minimum labour and equipment costs, enabling them to be produced more frequently and accomplishing the objectives of forest managers for establishing sustainable forest management.

Chapter 2

(4) Integrating the climatological and satellite remote sensing indices, we created an effective drought assessment tool for this study area, to assist the Malaysian Meteorological Department during drought season by determining the months with the probability of extreme dryness.

(5) The outcome from the study showed that the criteria used in M-SWM model—SWM, SPI, mean precipitation and temperature and spectral indices correlation analysis increased the M-SWM model sensitivity for use in tropical forest environments. Using the M-SWM model, July was identified as the driest month.

(6) This model can be used to support governmental policies for responding to climate change, particularly to more extreme drought seasons. Thus, full resources should be allocated during July.

Chapter 3

(7) The HANPP map can be useful for forest management as it represents different levels of human intervention on forest area: low, moderate, very highand extreme.

(8) The results highlight the usefulness of proximity analysis in GIS by employing the variables presented in the study. Maps showing the HANPP intervention levels may be the most sustainable medium for assessing human intervention associated with tropical forest landscapes.

(9) A detailed HANPP model can be developed by employing MODIS high spectral data and GIS techniques.

Chapter 4

(10) In the future, oil palm plantations will have the greatest impact on tropical forest regions.

(11) The population growth prediction for the next 30 years indicates an increase in the user extraction demand and subsequently in the consumption of net primary productivity per capita.

(12) Forest-management measures play an important role in safeguarding tropical forests.