Mapping and Monitoring Forest Cover Changes in Lao PDR Using Remote Sensing

A thesis submitted to the University of Adelaide in fulfilment of the requirements for the degree of Doctor of Philosophy

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Dedication

This thesis is dedicated to my beloved father, Dr. Bounlope Phompila

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Abstract

There has been a rapid change in forest and land cover globally, especially in tropical forests due to heavy deforestation. The highest rate of deforestation is found predominantly in the developing world. Tropical deforestation is a process of transforming forests into cleared land for other uses. Tropical deforestation is the second largest source of greenhouse gas emissions, responsible for about 17 - 30% of global emissions of CO_2 to the atmosphere, causing global warming. Precise and up to date information on the distribution and rate of forest cover change, especially in tropical regions, is required urgently for government policies aiming to control and manage forests and land development. Information on deforestation in tropical regions has been unavailable or inconsistent, including in the Lao PDR, due to socio-economic deficits, political interests and geographical constraints.

Remote sensing technology has played a crucial role in providing the information required for reliable mapping and monitoring of forest cover changes at local, regional and global levels, but its application in tropical regions has been lagging. The overall goal of this research was to demonstrate and evaluate remote sensing methods for assessing and monitoring forest cover changes in tropical environments, particularly in the context of the Lao People's Democratic Republic (PDR). The first aim of the research was to understand phenology of tropical forests and related vegetation types, which has been little studied. Improved understanding of the phenology of tropical forests and other land covers involved in forest clearance and land use change is an important step towards the use of remote sensing to identify and track changes in forest cover. Long-term averages of land surface temperature (LST) and enhanced vegetation index (EVI) 16-day time series of MODIS over the seven-year period from 2006 to 2012 were calculated and their monthly transitions compared for forests, and for land covers that commonly replace forests. The findings showed the complex interrelationship of LST and EVI and their monthly transitions for the different land covers: they each showed distinctly different intra-annual LST and EVI variations. Secondly, the research evaluated whether the combined use of these indices (LST and EVI) can classify these land covers. It was found that there was high overall accuracy of separation of land covers by long-term means of these indices (86%). This knowledge can be potentially useful for further broadscale mapping of land cover and detection of

deforestation in tropical forests. For the third objective, the use of remote sensing time series data for detecting spatial and temporal changes in forest cover in tropical environments was tested. The disturbance index (DI) model was applied to detect spatial changes in different forest cover types, whilst the Breaks For Additive Season and Trend (BFAST) approach was used to examine temporal changes in these land covers. Results showed that the DI was capable of detecting vegetation changes during a seven-year period with high overall accuracy (82%); however, it showed low accuracy in detecting forest clearance (42%). The BFAST analysis detected abrupt temporal changes in vegetation in the tropical forests, especially in large conversions of mixed wooded/cleared area into plantation (from 2004 to 2007). From these two approaches, it was found that MODIS time series data may be suitable for continental and national monitoring of land cover, although it may not provide the level of geographic detail and accuracy required for local assessments.

As a result of these findings, further analysis of forest cover changes at a finer resolution was required to improve monitoring approaches. Therefore, the fourth aim was to detect and map vegetation cover changes at a higher spatial resolution over a period of ten years between 2003 and 2012. Landsat ETM+ imagery from 2003 and 2012 was used in principal component analysis (PCA). This technique detected areas of vegetation cover change (both vegetation increase and loss) with high overall accuracy (87%). The results of these four studies provided new information on where and when recent forest cover changes have occurred in southern Lao PDR. The final step was to analyse the reasons underlying these changes. Thus, the final research task was to investigate potential factors associated with forest cover change in the study area, by using logistic regression analysis. The results of the analysis suggested that particular socio-economic and physical factors have a significant association with forest cover change. Forest clearance was associated strongly with elevation, distance to main roads and shifting cultivation practices. Meanwhile, vegetation increase was more likely to correlate with rubber plantations. Native forest and shifting cultivation lands were vulnerable to being converted into rubber plantations. This final research component contributes to a better understanding of ongoing land cover change processes to inform land use management. This is key information for policy and decision makers, and may be used to minimize deforestation and deal with potential risks associated with land cover changes.

Publications, conference papers and awards associated with this thesis

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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Chapter 1. Introduction

1.1 Introduction

It is widely acknowledged that forests play a key role in ecosystems, regulating the Earth's climate and contributing to mitigating climate change. Forests cover approximately 30% of the global land surface (FAO 2010), providing various environmental benefits. For example, tropical forests store large amounts of carbon in terrestrial ecosystems (Main-Knorn et al. 2013; Thapa et al. 2013) and play a significant role in the regional and global cycles of carbon and hydrology (Avitabile et al. 2012; Hilker et al. 2012; Liu et al. 2013; Schepaschenko et al. 2015; Thapa et al. 2013). Forests are recognized as a key factor in global climate change (Richardson et al. 2013; Xuanlong et al. 2013). However, tropical deforestation reduces carbon sinks which are major drivers of climate change. Recently, tackling carbon emissions from tropical deforestation and forest degradation in developing countries has been included in international climate change negotiations (Arcidiacono-Bársony et al. 2011; Goetz et al. 2009).

Despite the importance of forests, there has been a rapid change in forest and land cover globally through heavy deforestation (Bodart et al. 2011; Portillo-Quintero et al. 2012). Forests cover approximately 4 billion hectares of the Earth's land surface. However, the forest assessment in 2010, reported by the Food and Agriculture Organization (FAO), indicated that over 13 million hectares of forest area in developing nations are cleared each year (FAO 2010). The highest rate of deforestation is found predominantly in the developing world (Arcidiacono-Bársony et al. 2011). During 1990 and 2010, the deforestation in Latin America contributed about 60% of the total world tropical forest clearance, while Asia and Africa are responsible for 30% and 5% respectively (FAO 2010). In Asia, Indonesia appears to have the highest rate of deforestation (Arcidiacono-Bársony et al. 2011). Alongside this, Indonesia and Africa are the two largest sources of greenhouse gases, resulting from deforestation (Avitabile et al. 2012; Broich et al. 2011). Tropical deforestation is the second largest source of greenhouse gas emissions, responsible for about 17% to 30% of global emissions (Arcidiacono-Bársony et al. 2011; Goetz et al. 2009). This deforestation and forest degradation releases CO_2 to the atmosphere, causing global warming.

Our current forests are under intense pressure from both natural and anthropogenic disturbances (Schepaschenko et al. 2015). Natural disturbances include flooding, drought, fire, insects, and diseases (Coops et al. 2009; Verbesselt et al. 2010). Human disturbances involve clear-cutting for agriculture and settlement, thinning, and burning (Getahun et al. 2013; Vu et al. 2014a; Vu et al. 2014b; Webb et al. 2014). Anthropogenic activities are recognized as the most influential in tropical forest changes.

Tropical deforestation is a process of transforming forests into deforested land for other uses (FAO 2010; Van Kooten 2000). This transformation is normally undertaken without reforestation following afterwards. In developing countries, rapid population growth has led to an increase in the high demand for land use and forest resources which have put these resources under serious pressure (Ji et al. 2014; Nath and Mwchahary 2012; Ryan et al. 2014; Sassen et al. 2013; Tadesse et al. 2014; Vu et al. 2014a). Agricultural expansion, infrastructure development and timber extraction are blamed as direct causes for this change in land use and ecological composition in many countries. Where there is poverty, the population frequently relies heavily on forest resources, including food production, timber and non-timber forest products (Vu et al. 2014a).

Several key impacts have been associated with changes in forest cover. A number of studies show strong links between deforestation and climate change (McDowell et al. 2015; Ostendorf et al. 2001; Richardson et al. 2013; Rosenqvist et al. 2003; Zuidema et al. 2013). Deforestation is recognized as one of the main contributing factors to local, regional and global climate change, due to changes to the carbon cycle. Forest disturbances can also lead to the loss of biodiversity. Significant numbers of plant species and wildlife are losing their habitats to deforestation and then face extinction in many parts of the world (Benhin and Barbier 2004; Develey and Stouffer 2001; Jha and Bawa 2006). Changes in forest cover have a negative impact on soil quality and erosion, and have been widely studied (An et al. 2008; Khormali et al. 2009; Wang et al. 2016; Yoo et al. 2014; Zheng et al. 2005). Tree roots penetrate deeply into the soil surface. Without these roots, the soil and its chemical components are easily washed away after heavy tropical rain falls. This can lead to increased soil erosion and reductions in soil quality. In addition, forests play an important role in controlling landscape hydrological functionality (Setiawan et al. 2014).

Due to these concerns, adequate information on change in forest cover is essential for effective governmental policy, regulation and management. However, acquiring accurate information on time and locations of forest cover change on a broad scale, especially in tropical regions, has proven to be challenging. This is due to regressive social-economic conditions and political interest as well as the geographical constraints of the region. The areas are sparsely populated and poorly served by roads and transport, and they are vast and often inaccessible. Statistics on forest attributes in most of the developing countries were previously derived from field-based measurements and surveys. This intensive field-based forest monitoring was often expensive and it was difficult to acquire accurate, timely and consistent data over large areas. As a result, the data, where it exists, has often been inconsistent and unreliable. Now, however, technologies such as remote sensing may be the most effective tools for monitoring difficult to access tropical forests over large areas.

Remote sensing technology has played a crucial role in providing the information required for reliable mapping and for monitoring forest cover changes at local, regional and global levels (Setiawan et al. 2014). Over several decades, numerous satellite remote sensing instruments have been developed to acquire information from space, and sensors and their capabilities have improved over time (Lhermitte et al. 2011; Rosenqvist et al. 2003). Recent advances in remote sensing have provided relatively high spatio-temporal resolutions and now this technology offers greater opportunities for monitoring tropical forest change processes.

Remote sensing has been used to monitor and observe a wide range of environments. For example, remote sensing approaches have been used to detect burned forests (Matricardi et al. 2010; Monzón-Alvarado et al. 2012), estimate above-ground biomass (Avitabile et al. 2012), detect forest disturbances (Cohen et al. 2010; Griffiths et al. 2013; Kennedy et al. 2010; Zhu et al. 2012), monitor forest cover changes at large scales (Coops et al. 2009; Klein et al. 2012; Mildrexler et al. 2009), and study fire risks in Australia (Okin et al. 2013; Turner et al. 2011). Remote sensing has become a primary source of information and it could complement, combine with or replace traditional environment and natural resource monitoring approaches, especially for broad scale surveys (Goetz et al. 2009). The technology already provides unique data that can be used to analyze and distinguish forest and land use types on the ground at high resolutions (Hansen et al. 2013; Iqbal and Khan 2014; Miettinen et al. 2014; Phompila et al. 2014; Roy et al. 2014; Vieira et al. 2012; Zhai et al. 2012; Zhu and Woodcock 2014).

However, although there is significant benefit from applying remote sensing techniques, some limitations and challenges in tropical environments have been reported and have hindered their application in these regions. In particular the ability of satellite optical sensors to provide high quality observations of the land surface is often reduced by atmospheric and ground conditions, including cloud cover, atmospheric haze and rough terrain (Reimer et al. 2015). Active microwave remote sensing, such as radar, can overcome the persistent problem of cloud cover in these environments through its capability to penetrate the atmosphere under virtually all conditions. Various frequencies, polarizations and combinations of radar imagery from several sensors have shown promise for tropical forest clearance studies (e.g. Mahmudur and Sumantyo et al. 2010; Antropov et al. 2015). However global coverage of suitable radar imagery at appropriate time frames is not complete, and radar image processing and classification of land cover can be challenging (Antropov et al. 2015). Satellite optical imagery is often used to assess the accuracy of radar cover mapping projects.

Despite the cloud cover problems, there was considerable diversity of optical satellite imagery of appropriate spatial, spectral and temporal resolutions for use in this research. The products derived from MODIS and Landsat ETM were considered as the most suitable. MODIS aggregated images over observation periods (e.g. 1 to 2-days, 8-days, 16-days or monthly composites) potentially overcome some of the atmospheric and cloud problems over broad areas. Data from Landsat provides the most appropriate spatial resolution for finer mapping and monitoring of forest cover changes, with resolution of 30 m and 16-day repetition (Bodart et al. 2011; Avitabile et al. 2012; Czerwinski et al. 2014), while the availability of archived time series provided considerable opportunity for repeated analysis of vegetation cover changes.

Detailed information on deforestation has been inconsistent or unavailable in many parts of the world, despite the recognized importance of forest ecosystem services. Although the scope and scale of mapping and monitoring forest cover changes in the tropical regions has increased considerably due to its contribution to greenhouse gas emissions, land degradation and loss of biodiversity, this need still remains poorly addressed, particularly in developing countries. "*Nobody knows exactly how much of the world's rainforests have already been destroyed and continue to be razed each year. Data is often imprecise and subject to differing interpretations. However, it is obvious that the area of tropical rainforest is diminishing and the rate of tropical rain forest destruction is escalating worldwide,…*" (Sumit Chakravarty et al. 2012).

In Lao PDR, as in many developing countries, information on forest cover change is not well-documented. The country has a weak financial foundation from which to strengthen its human resources capacity and to establish national databases. Meanwhile, monitoring and estimating forest cover change is required as an initial task for carbon accounting in climate change mitigation activities, such as reducing emissions from deforestation and forest degradation schemes (REDD or REDD-plus). Spatially and temporally detailed information on national-scale forest change does not exist in Laos to date. The country experienced extensive deforestation during the early 1980s, and has undergone profound landscape transformation since the 2000s, due to agricultural expansion and land leases and concessions through foreign direct investments. However, this remains poorly assessed. The limitations of remotely sensed and GIS data availability and quality are also challenging. Thus, the development of appropriate remote sensing tools for this effort is needed urgently.

1.2 Problem statements

The specific gaps in relevant remote sensing research which were addressed through this research are as follows:

- Detecting and monitoring forest change through remote sensing requires an understanding of how vegetation growth and cover vary through seasons and years. Remote sensing indices related to vegetation growth have been used effectively to document broad-scale seasonal and phenological phenomena in many ecosystems (Richardson et al. 2013; Samanta et al. 2012; Sexton et al. 2013; Verbesselt et al. 2010; Xuanlong et al. 2013; Zhang et al. 2005), but study of vegetation phenology in tropical regions is challenging and not well documented (Moreau and Defourny 2012). Most previous studies have relied on measurements in permanent sampling plots, which required time and are labor intensive. There has been little work on the phenology of different land cover types in tropical environments. Improved understanding of the phenology of tropical forests and other land covers involved in forest clearance and land use change is an important step towards use of remote sensing to identify and track changes in forest cover. Thus, this is one of my research foci.

- Several studies have successfully applied MODIS enhanced vegetation index (EVI), often in combination with land surface temperature (LST) time series, to detect vegetation dynamics in broad landscapes including boreal, semiarid, arid and temperate forests (Chernetskiy et al. 2011; Coops et al. 2009; Herdianto et al. 2013; Hmimina et al. 2013; Prabakaran et al. 2013; Stroppiana 2014; Yue et al. 2007). However, the application of time series of these indices in a wider range of land cover types in tropical regions has not been conducted. Thus, my second objective was to evaluate whether the use of MODIS LST and EVI can improve classification of different land covers associated with tropical forests and deforestation activities. This knowledge can be potentially useful for further detection of deforestation in tropical forests.
- Use of time series data for monitoring and detecting spatial and temporal changes in forest cover in tropical environments has been little tested. Therefore, the disturbance index (DI) model and the Breaks For Additive Season and Trend (BFAST) approaches were selected and applied to detect spatial and temporal changes in different forest cover types in a tropical region. The disturbance index (DI) developed by Mildrexler et al. (2007); Mildrexler et al. (2009) to monitor global vegetation changes was successfully tested in the United States and Canadian forests (Coops et al. 2009). Meanwhile, the BFAST approach is a powerful technique to detect gradual and abrupt changes in satellite data time series (Verbesselt et al. 2010; Verbesselt et al. 2012). It has been successfully tested in south eastern Australia and South Somalia. However, there are known problems in tropical environments such as cloud cover, atmospheric water column content, and aerosol haze (Grogan and Fensholt 2013; Samanta et al. 2012). There is little known about the

performance of DI (Coops et al. 2007; Mildrexler et al. 2009, 2011) and BFAST and whether these two models could be useful in detecting changes in land cover in this little-studied tropical region. Therefore, this is the third focus of this study.

- While MODIS time series data may be suitable for continental and national monitoring of land cover, it may not provide the level of geographic detail and accuracy required for local assessments. Analysis of changes in forest cover is often required at a finer resolution to improve monitoring. This is another focus of this research.
- The literature suggests that both socio-economic and biophysical factors have important influences on forest depletion. Because of concerns about the alarming increase in rate of deforestation and the rapid progression of national socio-economic development in the Lao PDR, my final research question is to assess whether there is any connection between these phenomena. This knowledge may assist local forestry managers and ecologists for forestry policy and decision making as well as for guiding appropriate forest and land use management.

1.3 Research objectives

Due to concerns about several environmental issues related to deforestation, such as climate change and loss of biodiversity, studies on changes in tropical forests are urgently required, as identified in Section 1.1. The overall goal of this study is to demonstrate and evaluate remote sensing methods for assessing and monitoring forest cover changes in tropical environments, particularly in the context of Lao People’s Democratic Republic (PDR). The specific objectives are:

1. To assess the detectability of intra- and inter-annual changes in tropical forests using remote sensing and to observe relationships between vegetation phenology and climatic variables within a specific study area in the southern part of Lao PDR.

2. To test the use of selected remote sensing indices for classifying land cover in tropical environments. This knowledge will be useful for developing remote sensing approaches for detecting deforestation in tropical regions.

3. To demonstrate and evaluate remote sensing models for detecting change over time in different types of land cover. To achieve this objective, two models for detecting changes in remote sensing time series are tested and evaluated: BFAST and the Disturbance Index. The effectiveness of these approaches in detecting changes in land covers in tropical regions has been little investigated to date.

4. To detect and map vegetation cover changes at a higher spatial resolution over a period of ten years between 2003 and 2012. In order to monitor changes in vegetation cover at local scales, it is necessary to obtain greater detail of the types, variations and extent of the vegetation cover. While coarse resolution data may be suitable for continental and national monitoring of land cover, it may not provide the level of detail and accuracy required for local assessments. Consequently, further analysis of forest cover changes at a finer resolution was undertaken with the objective of improved monitoring.

5. To examine the spatial relationships between vegetation cover changes and associated physical and socio-economic factors. This knowledge can offer insights and tools to improve effective maintenance of forest resources. Such knowledge is essential for forestry policy and decision makers to minimize and prevent deforestation.

1.4 Thesis scope, outline and structure

Geographic and environmental scope

The studies comprising this thesis were based in Champasack Province in southwestern Lao PDR, a region which has undergone rapid changes in land cover in recent years, including clearance of native forest and large expansions of rubber plantations. Consequently it provided an ideal study area to test the suitability of several remote sensing approaches for land cover discrimination and change monitoring. Specific study areas for the component studies differed somewhat, influenced by the availability of suitable dates of historic or time-series of imagery. In addition, independent information was needed to validate the various coarse and medium resolution analyses. In the absence of comprehensive field data, Google Earth^{TM} high resolution images were the only available source of land cover information for this validation, so specific study areas were determined by their availability for key dates. Extent, geography and land use of the study areas for the component studies are described more fully in each chapter.

This investigation was conducted to map and detect the cover changes in Lao tropical forests from 2006 to 2012. "Forest cover" throughout the thesis refers to natural tropical forest of mixed species composition with high canopy densities. Several of the study components involved detecting and differentiating this dense canopy forest from more open woodlands and thinned or partially cleared forests, as well as clearance associated with agriculture and plantations of commercial tree crops.

The thesis is divided into seven chapters; each chapter is written as a published manuscript or intended for publication in international peer-reviewed journals, as follows:

Chapter 1: Introduction (this chapter).

The thesis starts with an introductory chapter which provides an overview of the tropical forest cover changes and the motivation behind this research, research objectives along with an outline of the thesis structure.

Chapter 2: Phompila, C., Lewis, M., Ostendorf, B. and Clarke, K. (2015). "MODIS EVI and LST temporal response for discrimination of tropical land covers". ***Remote Sensing*****, 7(5):6026-6040.**

Objectives one and two were addressed in this chapter. Understanding of tropical forest phenology is necessary background knowledge for the development of a remote sensing approach for detecting temporal changes in tropical forests. However, there has been no study on temporal characteristics and variation in the Lao tropical forests to date. Therefore, the annual vegetation phenological response of dominant land cover types associated with forest conversion in Lao PDR was investigated using time series of enhanced vegetation index (EVI) and land surface temperature (LST) indices of MODIS. Long-term averages of MODIS EVI and LST 16-day time series and monthly transitions of these two indices over the seven-year period from 2006 to 2012 were calculated and compared. The relationship between forest and land cover phenology and seasonal precipitation and temperature was also examined. My second objective was to test whether these indices can be used to classify four types of land cover associated with deforestation. The outcomes of this study thus contribute to improving our understanding of tropical vegetation characteristics, variability and their responses to climatic conditions.

Chapter 3: Phompila, C., Lewis, M., Clarke, K. and Ostendorf, B. (2015). "Applying the global disturbance index for detecting vegetation changes in Lao tropical forests". ***Advances in Remote Sensing*****, 4(1):73-82.**

Results from chapter two provided confidence that EVI and LST should be able to detect spatial change in land cover, which was addressed in objective three, chapter three. A combination of the LST and EVI indices, as time series, has been proven to be useful for detection and monitoring of changes in land cover at a continental scale. However, time series models have not been adequately applied or assessed across different land cover types in tropical regions. In Chapter 4, my objective was to demonstrate and evaluate a combination of LST and EVI time series in the DI model to detect spatial change in land cover in Lao's tropical forests. MODIS LST and EVI data across Champasack Province (15,415 km^2) from 2006–2012 were used and Google Earth images over a smaller area (2,500 km^2) from two dates in 2006 and 2012 were used as ground truth data for an accuracy assessment of the model.

Chapter 4: Phompila, C., Lewis, M., Clarke, K., and Ostendorf, B. (2014). "Monitoring temporal vegetation changes in Lao tropical forests". ***Malaysian Journal of Remote Sensing and GIS*****, 3(2):100-111.**

This chapter also addresses objectives one and three. It summarizes seasonal growth characteristics of selected tropical land covers as shown by long-term average MODIS EVI and examines their relationships with seasonal precipitation and temperature. The Breaks For Additive Season and Trend (BFAST) method was applied to examine longer term and historical changes in vegetation in Lao's tropical forests. The study area for this paper was a 1,000 km^2 subregion of Champasack Province, with averaged temporal signals analysed for each land cover. The result of this research component was presented as a conference paper at the 7th IGRSM International Conference and Exhibition on Remote Sensing and GIS, in Malaysia. The improved manuscript was published in a special issue of the *Malaysian Journal of Remote Sensing and GIS.*

Chapter 5: Phompila, C., Lewis, M., Clarke, K., and Ostendorf, B. (2014). "Monitoring expansion of plantations in Lao tropical forests using Landsat time series". ***Land Surface Remote Sensing Conference II, in Beijing, China: published in SPIE Library*****, 9260(1):1-11.**

This chapter addresses objective four. In previous chapters, the coarse resolution data from MODIS was unable to provide the necessary details of vegetation cover changes at a local scale. The MODIS results identified temporal changes in forest cover variations in the study area – there was massive clearance for plantations from late 2004 to 2007, and an increase in plantations in 2011 - but they had low classification accuracy in terms of spatial changes. My objective in this chapter was to test the higher resolution of Landsat ETM+ imagery in order to detect spatial changes in forest cover. The choice of image dates for change analysis was influenced by the availability of Landsat with little or no cloud cover, as well as the extent and dates of Google Earth^{TM} validation images. Principal component analysis (PCA) was applied to detect changes in land cover over the period 2003-2012. This can help in understanding of the changes in land cover in greater detail. The paper was presented as a conference paper at the Land Surface Remote Sensing II conference, in Beijing, China. The paper from the proceedings was published in the library of the International Society for Optics and Photonics (the SPIE Library).

Chapter 6: Phompila, C., Lewis, M., Clarke, K., and Ostendorf, B. (2016). "Vegetation cover changes in Lao tropical forests: physical and socio-economic factors are the most important drivers". ***Forest Policy and Economics. (Under review)***

This chapter addresses objective five. Socio-economic and biophysical elements have an important association with forest cover changes. Therefore, I investigated potential factors associated with forest cover changes in the south of Lao PDR. This was essential to gain a better understanding of ongoing land use management and land cover change processes. The results could be key information for policy and decision makers, and used to minimize deforestation and deal with potential risks associated with land cover changes. The analysis identifies the drivers and factors associated with vegetation cover changes and may also be useful for developing predictive deforestation models.

Chapter 7: Conclusion

This chapter summarizes the key findings and significance of the study and suggests important areas for further research. My key research contributions include several major advances towards international efforts to develop remote sensing and earth observation, so that communities can monitor deforestation in tropical regions more comprehensively and reliably. This research also helps to improve critical understandings based around monitoring forest clearances in Lao PDR, along with the demonstration and evaluation of remote sensing approaches and tools for this context.

Appendices:

The appendices contain software procedures implemented by author to derive some of the results in this research. Appendices include data preparation (i.e. performing geographic transformation/re-projection of MODIS data time series and masking time series data) and sample selection by extracting pixel values of MODIS time series data. These preliminary procedures were done to prepare data for analysis in Chapters 2, 3 and 4. Appendix 5 presents R scripts for Linear Discriminant Analysis, which was implemented in Chapter 2. Appendix 6 contains R scripts of BFAST for Chapter 4. The final appendix shows the steps used to extract and geo-reference Google Earth^{TM} images. These images were used as reference data for accuracy assessment.

Chapter 2. MODIS EVI and LST Temporal Response for Discrimination of Tropical Land Covers

Phompila, C., Lewis, M., Ostendorf, B. and Clarke, K. (2015). “MODIS EVI and LST Temporal Response for Discrimination of Tropical Land Covers”. *Remote Sensing*, **7**(5):6026-6040.

Abstract

MODIS enhanced vegetation index (EVI) and land surface temperature (LST) are key indicators for monitoring vegetation cover changes in broad ecosystems. However, there has been little evaluation of these indices for detecting changes in a range of land covers in tropical regions. In this study, we investigated the characteristics and seasonal responses of LST and EVI for four different land covers in Lao tropical forests: native forest, rubber plantation, mixed wooded/cleared areas and agriculture. We calculated long-term averages of MODIS LST and EVI 16-day time series and compared their monthly transitions over the seven-year period from 2006 to 2012. We also tested whether these indices can be used to classify these four land covers. The findings demonstrate the complex interrelationship of LST and EVI and their monthly transitions for different land covers: they each showed distinctly different intra-annual LST and EVI variations. Native forests have the highest EVI, and the lowest LST throughout the year. In contrast, agricultural areas with little or no vegetation cover have the highest LST. The transition of LST/EVI for the land covers other than native forests showed marked seasonality. Linear discriminant analysis (LDA) showed that there was high overall accuracy of separation of land covers by these indices (86%). The encouraging results indicate that the combined use of MODIS LST and EVI holds promise for improving monitoring of changes in a Lao tropical forest.

Keywords: vegetation characteristics; temporal response; monthly transition; hysteresis; linear discrimination analysis (LDA); MODIS LST; EVI.

2.1 Introduction

Vegetation cover changes in tropical regions are among the most significant contributors to global climate change (Hou et al. 2013; Setiawan et al. 2014; Thapa et al. 2013; Zuidema et al. 2013). These changes have resulted in changes in carbon stock, land degradation and rapid loss of biodiversity (Setiawan et al. 2014). Understanding how ecological systems are changing requires effective monitoring of vegetation changes in space and time (Forkel et al. 2013). Our knowledge of these changing events and processes can be improved using information from satellite observations. The majority of remote sensing approaches to monitoring these changes have used vegetation indices, most commonly the normalized difference vegetation index (NDVI) or enhanced vegetation index (EVI) (Hmimina et al. 2013; Prabakaran et al. 2013; Setiawan et al. 2014). However, many studies have suggested that use of additional parameters such as land surface temperature (LST) improves monitoring of land covers (Mildrexler et al. 2009, 2011; Sobrino and Julien 2013).

Used together, these indices may be suitable for monitoring land cover change in tropical regions. In tropical regions, EVI is more suitable than NDVI to study vegetation, as it has been shown to have improved sensitivity to high biomass through a de-coupling of the canopy background signal and a reduction in atmospheric influences (Coops et al. 2009; Huete et al. 2006; Huete et al. 2008; Senf et al. 2013; Xuanlong et al. 2013; Zhang et al. 2005). LST is used to measure the heat energy flux from the Earth’s surface (Coops et al. 2007; Herdianto et al. 2013; Jiménez-Muñoz et al. 2013; Mildrexler et al. 2011). It appears to be strongly correlated to the density of the canopy of various land covers (van Leeuwen et al. 2011). Using a combination of these two parameters can provide insight into surface energy fluxes and vegetation cover changes at regional and global scales (Coops et al. 2007; Coops et al. 2009; Hmimina et al. 2013; Prabakaran et al. 2013).

Several studies have applied these indices successfully to detect vegetation dynamics in broad landscapes including boreal, semiarid, arid and temperate forests (Chernetskiy et al. 2011; Coops et al. 2009; Herdianto et al. 2013; Hmimina et al. 2013; Prabakaran et al. 2013; Stroppiana 2014; Yue et al. 2007). Several studies suggest that the combination of measurements of temperature and vegetation indices provides a better classification and observation of land covers in the African continent (Ehrlich and Lambin 1996; Lambin and Ehrlich 1996), Sub-Saharan Africa (Lambin and Ehrlich 1997) and over the continental United States (Nemani and Running 1997). The most recent studies also used these two parameters to analyze global vegetation cover changes (Julien and Sobrino 2009; Mildrexler et al. 2007). In addition to these studies, LST and NDVI has been used to detect changes in land covers between non-forested and forest areas in Brazilian tropical forests (van Leeuwen et al. 2011). It was found that LST data can provide key information for classifying non-forested and forest areas, and can be further used for detecting long-term changes in land covers. However, although the combined use of LST and vegetation indices has provided better monitoring of land covers at broad scales, application of LST and EVI in a wider range of land cover types in tropical regions has not been adequately assessed. Frequent cloud cover, high levels of atmospheric water, and aerosol haze can be issues when employing these indices in tropical forest environments (Grogan and Fensholt 2013; Samanta et al. 2012; van Leeuwen et al. 2011). Furthermore, the vegetation cover and soil exposure for different land uses can vary substantially from dry to wet seasons. Thus, detecting the characteristics, distribution and variation of vegetation cover in tropical forests remains challenging.

In this study, our main goal was to investigate the characteristics and seasonal responses of EVI and LST for four different land covers in a tropical location: native forest, rubber plantation, mixed wooded/cleared areas and agriculture. This allowed us to gain a better understanding of how these tropical land covers influence the responses of these indices. We analyzed MODIS EVI and LST 16-day time series for a Lao tropical region over the seven-year period from 2006 to 2012. We compared monthly transitions of EVI and LST data for these four land covers within our study area. We also evaluated whether the combined use of these indices can classify these land covers. This knowledge will be potentially useful for further detection of deforestation in tropical forests, information which is essential for forest management and combating deforestation in developing countries in the tropics.

2.2 Methods

2.2.1 Study area

The focus of our investigations was the tropical forest lands of Champasack Province, in the south of Lao PDR. The study site covers an area of 2500 km^2, from 14°44'20"N to 15°25'52"N latitude and from 105°42'7"E to 106°0'30"E longitude (Figure 2.1). Comprehensive mapping of land cover types is not yet available for Laos, although monitoring of forest resources and land clearance is a high national priority, calling for development of suitable remote sensing approaches for land cover inventory and monitoring. Champasack Province has experienced rapid changes in land cover in recent years including clearance of native forest and large expansions of rubber plantations. Consequently it provided an ideal study area to test the suitability of our remote sensing land cover discrimination. In addition, we needed independent information to validate the MODIS coarse-resolution analysis. In the absence of comprehensive field data, Google Earth™ high resolution images were the only available source of land cover information, so our specific study area was determined by the availability of Google Earth images of the same site for two dates, in 2006 and 2012.

This area covers the northern part of the province and includes five administrative districts: Pakse, Xanasomboun, Bachieng, Pathumphon and Phonthong. The study area has relatively flat terrain comprising two different landscapes: about 10% of the area is upland and 90% is flat lowland. The altitude ranges from 10 to 922 m, but the majority of land is between 10 and 250 m above sea level. There are two distinct seasons in this location: rainy (May–October) and dry (November–April). During the rainy season, it is often windy and humidity is high, with average minimum and maximum temperatures of 21 °C and 31 °C respectively. Roughly 300–450 mm of precipitation falls per month in this season. In the dry season, conditions are mostly sunny, average minimum and maximum temperatures are 19 °C and 35 °C respectively and there is little rainfall (less than 100 mm per month). From the high resolution images we identified four main types of land cover: native forest, rubber plantation, mixed wooded/cleared area and agriculture. Agricultural lands mainly comprise areas of irrigated rice cultivation.

2.2.2 Satellite imagery

The research made use of two Moderate Resolution Imaging Spectroradiometer (MODIS) data products: the 16-day composite time series of EVI (MOD13A2) and the 8-day composite of LST (MOD11A2), from 2006–2012, both of which have a spatial resolution of 1 km. The study area was covered by MODIS tile h28v07. Data was downloaded from the National Aeronautics and Space Administration (NASA) website (http://reverb.echo.nasa.gov/reverb). MODIS data was reprojected to WGS84, UTM zone 48 North using the MODIS reprojection tool (version 4.01). Data quality was checked before further analysis and only good quality MODIS EVI and LST data (as rated by the MODIS quality flag) was used to reduce noise in our analysis.

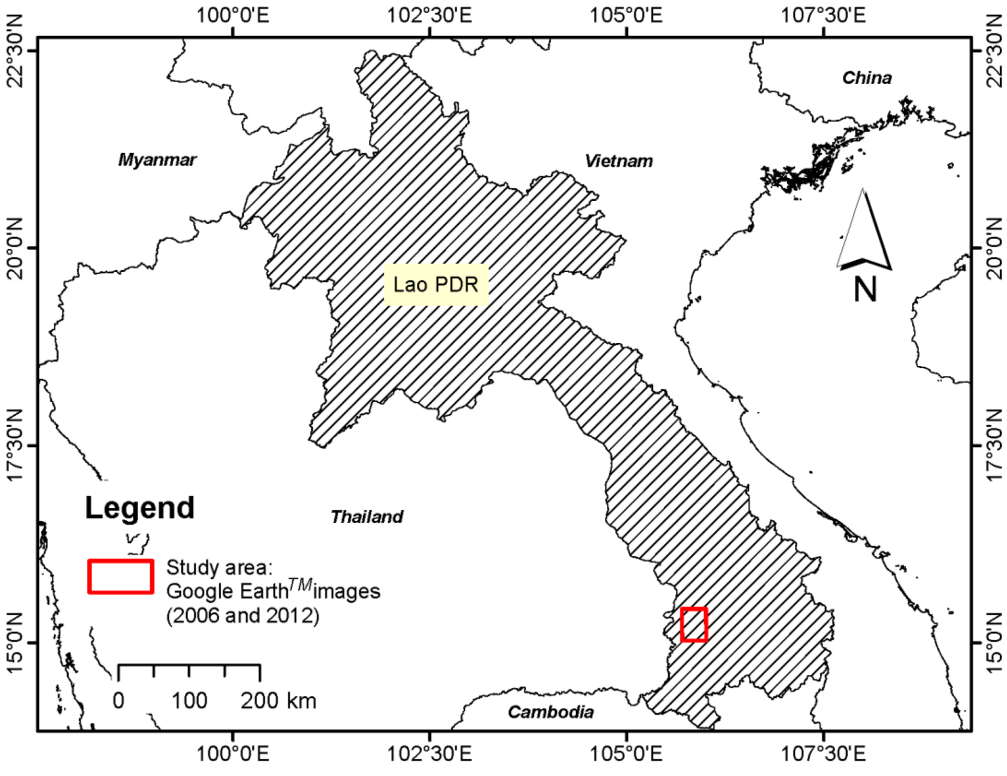


Figure 2.1. Location of the study area in the south of the Lao PDR.

2.2.3 Method overview

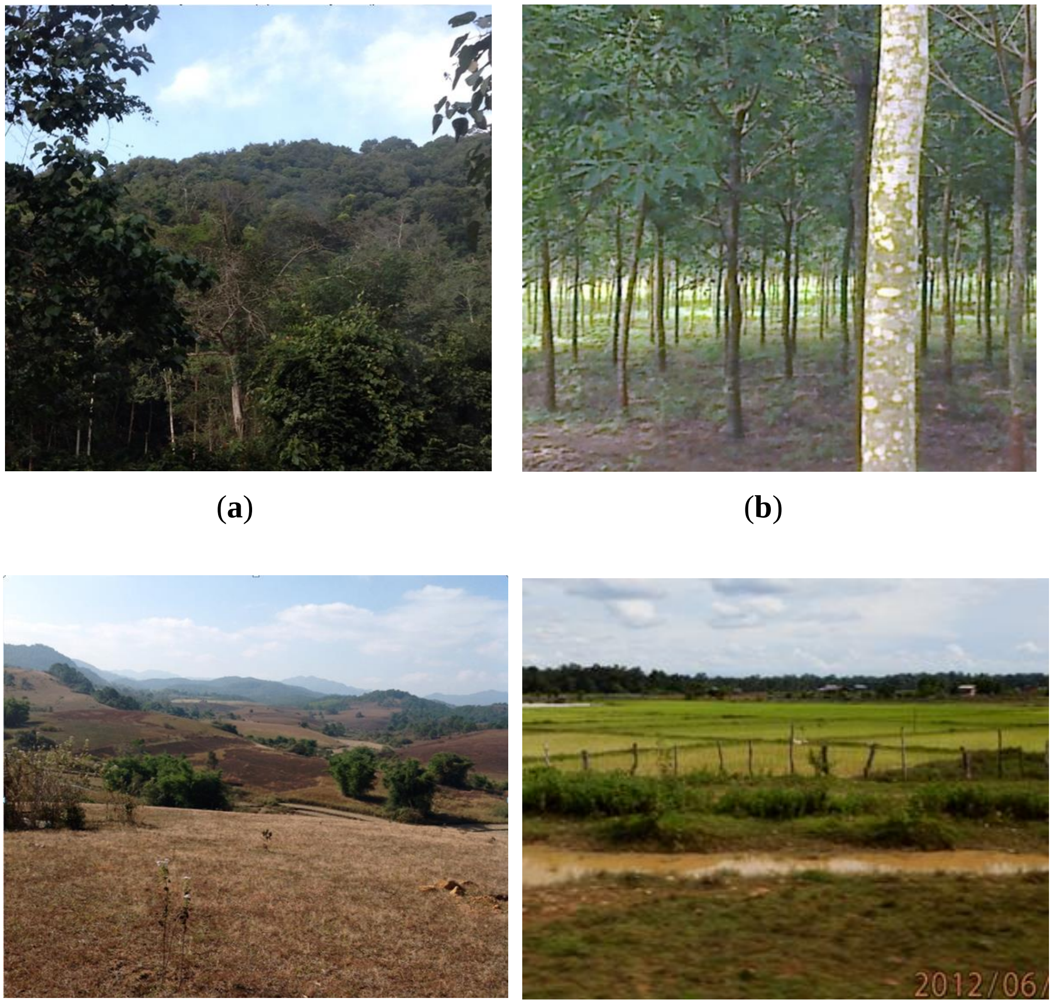
Two major research components were undertaken: (1) examination of long-term averages of seasonal responses of LST and EVI 16-day composite data and the monthly transitions for the four dominant land cover types, and (2) investigation of the effectiveness of using MODIS LST and EVI data to discriminate and classify these land cover types.

2.2.4 Temporal response of LST and EVI for different land cover types

We identified the four dominant land cover types on a high resolution colour Google Earth™ image from 2012: native forest, rubber plantation, mixed wooded/cleared land and agriculture (Table 2-1, Figures 2.2 and 2.3). Their distinguishing features are as follows: (1) native forest is usually a dense and homogeneous canopy of vegetation containing a number of tree species; (2) rubber plantations show consistent canopy patterns and textures comprising similar tree ages, with regular planted tree spacing; (3) mixed wooded/cleared areas are fragmented, usually with low vegetation cover and may include partly cleared areas, with some parts containing a mixture of trees, shrubs, grass and bare soils; and (4) agriculture includes mainly paddy fields and minor areas of shrubs, trees and water.

Table 2-1.Description of the four land cover types in the study area.

Class	Description
Native Forest	Native forest is exclusively native vegetation, with little or no clearance. It usually comprises a mixture of tree species with a dense homogeneous canopy.
Plantation	Plantations predominantly comprise trees established through planting and/or deliberate seeding of introduced species. Rubber plantations are common in this region. They display homogeneous canopy patterns and textures comprising similar tree ages and regularly planted spaces. They have dense canopies, with texture, pattern and homogeneity easily distinguished from natural forests.
Mixed Wooded/ Cleared Area	Comprises small or moderate patches of shrubs and trees and large areas of clearances. It usually has low vegetation cover comprised of small trees, grass and bare soils.
Agriculture	Exclusively agricultural utilizations. This class includes mainly paddy fields and water or irrigation channels. There is a large area of exposed soils and it is readily distinguished from other land covers.



(a) **(b)**

(c) **(d)**

Figure 2.2. Photos of the four land covers taken in the study area by Faculty of Forestry team researchers, May–June 2012. (a) native forest, (b) rubber plantation, (c) mixed wooded/cleared area, and (d) agriculture.

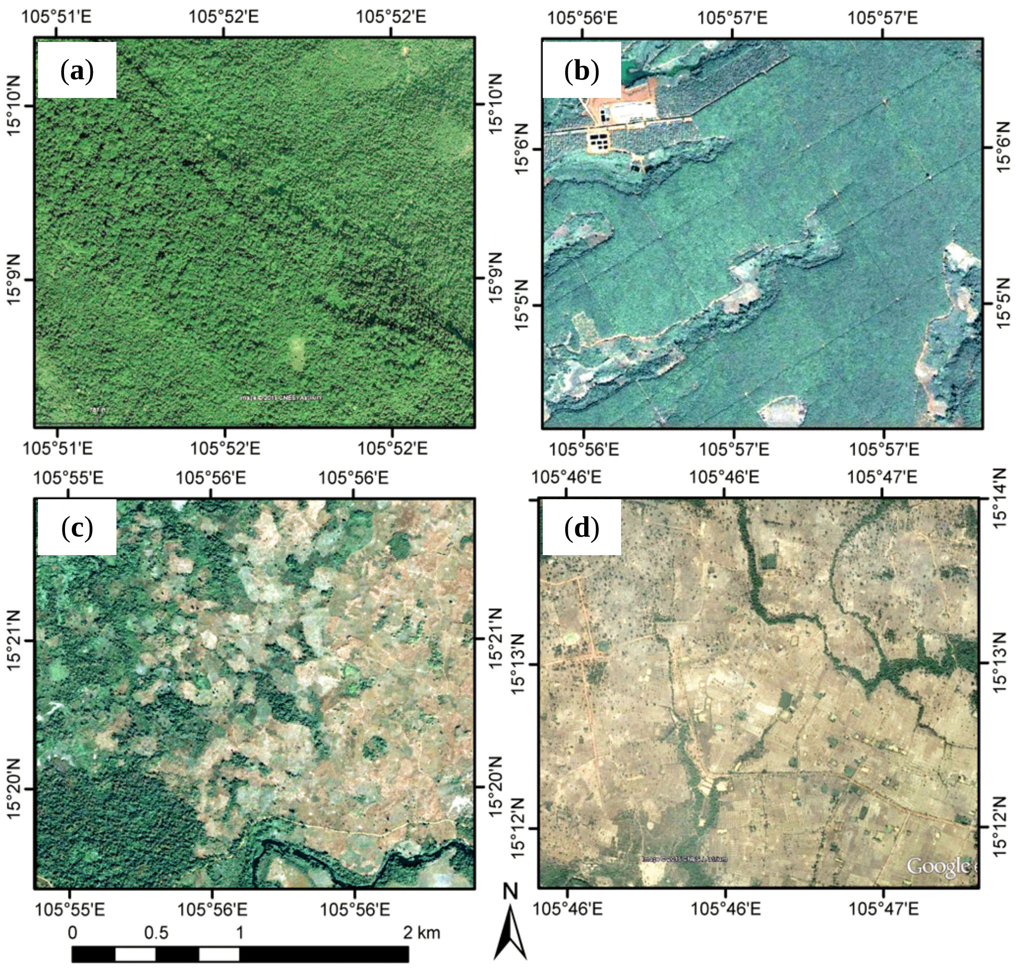


Figure 2.3. Google Earth TM images in 2012 representing the four land covers: (a) native forest, (b) rubber plantation, (c) mixed wooded/cleared area, and (d) agriculture.

We digitized the distribution of these four land covers as polygons on the 2012 image. Next, we used the Hawths Analysis Tools for ArcGIS 10.2.1 software to generate 800 random samples of the digitized data, stratified to give 200 samples of each of the four land cover types. To ensure sample representation of each land cover class, we set selection rules. These rules were: (1) each location must be the central point of a MODIS pixel of 1 × 1 km and at least 2 km away from any other selected location; and (2) the land cover must be homogeneous and cover 100% of the MODIS pixel. These procedures were then repeated for the Google Earth^{TM} 2006 image of the same site. This was to ensure we selected only samples representing the four land covers in both periods (2006 and 2012). Finally, corresponding pixel values of both LST and EVI time series (2006–2012) were extracted from the samples. In total 161 MODIS EVI (23 per year) and 322 LST composite images (46 per year) were used. LST scenes were averaged to 16-day composites to ensure an equivalent number of EVI and LST scenes and dates.

Finally, we calculated long-term averages and standard deviations of LST and EVI for the 16-day composites for the four different land cover types over the period 2006–2012. In addition, we further investigated the monthly transitions of these indices throughout the year for the four land covers. An analysis was undertaken of the hysteresis patterns based on the monthly long-term average of EVI plotted against the monthly long-term average of LST. These plots show the relationship over time of the two indices.

2.2.5 Discriminating the different land cover types using LST and EVI

In order to test whether LST and EVI can provide sufficient information to separate the four different land cover types, we applied linear discriminant analysis (LDA), using the LDA package in R software (Vienna University of Economics and Business, in Vienna, Austria, http://www.r-project.org/, http://www.statmethods.net/advstats/discriminant.html). We used the overall seven-year means of EVI and LST as the two independent variables in our model to discriminate and classify the four different land covers. Prior probabilities of groups or a number of group variables were equal proportions (25% or 200 samples for each land cover type). The resultant confusion matrix and error rate of the land cover classification was summarized.

2.3 Results

2.3.1 Temporal response of LST and EVI for different land cover types

The 2006–2012 16-day averages and standard deviations of the MODIS EVI and LST show the intra-annual responses of the native forest, rubber plantation, mixed wooded/cleared areas and agriculture (Figure 2.4a–d). Figure 2.4 shows that each of these land cover types has distinctly different EVI and LST trajectories throughout the year.

Long-term annual means of EVI for native forest (0.47) and rubber plantation (0.45) were relatively similar (Figure 2.4a,b), higher than those of mixed wooded/cleared land (0.39) and agriculture (0.30) (Figure 2.4c,d).

A strong seasonal pattern of EVI is illustrated in all land cover classes except forest lands. The temporal EVI profile of native forests differed substantially from the other classes, with only weak seasonality. Although EVI values of native forests were highest and generally maintained throughout the year, there were higher variations in the signal during the rainy period (May–October) (Figure 2.4a). In contrast, EVI values of the other land covers increased from May to Oct (Figure 2.4b–d) and dropped to their minima between December–April (dry season). Rubber plantations and mixed wooded/cleared areas had similar seasonal patterns of EVI, but these land cover types could be distinguished in the dry season. EVI for the mixed wooded/cleared area was relatively low and closely similar to that of agricultural areas in the dry season, while rubber plantations still retained their greenness. The EVI was just lower than that of native forest lands.

The annual average LST of native forests was markedly lower than that of the other land cover types (25 °C) (Figure 2.4a–c). In contrast, annual average LST for the three other land cover types was relatively similar. Agricultural lands had the highest LST (30 °C), followed by that of rubber plantations (29 °C) and mixed wooded/cleared areas (28.5 °C).

The seasonal pattern of LST was quite distinctive for each land cover. Native forest LST varied less throughout the year than that of the other land cover types (Figure 2.4a), with highest temperatures in late summer (February–April). The annual LST pattern of variation for the other three land covers showed some similarities. This pattern started to increase gradually from February–March and reached a peak (March–April). In contrast, LST was lowest during the rainy season. LST for all land cover types appeared to drop from May until October, and then repeated the seasonal cycle. Although the three land covers have similar patterns of LST, the period of LST maximum differed for each: in March for rubber plantations, in early February for mixed wooded/cleared and agricultural areas.

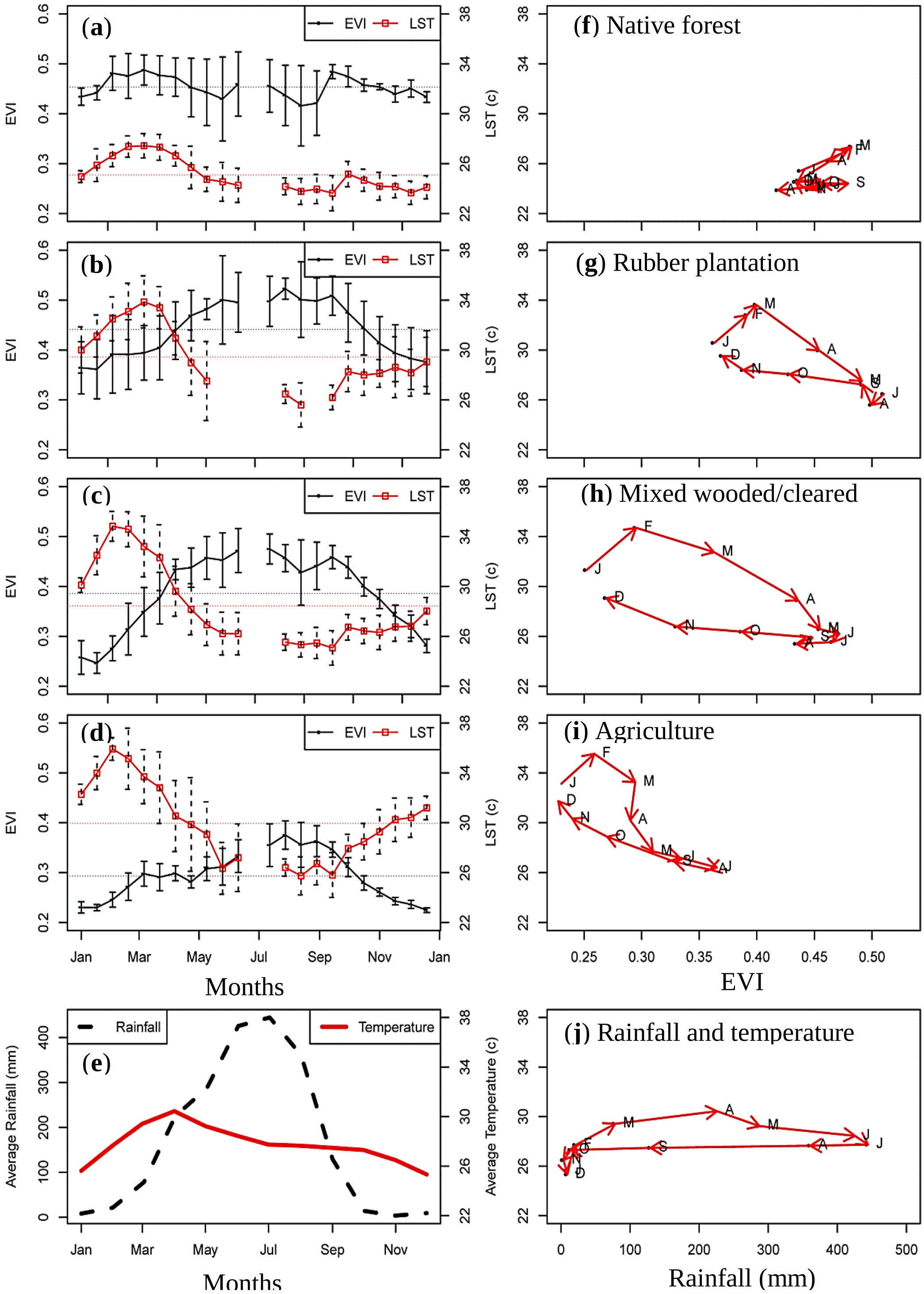


Figure 2.4. The average temporal responses of land surface temperature (LST) and enhanced vegetation index (EVI) from 2006–2012 in four different forest covers: (a) native forest, (b) rubber plantation, (c) mixed wooded/cleared area, (d) agriculture (the red line is LST in Celsius and its standard deviations (SD), while the black line is EVI and its SD), and (e) average temporal responses of rainfall and temperature, (f–i) are hysteresis patterns of LST/EVI for these land covers, (j) seasonal transitions of average rainfall and temperature.

The LST for agricultural lands tended to increase rapidly after its minimum in May–October (Figure 2.4d). This may be a result of rice harvesting activities, which start from November–January. Agricultural lands are left untouched until land preparation in May or June (depending on rainfall), followed by rice cultivation activities. The rice growing season usually starts from June–October.

2.3.2 Monthly transition of LST and EVI

The monthly transitions of LST and EVI across the four different land covers in this study are exhibited in hysteresis plots (Figure 2.4f–i). These plots show the complex relationships and intra-annual variation of average LST and EVI for these land covers. The hysteresis loop behaviour of all land covers other than forests is in the same clockwise direction, but the loops differ in width. The similar pattern of rising and falling limbs in the LST and EVI trajectories tends to depend on seasonality. The width of the hysteresis loop for each land cover shows some variations resulting from the differences in LST and EVI over the course of the year.

The hysteresis loop for native forests shows characteristics that are quite different from the other plots. There is little change in EVI and LST across the seasons. However, the hysteresis loops for the other land covers depict pronounced seasonal transition cycles in their EVI/LST trajectory. LST in the falling limb has a higher corresponding EVI value, but in the rising limb LST has a lower corresponding EVI. This response type indicates changes in vegetation cover and land surface temperature during the annual seasonal cycle. However, the width of the hysteresis loops starts to decrease when EVI increases towards 0.45 or at LST of 28 °C for rubber plantation and mixed wooded/cleared area.

The width of the hysteresis loops for three land covers (plantation, mixed wooded/cleared area and agriculture) differs and the loops occupy different spaces throughout the year. For mixed wooded/cleared lands, the hysteresis loop of LST/EVI is wider than those for the other land covers. This indicates more variations in LST and EVI in each month of the year (Figure 2.4h). Agriculture and plantations have a similar shape and width of LST/EVI trajectory (Figure 2.4i,g). This similar hysteresis pattern indicates a similar seasonal transition over time.

However, their loops are located in different spaces, which show the different values of EVI/LST for these two land covers.

Figure 2.4e,j show the long-term averages of rainfall and temperature from 2006 to 2012 and their monthly transitions. The rainy season runs from May–October and the dry season from November to April. In the rainy season, an increase in EVI begins when rainfalls starts while LST starts to decrease, for example in rubber plantation, mixed wooded/cleared area and agriculture. A point of inflection of the hysteresis loops occurs at the maximum of EVI when LST is close to about 26 °C–28 °C. During rainy period, the hysteresis loops for these three land covers remain stable until late September, as a result of less variation in EVI and LST.

2.3.3 Discriminating the different land cover types using LST and EVI

The 2006–2012 long-term averages of LST and EVI for the 200 samples of the four land covers are illustrated in Figure 2.5. In general, the four land covers appear to be well separated in the plot, although there are some overlaps of EVI and LST among them. Forests have the highest values of long-term average of EVI but the lowest LST. Rubber plantation is the second highest for EVI and the second lowest for LST, followed by mixed wooded/cleared area. Agriculture shows the highest LST but with lower EVI than the others. Thus this comparison potentially enables separation or classification of these land cover classes.

Table 2-2 summarizes the result of linear discriminant analysis (LDA) on 800 samples of long-term averages of LST/EVI. The LDA output shows that LST and EVI can be used to classify the differences between the four land covers. The first discriminant function (LD1) achieved 83.37% separation between the four land covers, with the second discriminant function (LD2) improving the separation of the groups by a further 16.63%. The variable with the largest standardized regression coefficients is the one that contributes most to the prediction of group membership. In our case, EVI is clearly the greater contributor to the discrimination of the four land covers (coefficients of 19.96 and 29.52 in LD1 and LD2), while those of LST were −0.53 and 1.00 respectively. The analysis revealed significant differences between the four land cover classes, with 86% overall accuracy in group classification. Misclassification occurred in only 14% for the samples overall.

The native forest had the highest accuracy of classification (95%), followed by agriculture and plantation (92% for both classes). However, mixed wooded/cleared class was lowest (67%) (Table 2-2). Misclassification is seen in 4% of the native forest class, 7% of rubber plantation, 8% of agriculture and 24% of mixed wooded/cleared areas. The findings indicate that there is a high possibility of separating these land covers in tropical forests by using a combination of EVI and LST.

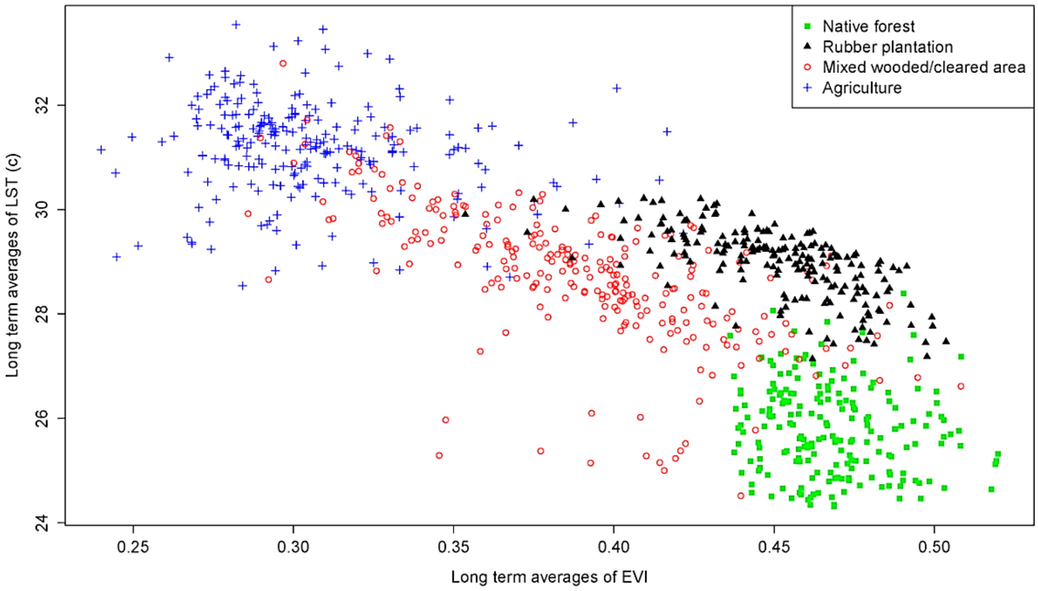


Figure 2.5. Long-term means (2006–2012) of LST and EVI for 800 MODIS samples within the four land cover types.

Table 2-2. Summary of accuracy of classification predicted by LDA.

Actual	**Predicted**			
	Agriculture	**Native Forest**	**Plantation**	**Wooded/Cleared**
Agriculture	0.92	0	0.03	0.05
Native Forest	0	0.95	0.04	0
Plantation	0	0	0.92	0.07
Wood/Cleared	0.14	0.1	0.09	0.67
Overall accuracy				**0.86**

2.4 Discussion

The analysis of LST and EVI from the MODIS time series in this study showed promise in characterizing the temporal responses of the four different land cover types. There are distinctly different EVI and LST temporal responses for these land covers. Dense vegetation cover such as native forest tends to have the lowest LST and the highest EVI throughout the year compared to the others. In contrast, agricultural land has the lowest EVI and the highest LST. This finding is similar to those of previous studies that non-forested areas have higher temperatures than forested lands (Chernetskiy et al. 2011; Lambin and Ehrlich 1996; Mildrexler et al. 2011). This indicates that if vegetation cover is reduced due to clearance, it can contribute to an increase in heat energy transferred from the land surface. Our finding was also similar to that of Julien and Sobrino (2009) which suggested that the closed canopy of tropical rainforests plays an important role in regulating and maintaining its LST constant throughout the year. Native forests maintain their leaves or canopies with adequate soil moisture and evapotranspiration throughout the year, allowing regulation of temperature. Temporal patterns of EVI and LST for rubber plantations and mixed wooded/cleared areas are similar in the rainy season, and these land covers can be distinguished only in the dry season, when there is less greenness in mixed wooded/cleared areas than rubber plantations. In the dry season, rubber plantation may have less greenness than native forests, but still more than mixed wooded/cleared areas. The mixed wooded/cleared area consists of some deciduous trees and great extent grassland in cleared areas. They become greener with higher EVI in the rainy season compared with the dry season.

We found a complex relationship between monthly averages of LST and EVI for the four land covers. The hysteresis loops of LST/EVI for three of the four land covers tended to be determined by seasonality, but not for forests (Figure 2.4f–i). The study shows that in the rainy season there is more photosynthesis activity of vegetation in the three land covers: rubber plantation, mixed wooded/cleared area and agriculture than in forests. Native forest shows higher EVI throughout the year, while the other land covers show seasonal patterns and more variations. This result suggests that the changes in vegetation covers in these three land covers are associated with changes in temperature and rainfall. In the hysteresis loops, we found that EVI increases as annual precipitation increases, but LST decreases. In contrast, when LST begins increasing and reaching its maximum in the dry period, EVI correspondingly decreases. However, this synchronization is not found in native forest. A similar result was also found in our previous research (Lambin and Ehrlich 1997). This suggests that rainfall and the resulting soil moisture and ground water from the wet season are sufficient for native forest plants to maintain almost full canopy during the dry season. There is approximately 300–450 mm of average precipitation per month. However, in dry season from November to April, there is the minimum growth of vegetation (or low EVI) due to low precipitation (less than 100 mm per month) and high temperature (up to 30 °C–35 °C). Between November and December, there is little or no rainfall and coolest temperatures. Mixed wooded/cleared areas consist of deciduous trees that usually lose their leaves during this period. This hysteresis behavior of LST/EVI was also found similarly in the West African woodlands (Lambin and Ehrlich 1996).

The second research question concerned whether we can use the information of EVI and LST to classify the four land covers, which could allow us to identify and detect land cover changes in tropical regions. The LDA implemented on the long-term averages of LST/EVI shows a high classification accuracy for the four land cover classes (86%). This accuracy was similar to a study of Julien et al. (2011) which used NDVI/LST for crop type classification (87%), although Landsat-5 data time series and different approaches were used.

2.5 Conclusions

Detection of land cover change in tropical regions is an important application of remote sensing methods. Using a combination of MODIS EVI and LST may improve monitoring of changes in tropical vegetation cover. In this study, we examined the long-term averages (2006 to 2012) of EVI and LST time-series data 16-day composites and their intra-annual seasonal transitions for four different land covers in Lao tropical forests. Finally, we applied LDA to test whether the information from EVI and LST can be used to discriminate the major land covers in our study area. The results show that EVI contributed most to discrimination of cover types, with LST making a smaller contribution. When used in combination with LST and EVI provided detailed information on the characteristics and temporal responses of the four land covers. Using these two indices we can classify the four land covers with high overall accuracy (86%). The outcomes of this study thus contribute to improving our understandings of tropical vegetation changes and responses to climate conditions. This study is a pathfinder toward providing an improved option for monitoring and detecting land cover changes in tropical regions.

2.6 Acknowledgments

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2.6.1 Author contributions

Chittana Phompila designed the research, collected satellite data used and implemented data analysis. Megan Lewis assisted in the research design, data analysis and interpreting results, especially LDA outputs. Kenneth Clarke and Bertram Ostendorf helped to write Python and R scripts for image pre-processing or selecting data quality of MODIS EVI and LST data time series. All the authors worked on the interpretation of results, manuscript writing and revisions.

2.6.2 Conflicts of interest

The authors declare no conflict of interest.

Chapter 3. Applying the Global Disturbance Index for Detecting Vegetation Changes in Lao Tropical Forests

Phompila, C., Lewis, M., Clarke, K. and Ostendorf, B. (2015). "Applying the Global Disturbance Index for Detecting Vegetation Changes in Lao Tropical Forests". *Advances in Remote Sensing*, **4**(1):73-82.

Abstract

Land cover change is a major challenge for many developing countries. Spatiotemporal information on this change is essential for monitoring global terrestrial ecosystem carbon, climate and biosphere exchange, and land use management. A combination of LST and the EVI indices in the global disturbance index (DI) has been proven to be useful for detecting and monitoring of changes in land covers at continental scales. However, this model has not been adequately applied or assessed in tropical regions. We aimed to demonstrate and evaluate the DI algorithm used to detect spatial change in land covers in Lao tropical forests. We used the land surface temperature and enhanced vegetation index of the Moderate Resolution Imaging Spectroradiometer time-series products from 2006–2012. We used two dates Google Earth ™ images in 2006 and 2012 as ground truth data for accuracy assessment of the model. This research demonstrated that the DI was capable of detecting vegetation changes during seven-year periods with high overall accuracy; however, it showed low accuracy in detecting vegetation decrease.

Keywords: Tropical vegetation change, disturbance index, land surface temperature (LST), enhanced vegetation index (EVI), Lao PDR

3.1 Introduction

Global measures of land cover change are important for global terrestrial ecosystem carbon schemes, climate and biosphere exchange modeling (Chernetskiy et al. 2011; Coops et al. 2007; Mildrexler et al. 2007), and for improving our understanding of human and environmental interactions (Klein et al. 2012; Lu et al. 2004; Xin et al. 2013) with vegetation condition and structure (Coops et al. 2009). Biodiversity loss due to land cover change is one of the core management challenges at both global and regional scale (Bradshaw 2012; Ghazoul 2013). Adequate spatiotemporal information is critical for monitoring this change (Hilbert et al. 2001; Ostendorf 2011; Ostendorf et al. 2001). However, obtaining accurate spatiotemporal information of the timing and location of land cover change is especially challenging under logistically constrained conditions such as tropical forests in developing countries.

A remote sensing approach is essential and such an application has provided key information for the comprehension of ecological system dynamics. For example, it has been used to study the responses of both the Amazon forest canopy to drought (Asner and Alencar 2010), and the intra-annual and inter-annual variations of the enhanced vegetation index (EVI) in Brazilian tropical forests (Moura et al. 2012). Remote sensing has also been used to predict and map forest structure and density in southeastern Madagascar (Ingram et al. 2005), and to examine the relationship between Mexican tropical vegetation and rainfall (Miranda-Aragón et al. 2012). Moreover, a number of change detection algorithms for use with satellite imagery have been tested and applied (Lu et al. 2004).

Another approach is to use the differential surface heat flux response of bare versus vegetated land. This appears to offer a means for the investigation of the status of land surface cover, and a number of studies have investigated the relationship between temperature and vegetation cover (Jiang and Tian 2010; Raynolds et al. 2008; Weng and Lu 2008; Weng et al. 2004; Xiao and Weng 2007; Zhang et al. 2010; Zhou et al. 2011). It is widely acknowledged that land surface temperature (LST) is determined by different land cover characteristics. Yue et al. (2007) suggested that dense vegetation cover might cause relatively higher evapotranspiration from the land surface to the atmosphere. This evapotranspiration could reduce land surface heat in comparison with open or bare land. In contrast, if vegetation loss occurred (i.e., large-scale forest clearance), this would be likely to increase LST.

Research has proven that using LST and the EVI can be useful for distinguishing differences in land cover (Chernetskiy et al. 2011; Coops et al. 2009; Mildrexler et al. 2009; Webb et al. 2014). Using LST and EVI time-series data from the Moderate Resolution Imaging Spectroradiometer (MODIS) offers the potential to detect changes in land covers, such as with the disturbance index (DI). The DI was developed by Mildrexler et al. (2007); Mildrexler et al. (2009) to monitor global vegetation changes, and the approach was tested and shown to work well in forests of the United States and Canada (Coops et al. 2009).

In theory, the DI uses a combination of the EVI and LST indices for detecting and monitoring the changes in land covers on global scales. However, there are known problems related to cloud cover, atmospheric water column content, and aerosol haze when employing the EVI in tropical regions (Grogan and Fensholt 2013; Samanta et al. 2012). There has been no implementation or evaluation of the DI model in tropical regions (Coops et al. 2007; Mildrexler et al. 2009, 2011) and there is little known about whether EVI and LST could be useful in detecting changes in land covers in this region. Therefore, the aim of this research was to demonstrate and evaluate the DI for detecting spatial change in land covers in the south of Lao People's Democratic Republic (PDR). We used MODIS EVI and LST data time series from 2006–2012 in the DI model, and used high resolution Google Earth™ images (2006 and 2012) to evaluate the performance of the DI.

3.2 Methods

3.2.1 Study area

The study area is located in Champasack Province in the south of Lao PDR. This area was selected because of its reasonably high geographic uniformity and large areas of homogeneous land cover. Additionally, this area was selected because of the availability of images from Google Earth™ for the evaluation of the success of the DI model.

The study site shown in Figure 3.1 covers an area of 15,415 km^2 (13°55'00"–15°22'00"N, 105°13'00"–106°55'00"E). Approximately 58% of Champasack Province is covered by native forests, which comprise a range of natural ecosystems such as dry, mixed evergreen, deciduous tropical forests, savanna, and semi-dry evergreen forests. Two of the largest national protected areas of Lao PDR are encompassed within the area: Xepian and Dong Houa Sao. Champasack is divided by the Mekong River. The majority of the terrain is relatively flat (74%), while 26% of the area has higher elevations. Overall, the elevation ranges from 75–1,284 m, but the majority of land is around 75–120 m above sea level. There are two distinct seasons: rainy (May–October) and dry (November–April). During the rainy season, it is often windy; humidity is high, and most of the annual average rainfall of 2,279 mm occurs. During the dry season, conditions are mostly sunny with average temperatures of 21–35°C and little rainfall. The volcanic soil of the area provides suitable growing conditions for coffee trees.

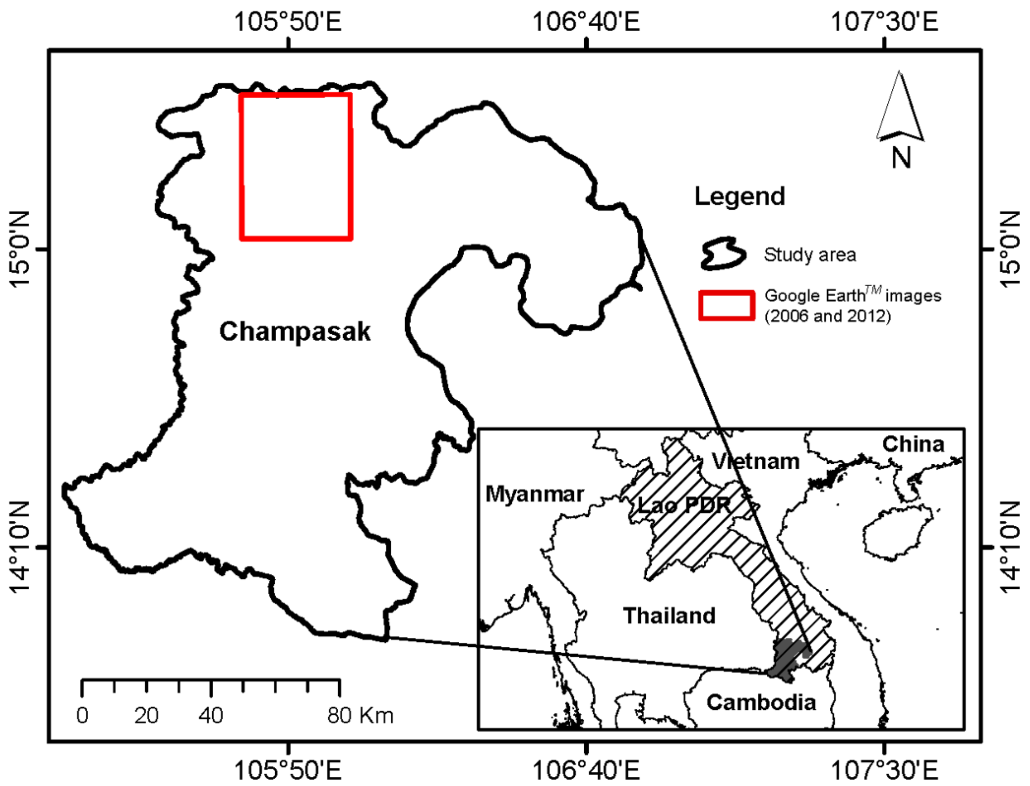

Figure 3.1. Location of the study area in Champasack Province, southern Lao PDR.

3.2.2 Method overview

Our research comprised three major steps: (1) data collection and image preprocessing, (2) application of the DI algorithm to detect vegetation cover change, and (3) evaluation of the results of the DI (Figure 3.2).

3.2.3 Data collection and image preprocessing

We used the MODIS Terra vegetation index products (MOD13A2 and MOD11A2, tile h28v07) from Collection 5 with 1-km spatial resolution. MODIS data were retrieved from the Earth Resource Observation and Science Center (EROS), National Aeronautics and Space Administration (NASA) using the ModisDownload R script. The time series spans the period from January 2006 to December 2012 with 16-day intervals (23 time steps) for MOD13A2 and 8-day intervals (46 time steps) for MOD11A2. The EVI is a vegetation index using the red, blue and NIR reflectance, as shown in Eq. [1]:

$$EVI = 2.5\,x\,\frac{(\mathrm{NIR} - \mathrm{red})}{(1 + \mathrm{NIR} + 6\,x\,\mathrm{red} - 7.5\,x\,\mathrm{blue})} \qquad (1)$$

The EVI was selected because the algorithm is improved both for sensitivity to regions of high biomass and for vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmospheric influences (Coops et al. 2009; Huete et al. 2006; Huete et al. 2008; Senf et al. 2013; Zhang et al. 2005).

In this research, image preprocessing selected only good quality pixels of the MODIS data to avoid bias. Thus, we extracted pairs of MODIS EVI and LST time series data and their quality assurance layers (QA). Then, bad quality pixels were masked by the QA or via enclosed Pixel Reliability datasets (value = 0; good data, use with confidence). Those time-series datasets were subsetted and reprojected to WGS84, UTM zone 48N, using the MODIS reprojection tool (version 4.01).

3.2.4 Applying the DI algorithm

The DI algorithm was tested for detecting changes in vegetation cover for the entire Champasack Province using the MODIS EVI and LST data time series from 2006–2012. The DI created by Mildrexler et al. (2007) and refined by Mildrexler et al. (2009) is calculated as:

$$DI_i = \frac{\left(\frac{LST_{imax}}{EVI_{imax}}\right)}{\sum_{i-1}\left(\frac{LST_{max}}{EVI_{max}}\right)} \qquad (2)$$

where DI_i is the disturbance index value for year i; LST_{imax} is the annual maximum eight-day composite LST for year i; EVI_{imax} is the annual maximum 16-day EVI for year i; LST_{max} is the multiyear mean LST (maximum) up to, but not including the analysis year ($i-1$); and EVI_{max} is the multiyear mean of EVI (maximum) up to, but not including the analysis year ($i-1$).

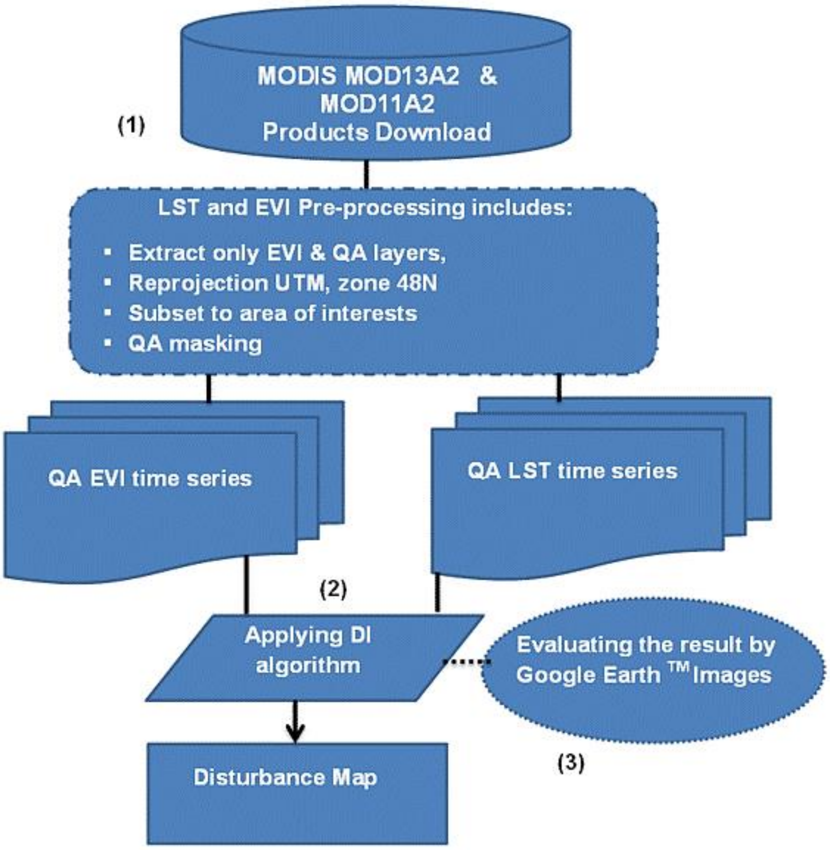

Figure 3.2. Research Steps.

The DI was designed for detecting changes in land covers on a pixel-by-pixel basis (Mildrexler et al. 2007; Mildrexler et al. 2009). The output from our pixel calculations is unitless. We used the same standard of threshold setting as in previous research (Coops et al. 2007; Coops et al. 2009; Mildrexler et al. 2007; Mildrexler et al. 2009), and values of DI were set as the mean $\pm$ 1 standard deviation (SD). An output map of the DI was classified into three classes: increased, stable, and decreased vegetation. Larger the mean (+) 1SD was assigned to decreased vegetation, whereas less than the mean (-) 1SD, signified increased vegetation. The rest was designated as stable vegetation. Normally, DI values of natural variability with no substantial change in land covers or stable vegetation fall within a narrow range around 1.0.

3.2.5 Evaluating the results of the DI model

The final research step was to evaluate the effectiveness of the DI in detecting spatial changes in vegetation cover within the study area. We evaluated the output map of the DI by Google Earth ™ Images in 2006 and 2012.

Table 3-1 represents our interpretation of the change in land covers between 2006 and 2012, from the Google Earth™ images. Firstly, we identified and classified land covers from the Google Earth ™ imagery into four dominant land cover types: native forest, plantation, mixed wooded/cleared area and agriculture. Secondly, we digitized these land covers as polygons in order to calculate their changes between 2006 and 2012 using ArcGIS10.2.1 software. This vegetation change map was assigned into the same three categories corresponding to those used in the DI application: (1) Stable vegetation is an area that appears to exhibit little or no change between the images; (2) Increased vegetation means an area that shows an increase in vegetation cover such as the transition from mixed wooded/cleared areas or bare land to plantation; (3) Decreased vegetation indicates the clearance or loss of vegetation, i.e., the transition of native forest to mixed wooded/cleared areas or agricultural land. This information was used as evaluation data for the DI.

Table 3-1. Matrix of interpreted land cover transitions.

Transition of Land Cover from/to	Native forest	Plantation	Mixed wooded/cleared	Agriculture
Native forest	S	DV	DV	DV
Plantation	NA	S	NA	DV
Mixed wooded/cleared	IV	IV	S	DV
Agriculture	NA	IV	IV	S

Note: IV = increased vegetation, S = stable vegetation, DV = decreased vegetation, NA = not found in our case.

Thirdly, the output map of the DI and the evaluation data from the Google Earth ™ were overlaid (Figure 3.3). This comparison was to evaluate whether the DI can detect detailed changes in land covers. We used 1,207 random samples within the total assessment area of approximately 2,500 km^2. This area was determined by the availability of high resolution Google Earth ™ images in two dates 2006 and 2012 over the same location (Figure 3.4). The unit of comparison was based on a pixel of MODIS (1x1 km). Finally, summary of the Disturbance Index accuracy assessment was provided.

3.3 Results and discussion

3.3.1 DI accuracy assessment

The DI was implemented to detect spatial changes in land covers within our study area during the seven-year period from 2006–2012. The results of its accuracy assessment are presented in Table 3-2, and an example of a comparison of the results with the Google Earth™ imagery is shown in Figure 3.3. The overall accuracy of the DI output is 82% and its Kappa statistic is 0.59, although the user's and producer's accuracies for individual classes differ. The producer's and user's accuracies for the class of stable vegetation (areas of little change or minor disturbance; 90.37% and 89.95%, respectively) are higher than for the other vegetation change classes. Increased vegetation suggested by the DI shows lower percentages of both producer's (66.67%) and user's accuracy (65.72%), and areas of decreased vegetation cover have the lowest accuracy (producer's 42.42% and user's 48.28%). The DI appears to detect changes in vegetation cover within the study area with high overall accuracy, but lower accuracy for areas in which the vegetation has decreased.

3.3.2 Visualizing changes in Google Earth™

Figure 3.3 shows the spatial changes in land covers detected by the DI model and its comparison of changes with high-resolution images from Google Earth™ in the same period (2006 and 2012). The model appears to detect and locate patterns of change in land covers, especially highlighting areas where vegetation has increased or remained unchanged. Increased vegetation is found mostly in plantation areas, but stable vegetation areas are located in agricultural regions and some parts of the native forest within the protected areas (Figure 3.4). The DI can indicate areas of vegetation decrease; however, some of these areas were not detected well, including native forest clearances. The interpretation of the Google Earth™ indicates that most forest clearance has occurred in relatively tiny areas, due to shifting cultivation practices and small-sized agriculture. Some of these small scattered areas of forest clearances went undetected by the model. This approach tends to capture large spatial changes in land covers, preferably >1 km^2. For example, continuous extended areas showing an increase in vegetation cover were well detected, such as rubber plantations.

Table 3-3 indicates that about 2.5% of the total area of vegetation cover was lost from 2006 to 2012, while approximately 6.65% of the entire provincial land shows an increase in vegetation cover. This increase was the result of the expansion of rubber plantations within this area. A large proportion of the vegetation decrease was found in native forests, near the protected areas, and in the mixed wooded/cleared area in the north of Champasak Province.

Table 3-2. Summary of the Disturbance Index accuracy assessment.

Google Earth™ (2006 and 2012)	Disturbance Index			Total	Producer's Accuracy (%)
	IV	S	DV		
IV	186	87	6	279	66.67
S	59	779	24	862	90.37
DV	38	0	28	66	42.42
Total	283	866	58	1207	
User's Accuracy (%)	65.72	89.95	48.28		82 %

IV = increased vegetation, S = stable vegetation, DV = decreased vegetation.

Table 3-3. Estimated area of vegetation cover changes from 2006–2012.

Vegetation Cover Changes	Years 2006–2012		Total area (km^2)
	Area (km^2)	Percentage (%)*	
Decreased vegetation	386	2.50%	15,415
Increased vegetation	1026	6.65%	

*The percentage of vegetation cover change was calculated from numbers of pixels (1 km2) indicating change, divided by the total area (15,415 km2), and multiplied by 100.

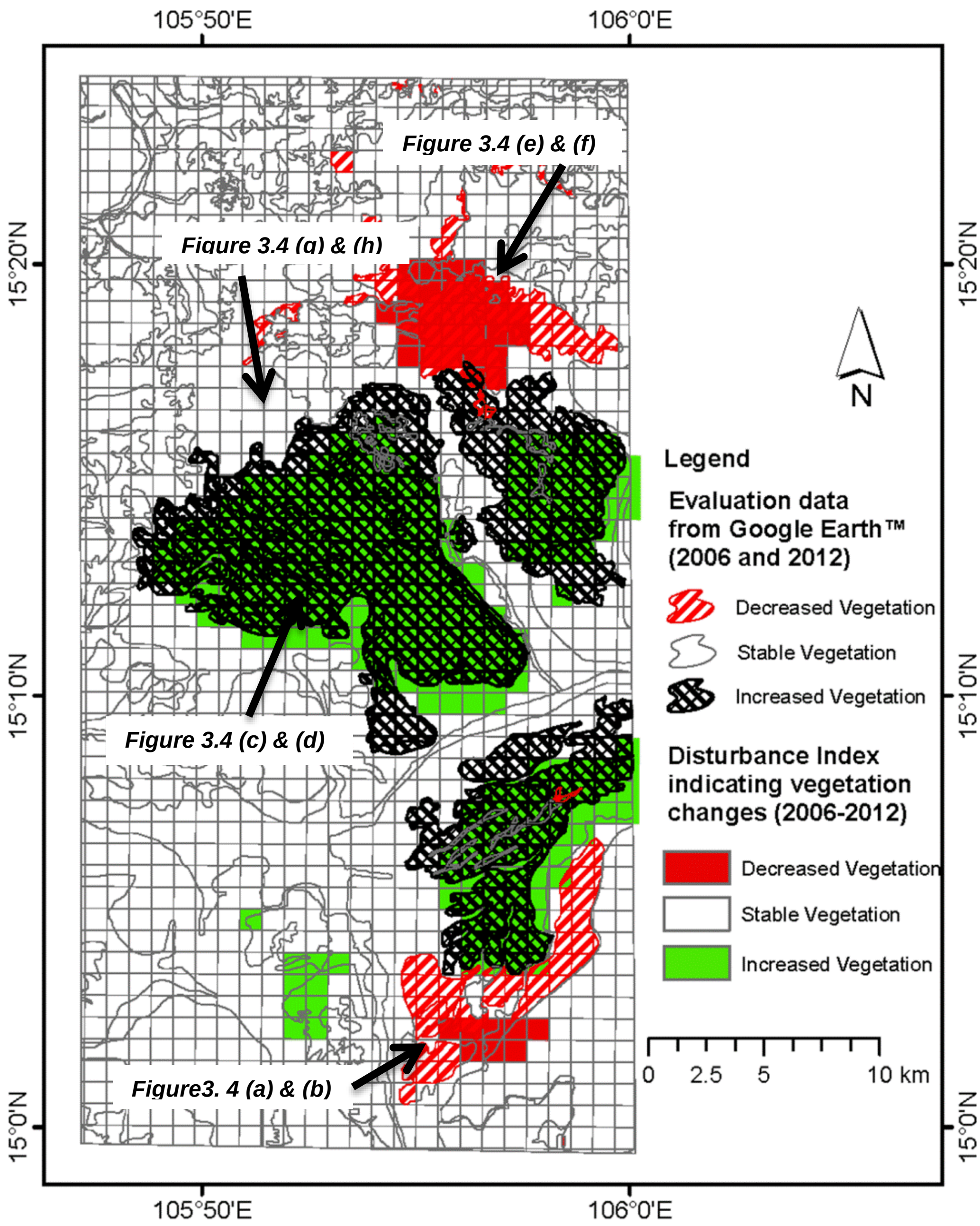

Figure 3.3. Comparison of changes in land covers over the seven–year period (2006–2012) detected by the Disturbance Index with the evaluation data from Google Earth™ images. Red pixels and red striped lines indicate decreased vegetation, green pixels and green striped lines indicate vegetation increase, and white pixels and white polygons show stable vegetation.

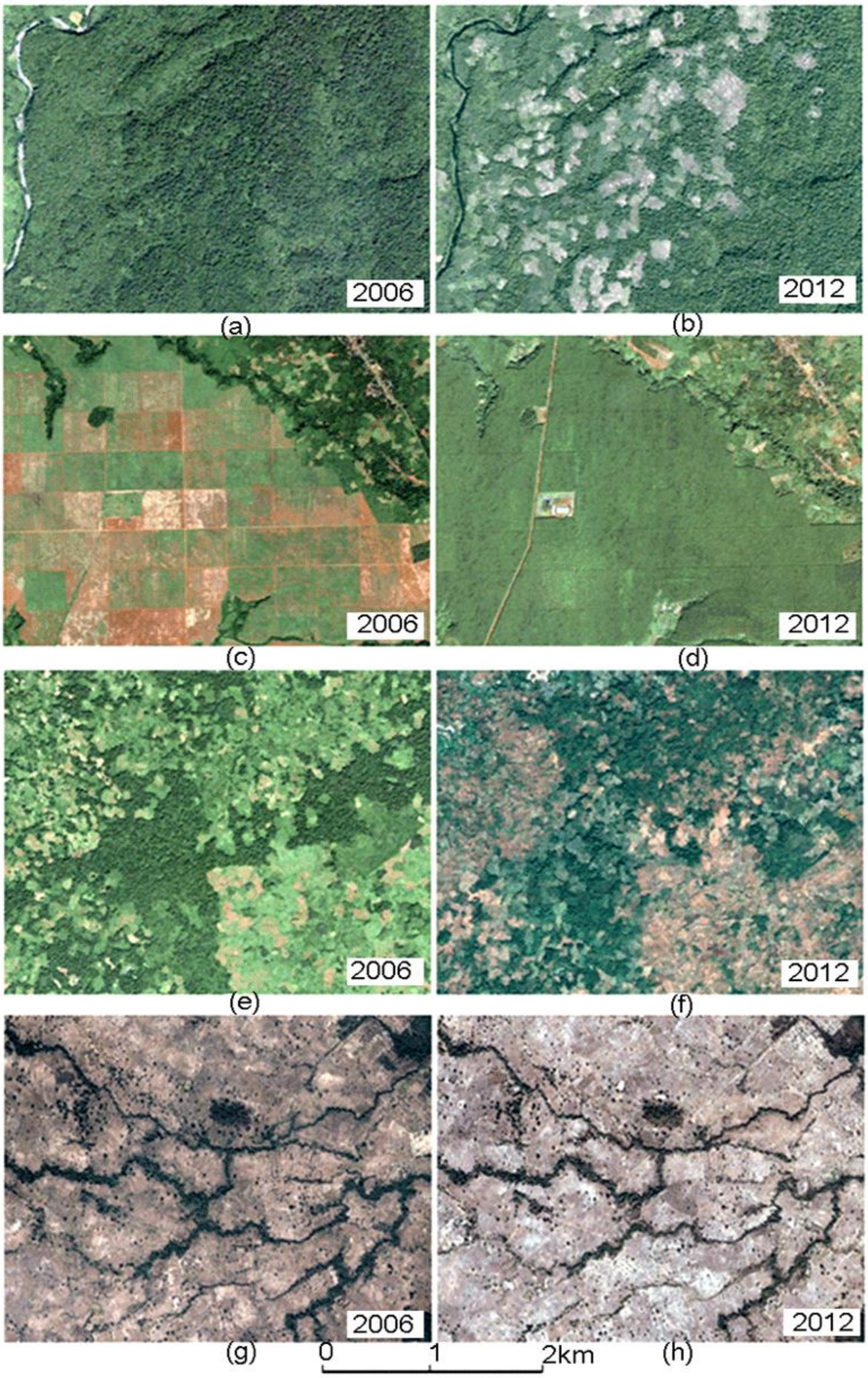

Figure 3.4. Example of the Google Earth™ images showing land cover changes between 2006 and 2012, from locations in Figure 3.3(a) undisturbed forest in 2006, (b) disturbed native forest in 2012; (c) land clearance in 2006, (d) rubber plantations in 2012, (e) mixed wood and cleared areas in 2006, (f) reduced areas of wood and increased clearances in 2012, (g) & (h) unchanged agricultural areas in 2006 and 2012, respectively.

3.4 Conclusions

In this research, we demonstrated and evaluated the global disturbance index, which uses a combination of EVI and LST indices. We used MODIS EVI and LST time series data (from 2006–2012) to test whether this approach is useful for detecting land cover change in Lao tropical forests. An evaluation of the performance of the DI was performed by comparing its results with corresponding high-resolution images from Google Earth™. The key findings were that the DI was capable of detecting vegetation changes within our study area during the seven-year period with high overall accuracy (82%); however, it showed low accuracy in detecting decreases in vegetation (about 42%). Even though this model is straightforward and can be used for rapid assessment of land cover changes in the tropics, it may not be useful for assessing vegetation loss when high accuracy is required. Further investigation is required into the atmospheric and climate effects on MODIS LST and EVI in the application of the model.

3.5 Acknowledgements

This study was supported by the Australian Agency for International Development (AusAID). Special acknowledgment is given to the National Aeronautics and Space Administration (NASA) and Google Earth™ for providing freely available images that were used for this research.

Chapter 4. Monitoring Temporal Vegetation Changes in Lao Tropical Forests

Phompila, C., Lewis, M., Clarke, K., and Ostendorf, B. (2014). “Monitoring Temporal Vegetation Changes in Lao Tropical Forests”. *Malaysian Journal of Remote Sensing and GIS*, **3**(2):100-111.

Abstract

Studies on changes in vegetation are essential for understanding the interaction between humans and the environment. These studies provide key information for land use assessment, terrestrial ecosystem monitoring, carbon flux modelling and impacts of global climate change. The primary purpose of this study was to assess whether it is possible to detect temporal vegetation changes in tropical forests using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery. The study investigated the annual vegetation phenological response of dominant land cover types across the study area in southern Lao PDR and its relationship to seasonal precipitation and temperature. Improved understanding of intra-annual patterns of vegetation variation was useful to detect longer term changes in vegetation. The Breaks For Additive Season and Trend (BFAST) approach was implemented to detect changes in land cover types from 2001-2012. We used the enhanced vegetation index (EVI) data from MODIS (MOD13Q1 products), high resolution multispectral satellite images accessed through Google Earth, and local monthly rainfall and temperature data. EVI documented the annual seasonal growth of vegetation and clearly distinguished the characteristic phenology of four different land cover types: native forest, plantations, agriculture and mixed wooded/cleared areas. Native forests maintained high EVI throughout the year, while plantations, wooded/cleared areas and agriculture showed greater inter-annual variation, with minimum EVI at the end of the dry season in April and maximum EVI in September-October, around two months after the wet season peak in rainfall. The BFAST analysis detected abrupt temporal changes in vegetation in the tropical forests, especially in large conversions of mixed wooded/cleared area into plantation. Within the study area from 2001-2012 there was an overall trend of decreasing vegetation cover in native forests and mixed wooded/cleared lands, and by contrast an increase in cover and area of plantations after 2008.

Keywords: Lao tropical land covers; vegetation changes; Breaks For Additive Season and Trend (BFAST); Moderate Resolution Imaging Spectroradiometer (MODIS); enhanced vegetation index (EVI).

4.1 Introduction

Forests play important roles in balancing the global climate, storing or exchanging terrestrial carbon, maintaining hydrological systems and in providing biodiversity and habitats. Most international attention has been given to changes in forest resources because scientific evidence suggests that these changes are associated with greenhouse gas emissions, land degradation and loss of biodiversity (Setiawan et al. 2014). Information on spatial and temporal changes in vegetation at local, regional and global scales is important for improving our understanding of human - environment interactions (Zhang et al. 2005; Chernetskiy et al. 2011; Huang and Friedl 2014) including alterations to terrestrial ecosystems, carbon fluxes and global climate (Viña et al. 2012; Papes et al. 2013).

Studies of vegetation phenology could provide essential information to support modelling and monitoring of climate change. This information is useful for detecting and monitoring regional and global environmental change as vegetation response is sensitively interrelated to environmental and climate influences (Jeganathan et al. 2014) such as temperature, soil moisture and human activity (Zhang et al. 2005). Moreover, monitoring and forecasting changes in phenology is useful to understand the response of vegetation under changing climatic conditions (Prabakaran et al. 2013).

Although several studies have been done in a wide range of environments, little is known about changes in tropical forest regions (Huete et al. 2008; Setiawan et al. 2014). The tropical forest is one of the most complex ecosystems on our planet (Avitabile et al. 2012). Acquisition of adequate information from on-ground observations and samples is difficult. These generally provide only species-specific information for specific sites, and lack comprehensive spatial coverage. Information captured by earth-observing remote sensing instruments provides opportunities to overcome this challenge (Ostendorf et al. 2001; Setiawan et al. 2014). Information from space is essential for analysing the spatial and temporal patterns of vegetation from local to regional and continental scales (Verbesselt et al. 2010; Viña et al. 2012; Forkel et al. 2013). For example, multiple-year satellite images allow us to understand characteristics and response of vegetation over time periods, including changing events and processes. Changes in vegetation can be analysed using remote sensing data time series, such as NDVI (Mao et al. 2011; Klein et al. 2012; Forkel et al. 2013) and EVI (Coops et al. 2009; Moreau and Defourny 2012).

Several remote sensing approaches have been tested and successfully applied to study changes in vegetation composition, cover and structure (Coops et al. 2009). They have used a diversity of satellite datasets, with varying spatiotemporal resolutions, and have employed a range of statistical methods (Forkel et al. 2013). Amongst these, the BFAST approach is a powerful technique to detect gradual and abrupt changes in satellite data time series (Verbesselt et al. 2010; Verbesselt et al. 2012). It has been successfully tested in south eastern Australia and South Somalia. However, there is little known about the performance of BFAST in tropical forests. Monitoring vegetation in this region using satellite remote sensing is challenging due to atmospheric effects such as frequent cloud cover and high levels of aerosols. As a result, vegetation phenology in tropical forests is not well documented (Moreau and Defourny 2012).

Therefore, the primary purpose of this study was to detect intra and inter-annual changes in the tropical forests and vegetation cover across a study area in the southern part of Lao PDR, through analysis of MODIS satellite vegetation index data. The response of vegetation phenology to monthly average precipitation and temperature was investigated, providing understanding of intra-annual response, against which longer term changes in vegetation could be detected. The BFAST approach was used to detect vegetation changes in land cover types between 2001 and 2012.

4.2 Materials and method

4.2.1 Study area

The study area was situated in the north of Champasack Province, in the south of Lao PDR. It covered an area of approximately 1,000 km^2, from 14°99'00"N to 15°41'00"N latitude and from 105°77'00" E to 106°00'00" E longitude (Figure 4.1). The study area partially covered five districts, Xanasomboun Pakse, Phonetong, Phatumphone and Bacheingchalernsouk, and also included about 2% of the Dong Houa Sao National Biodiversity Conservation Area. Land use throughout the area is mixed, with predominance of land under plantations, mixed wooded/cleared areas, agriculture (mainly irrigated rice) and native forests. While some of the study area is mountainous (approximately 10%), the majority is relatively flat lowlands (approximately 90%). The altitude ranges from 100-950 m, but the majority of land is between 100-130 m above sea level. There are two distinct seasons; rainy (May-October) and dry (November-April). During the rainy season, it is often windy, humidity is high and most of the 2,279 mm average annual rainfall occurs. In the dry season, conditions are mostly sunny, average temperatures are 28°C - 31°C and there is little rainfall.

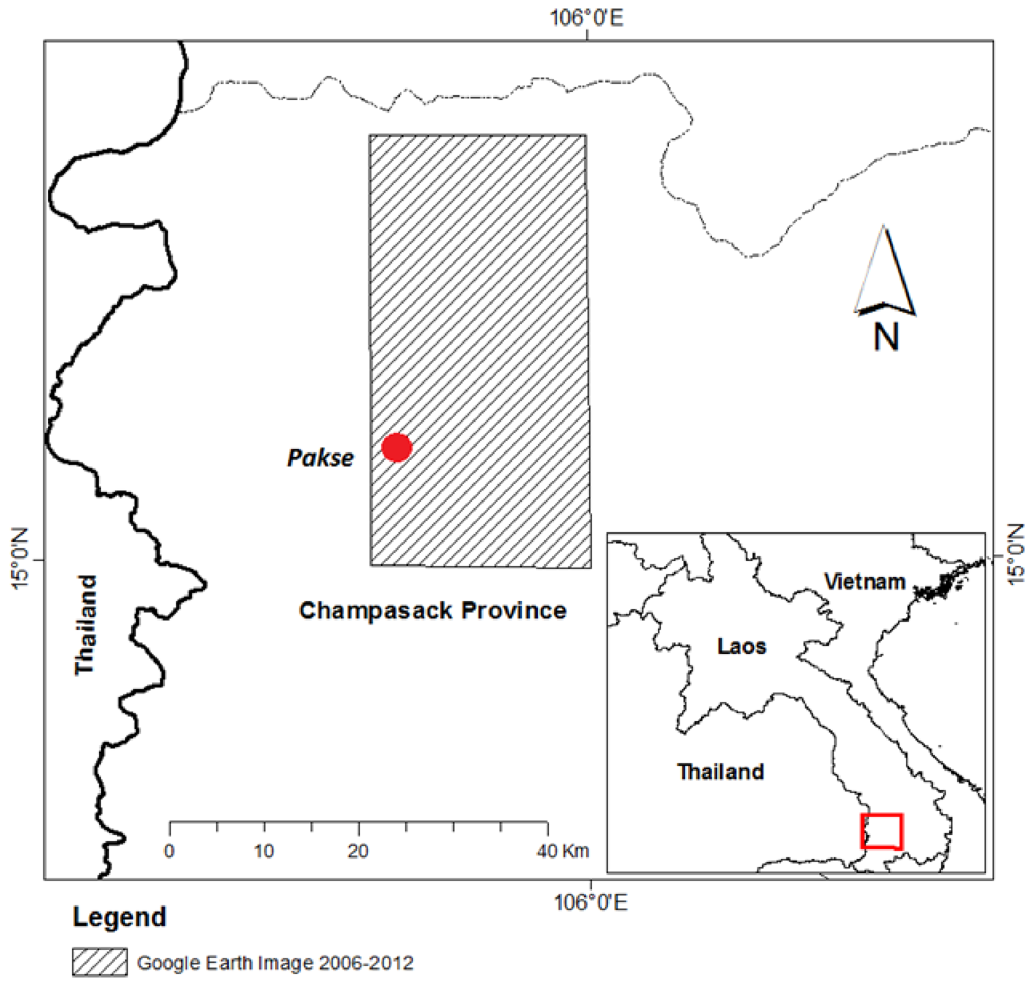

Figure 4.1. Location of the study area in the north of Champasack Province, Lao PDR.

4.2.2 Data

Two primary sources of data were used in this study; MODIS EVI and high resolution colour satellite imagery from Google Earth. The MODIS EVI is a 16-

day composite product (MOD13Q1) with a spatial resolution of 250 m, and is available from 2001-2012. NDVI and EVI have been commonly used to study changes in vegetation in tropical regions. However, we used only MODIS EVI in this study. The EVI was introduced by the MODIS Land Discipline Group as a standard satellite vegetation product for MODIS Terra and Aqua. This algorithm has improved sensitivity to high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmospheric influences (Zhang et al. 2005; Huete et al. 2006; Huete et al. 2008; Coops et al. 2009; Ma et al. 2013; Senf et al. 2013). Its formula is as follows:

$$EVI = 2.5\ x\ \frac{(P_{NIR} - P_{red})}{(1 + P_{NIR} + 6\ x\ P_{NIR} - 7.5\ x\ P_{blue})} \qquad (1)$$

where P_{NIR}, P_{red} and P_{blue} are near infrared, red and blue reflectance respectively.

The study area was covered by MODIS tile h28v07. The data was downloaded from the National Aeronautics and Space Administration (NASA) using the MODISTools package in R[1], and reprojected to WGS84, UTM projection and zone 48 (MODIS reprojection tool version 4.01).

The high resolution colour satellite images were accessed through Google Earth for two periods, 2006 and 2012, and were used for two purposes: to generate random samples, and to visualize and interpret the results of the BFAST analysis. We also used monthly average rainfall and temperature data (2001-2012) from the Lao Meteorology and Hydrology Department, Ministry of Agriculture-Forestry, published by the Lao National Statistical Centre. The data was recorded at the Pakse meteorological station, in the centre of Champasack Province.

4.2.3 Analysis

Processing flow

Figure 4.2 provides an overview of the processing sequence for the research. The analysis was divided into two components; sample preparation and selection, and sample analysis. The sample preparation and selection included image digitising, selection of random samples and extraction of EVI time series. The

[1] *http://cran.fhcrc.org/web/packages/MODISTools/index.html*

sample analysis included calculating long term averages of EVI, comparing them with average rainfall and temperature, and finally, applying and interpreting the BFAST model. More details are explained in the following sections.

Image digitizing

The 2012 Google Earth image was interpreted and digitised to record the distribution of dominant land cover types over the whole study area. Four different land covers were distinguished and digitised from visual interpretation of the high resolution colour imagery; native forest, plantations, mixed wooded/cleared areas and agriculture (Figure 4.3).

Random sample selection

Samples were randomly generated within the land use/cover polygons digitised from the Google Earth 2012 imagery. To ensure that the samples represented single homogeneous land covers, only MODIS pixels falling completely within the digitised cover class polygons were used. The samples were defined by the central point of the 250 x 250 m grid cells corresponding to MODIS pixels, and were at least 500 m from each other. In total, 1,000 random samples comprising of 250 samples for each land cover were generated using ArcGIS.

MODIS EVI time series extraction

These 1,000 random samples were used to extract MODIS EVI time series from the 2001-2012 records, which were used consistently throughout the research. The resulting MODIS series comprised of 276 16-day EVI composites. A script in R was developed to extract these datasets using the *raster*[2] and *rgdal*[3] packages.

[2]*http://cran.r-project.org/web/packages/raster/index.html*
[3]*http://cran.r-project.org/web/packages/rgdal/index.html*

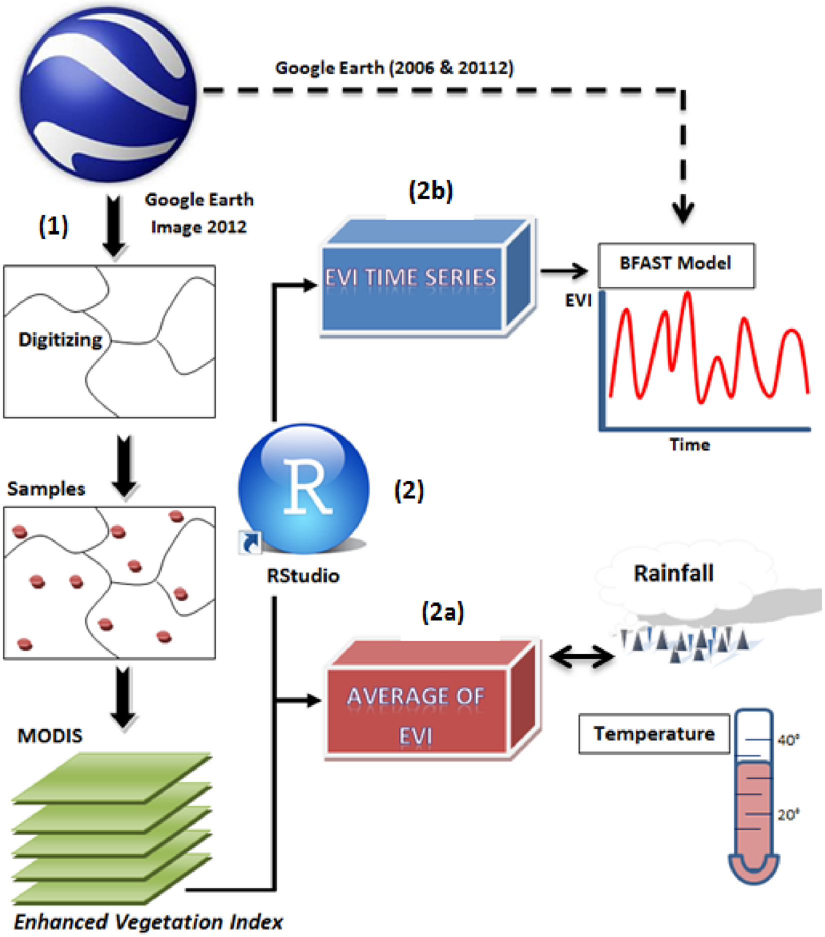

Figure 4.2: Research processing flow.

Data analysis

Firstly, we examined the characteristics and seasonal patterns of vegetation within the four dominant land cover types by calculating their long term average EVI from 2001 to 2012 using the 250 random samples for each land cover. We investigated the relationship between the seasonal vegetation responses and climatic conditions by comparing the EVI response to monthly average precipitation and temperature. Secondly, we applied the BFAST algorithm to detect temporal changes in these tropical land covers. BFAST analysis was applied to the average EVI time series derived from the 250 samples for each land cover class. The BFAST algorithm decomposes input time series datasets into three components; trend, seasonal and remainder components (Verbesselt *et al*., 2010; Verbesselt *et al*., 2012). Its formula is as follows:

$$\boldsymbol{Y_t = T_t + S_t + e_t} \quad (2)$$

where $\boldsymbol{Y_t}$ is the observed data at time t; $\boldsymbol{T_t}$ is the trend component; $\boldsymbol{S_t}$ is the seasonal component; and $\boldsymbol{e_t}$ is the remainder or residual component. The result of the BFAST analysis was visualized and interpreted against two dates of high resolution imagery from Google Earth (2006 and 2012).

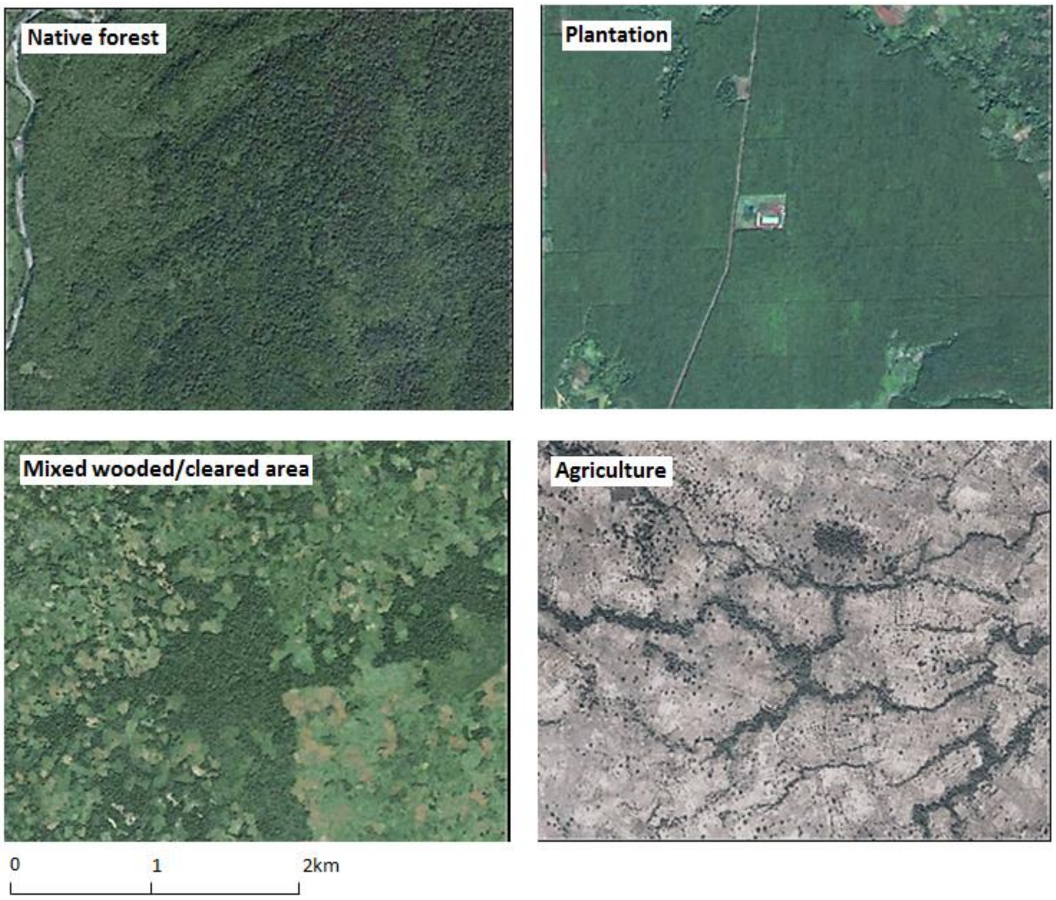

Figure 4.3: Four different land cover types digitised from Google Earth: native forest is a dense or highly homogeneous canopy of natural forests/trees; plantations shows distinctive canopy patterns and textures of regularly spaced planted trees with similar ages; mixed wooded/cleared area is fragmented and usually of low vegetation cover, which is often comprised a mixture of partly cleared areas and some trees, shrubs, grass, and bare soil; agriculture mainly includes paddy fields, minor shrubs/trees and water.

4.3 Results and discussion

4.3.1 Seasonal patterns of vegetation

The four land cover types had distinctly different seasonal patterns of vegetation response as shown by the average MODIS EVI (Figure 4.4(a)). Native forest had the highest overall EVI with the least variation throughout the year, but a minor peak in July and then slightly higher EVI maintained through to December.

Plantations also had high overall EVI, but with greater seasonal variation. Their EVI was lower than that of the native forest for January-June, but higher for August-November. Mixed wooded/cleared areas showed even greater intra-annual range of EVI. It was much lower than forest and plantations for January-July, but with similarly high EVI in the latter half of the year. Both plantations and mixed wooded/cleared areas showed evidence of two peaks in EVI in August and October. By contrast, agricultural land had overall lower EVI, but with greater variation between seasons. Its EVI reached a maximum in September-November.

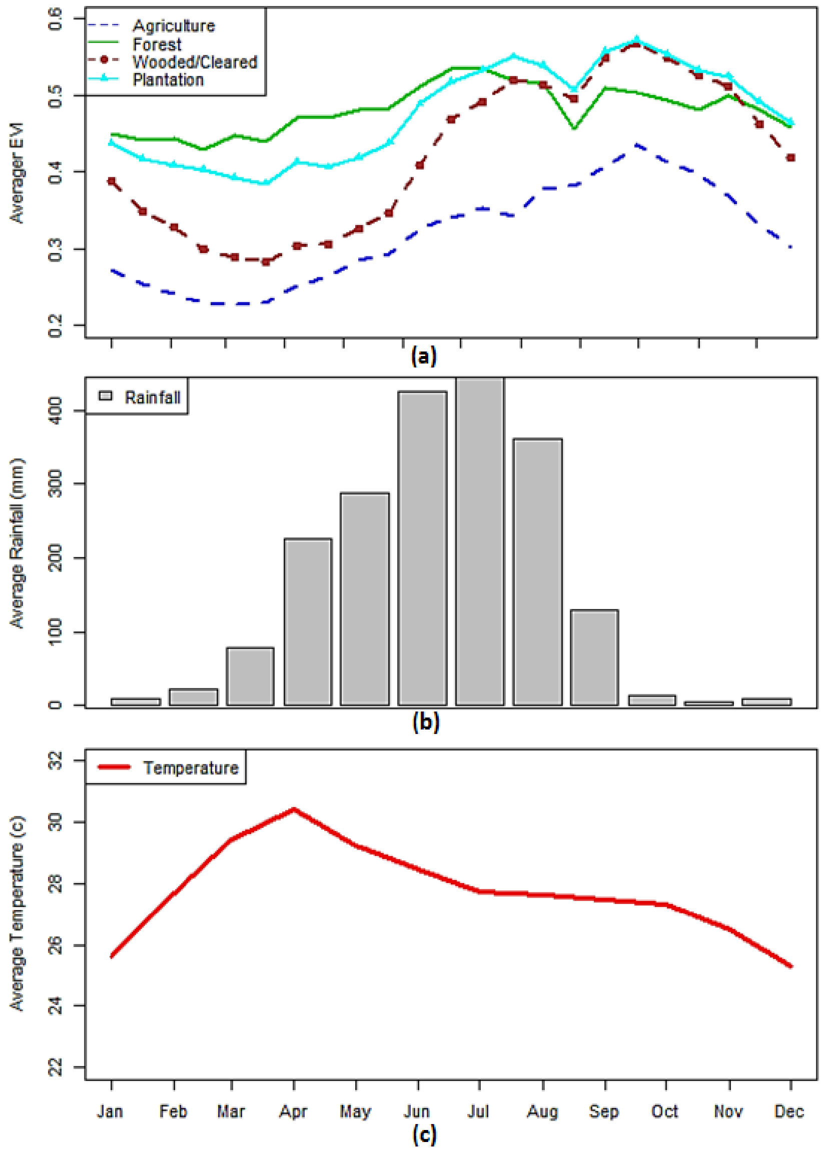

Figure 4.4. Comparison of (a) long term averages of EVI (from 2001-2012) for the four land cover types with 12-year monthly average (b) rainfall and (c) temperature.

The EVI dynamics exhibited systematic differences based on vegetation cover, species and management practices in the four land cover types. For example, high canopy cover was maintained throughout the year for forests and plantations. In contrast, the single-species plantations showed more seasonal variation than forest. In mixed wooded/cleared areas, more deciduous trees and shrubs were prevalent, resulting in a pronounced seasonal contrast in EVI. Agricultural areas displayed a distinct annual cycle of land clearance/preparation (January-April), followed by crop planting and growing (June-October), and harvesting (November-December). During the land preparation, there was greater soil exposure, resulting in relatively low EVI. However, it gradually increased during growth of the crops (predominantly rice) and reached a maximum in October.

4.3.2 EVI responses to monthly precipitation and temperature

Rainfall and temperature are the crucial drivers of vegetation growth in our study area. There is clear evidence that intra-annual variations of average EVI are strongly influenced by seasonal rainfall. The annual vegetation growth cycles for all vegetation/land cover types closely followed the precipitation pattern with a lag of two to three months when temperature also reduced. From January to April, average rainfall was less than 250 mm (Figure 4.4(b)), while average temperatures climbed from a low of 26 ^{o}C in January to the annual high of 31 ^{o}C in April (Figure 4.4(c)). During this period, vegetation cover or photosynthesis was lower, resulting in lower EVI for all land uses. However, when rainfall increased from late May to September (300-400 mm), the greenness of vegetation started to increase and peaked in October, two months after the July peak of rainfall. This EVI signal still remained high almost for almost two-three months after the end of the rainfall, and then gradually declined in November-December. This is possibly due to persistence of soil moisture and its availability to the deep-rooted perennial trees and shrubs of the forests, plantations, and wooded/cleared areas during this period.

Temperature also seemed to directly influence EVI. Figure 4.4(c) shows an inverse relationship between monthly average temperature and EVI within all four land-use covers. The minimum EVI coincided with higher temperatures in the dry period (March-April), while the different vegetation types showed more active growth during the mid-range temperatures in June-November. From this figure, it is clear that vegetation growth in this region is strongest during the rainy season (Jun-November) through to the beginning of dry season because of the relatively suitable temperature (26-28°C) and availability of soil water after the period of peak rainfall.

4.3.3 Detecting temporal changes of vegetation with the BFAST model

Figure 4.5 shows the time series of mean EVI (250 samples) for each of the four different land covers analysed by the BFAST algorithm. The trend component of the analysis indicates gradual and abrupt changes in relation to the average EVI for the four land cover types. EVI in native forests remained stable from 2001 to 2010, but there was an abrupt decrease in its response in 2011, after which it increased slightly (Figure 4.5(a)). More temporal changes were detected across plantation areas. The BFAST trend component suggests that clearing for plantations commenced from the beginning of 2004 to late 2007, followed by maturation and increase in plantation canopies from 2008 until 2011. Their EVI dropped in early 2012 and then continued to increase (Figure 4.5(b)). The overall trend of vegetation in mixed wooded/cleared areas was downward, with two abrupt changes detected in early 2005 and 2010 (Figure 4.5(c)). Figure 4.5(d) shows an overall gradual downward trend of vegetation in agriculture areas.

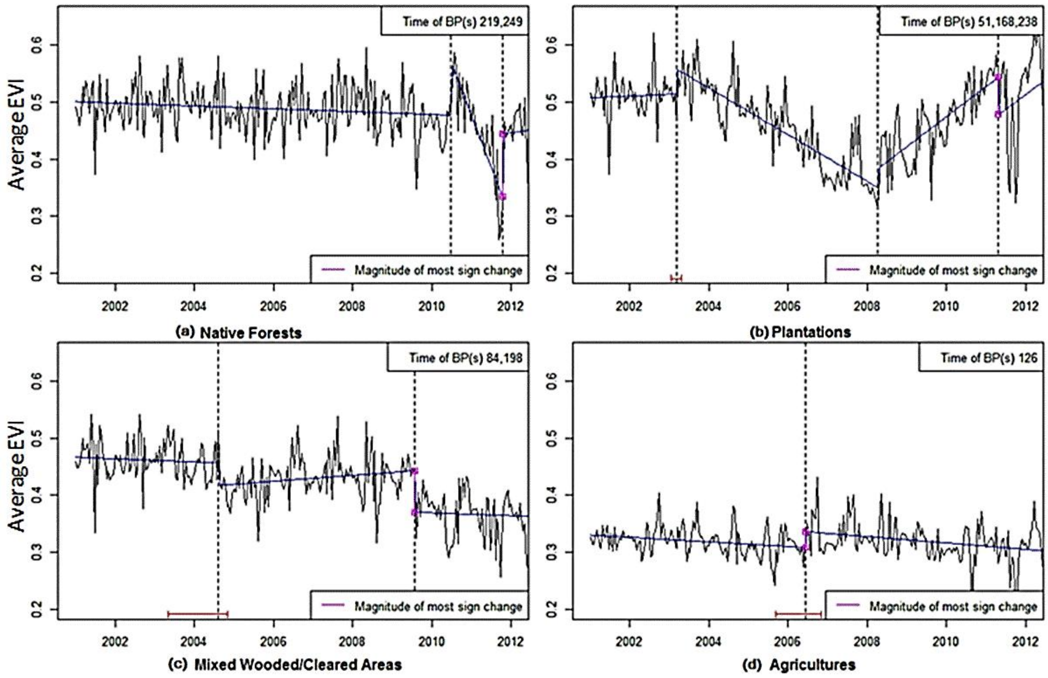

Figure 4.5. Temporal changes in vegetation for the four different land covers: (a) Native forest (b) Plantations (c) Mixed wooded/cleared areas (d) Agriculture. The plots show average EVI, with trends and abrupt changes in the time series detected using the BFAST analysis.

The temporal changes in these land covers are illustrated by examples from within the study area through comparison of high resolution images from Google Earth for 2006 and 2012. As shown in Figure 4.6(a), native forests had dense, almost continuous canopy in the 2006 image, with little evidence of disturbance. However, more disturbances were observed in 2012 (Figure 4.6(b)). BFAST indicated that EVI dropped from 2004 to 2007 and land clearance for plantations is clearly shown in the 2012 high resolution image. This activity is illustrated in Figures 4.6(c) and 6(d), where land preparation and early-growth plantations were seen in 2006, developing into mature plantations in 2012. Expansion of clearance from 2006 to 2012 was also seen in mixed wooded/cleared areas (Figures 4.6(e) and 4.6(f)). However, only agricultural lands showed no change in both images (Figures 4.6(g) and 4.6(h)). The EVI trend in this area was steadily downward, suggesting a possible decrease in agricultural production or a change of crop types.

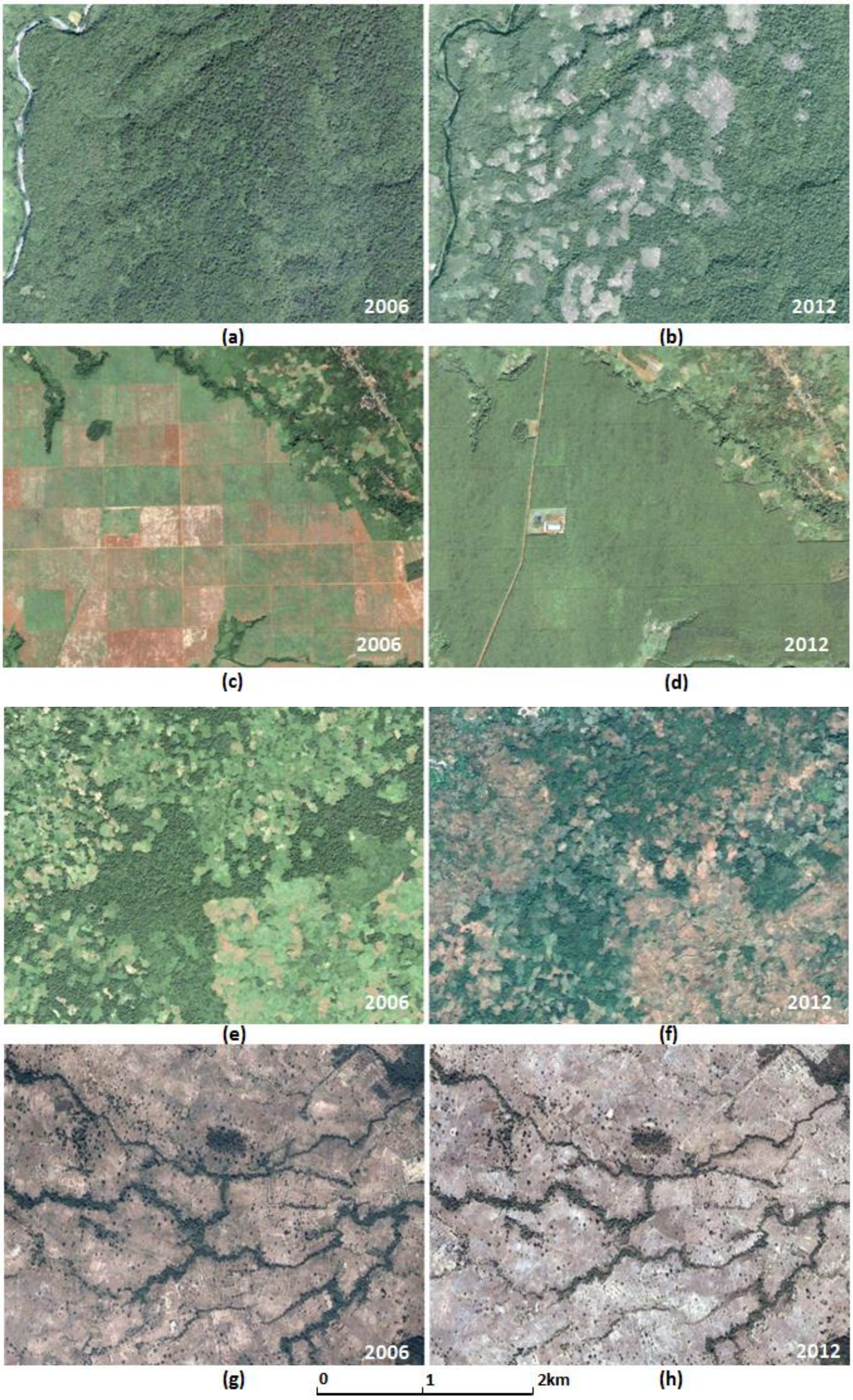

Figure 4.6. An illustration of examples of spatial changes from Google Earth imagery in 2006 and 2012: (a, b) Native forest (c, d) Plantations (e, f) Mixed wooded/cleared areas (g, h) Agriculture.

These results show that BFAST was capable of detecting abrupt changes in vegetation dynamics in the land covers in this tropical region and that some of these changes were related to forest clearance and land use change. The most notable changes in the study area were clearance of native forests and conversion of large areas of mixed wooded/cleared areas to plantations.

4.4 Conclusions

This study aimed to investigate the seasonality of vegetation response and to detect temporal changes in tropical land covers across the study area in southern Lao PDR, using the enhanced vegetation index time series data of MODIS. Firstly, the intra-annual responses of vegetation of different land covers were investigated to provide an understanding of typical seasonal patterns. Secondly BFAST was applied to examine inter-annual changes in vegetation responses over the 2001-2012 period. It was found that average EVI distinguished the annual seasonal growth and characteristic phenological patterns of four different land covers; native forest, plantations, agriculture and mixed wooded/cleared areas. In general, maximum vegetation growth occurred two months after the peak of annual precipitation, coinciding with mid-range monthly temperatures. This suggests that typical seasonal patterns of vegetation growth were primarily determined by water availability and temperature. The BFAST analysis revealed an overall trend since 2001 of decreasing cover or area in native forests and mixed wooded/cleared areas, while plantations increased. Independent evidence derived from Google Earth image interpretation demonstrated that the BFAST analysis of the MODIS EVI time series was capable of detecting areas of known clearance in native forests and their replacement by plantations of perennial trees. Thus, it can be concluded that BFAST analysis of MODIS EVI is a promising tool for assessing tropical land cover type changes.

4.5 Acknowledgements

This study was supported by the Australian Agency for International Development (AusAID) and the University of Adelaide. Acknowledgements are given to the National Aeronautics and Space Administration (NASA), Google Earth and the Lao National Statistical Centre for providing freely available satellite images and data which were used for this research.

Chapter 5. Monitoring Expansion of Plantations in Lao Tropical Forests Using Landsat Time Series

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Abstract

Clearing of native forest for plantation expansion is a significant component of land use change in many tropical regions. The continuing expansion of plantations has many environmental consequences, including the loss and fragmentation of habitat, alteration of nutrient cycling processes, reduction in environmentally sequestered carbon, increased soil erosion and land degradation, and loss of biodiversity. The primary goal of this research was to demonstrate and evaluate a remote sensing method to detect spatial changes in vegetation cover. The specific objectives were to map the expansion of plantations in the southern part of the Lao People’s Democratic Republic (PDR) and to observe temporal change in the extent of those plantations by using annual averages of NDVI. We used Landsat satellite imagery acquired between 2003 and 2012. Principal component analysis (PCA) was applied to three Landsat temporal image pairs (2003-2006, 2006-2009 and 2009-2012) to identify areas of change. Change identification accuracy was evaluated by comparison against 1,240 random sample locations which had been independently classified from Google Earth imagery from 2006 and 2012. It was found that one of the principal components detected change in areas of plantation in the study area, with producer's accuracy of 92% and user's accuracy of 79%. This method was relatively easy to implement, involved no image purchase costs, and could be used by ecologists or forestry managers seeking to monitor forest loss or plantation expansion.

Keywords: rubber plantation, tropical forest, changes, Landsat time series, principal component analysis, Lao PDR

5.1 Introduction

The forest areas on our planet are continually changing. The agents of change can be natural, including natural disasters such as flooding and windstorm, insect pests and diseases, or anthropogenic such as land clearing, preparation or harvesting, and the building of infrastructure (Coops et al. 2009). However, in recent decades, anthropogenic activities have been the major cause of changes to forest areas. These activities include agriculture expansion, plantation establishment, infrastructure development, hydropower or energy development and mining. Conversion to plantation and agriculture represents a significant contributor to loss of native forest that has been rapidly increasing in tropical regions (Hou et al. 2013; Thapa et al. 2013; Zuidema et al. 2013; Setiawan et al. 2014). This conversion impacts on energy stability, carbon flux and hydrological systems.

Documentation of land use and land cover change is required. These studies are crucial not only for monitoring the climate and biogeochemistry of earth systems but also for identifying and implementing appropriate land management (Zhu et al. 2012). Knowledge of vegetation cover and patterns, trends and rates of change is crucial for the management and can help to evaluate the success of various management tools (Czerwinski et al. 2014). The location and time of vegetation changes are key elements to analyse management impacts and to identify changes of vegetation in ecosystems (Lehmann et al. 2013).

The investigation of forest cover change due to plantation is important. Establishment of plantation is a crucial process in forest environment dynamics. Plantations involve clearance and replacement of natural forests with an introduction of new plants. This vegetation regrowth represents a case of an increase in live green biomass resulting from anthropogenic activities (Main-Knorn et al. 2013). However, plantation establishments have impacts on various functions of ecological systems such as water balance, carbon cycle, and biodiversity (Senf et al. 2013). Thus, the investigation of forest conversion is necessary and useful for improving our understanding of land use change and carbon and water cycles.

The best way to monitor land-use change involves the use of satellite imagery. This is particularly true in the rugged and remote areas where forest cover predominates. The free accessibility of high resolution Landsat imagery facilitates the detection of loss or recovery of vegetation. The use of frequent Landsat time series enables repeated analysis of vegetation change on broad scales (Cohen et al. 2010; Zhu et al. 2012; Main-Knorn et al. 2013; Sexton et al. 2013; Czerwinski et al. 2014) so that anthropogenic disturbances can be recorded. However, there are a number of challenges related to the remote sensing of such change in tropical forest environments, including frequent cloud cover and atmospheric effects (Dong et al. 2012; Zhu and Woodcock 2014). A remotely sensed approach needs to be developed to overcome these challenges. In this paper, the overall goal was to demonstrate and evaluate a remote sensing method in tropical forests using freely available satellite imagery. Our primary purpose was to detect spatial changes in forest cover in the southern part of Lao People's Democratic Republic (PDR). The specific objectives were to map expansion of rubber plantations, and to observe temporal changes in this plantation area over a period of ten years, between 2003 and 2012 by using NDVI. Knowledge of monitoring Lao vegetation cover changes is necessary for local forestry managers and ecologists for forestry policy and decision making as well as for measuring appropriate forest and land use management.

5.2 Methods

5.2.1 Study area

The research site is within the geographic region 14°50'32" to 16°10'3" N latitude and 105°17'2" to 106°47'29" E longitude. It extends from the north of Champasack Province to the middle of Salavan Province, the south of Lao PDR (Figure 5.1). The study zone covers an area of approximately 12,000 km^2 and includes 12 administrative districts of these two provinces. The area is characterized by a tropical monsoon climate with two seasonal regimes; a hot dry season and a warm rainy season. It usually experiences frequent cloud cover and hazy atmospheric conditions during the rainy season. Coffee plantations have been predominant in this region for several years. However, increasingly rubber plantations are being established, particularly in the south.

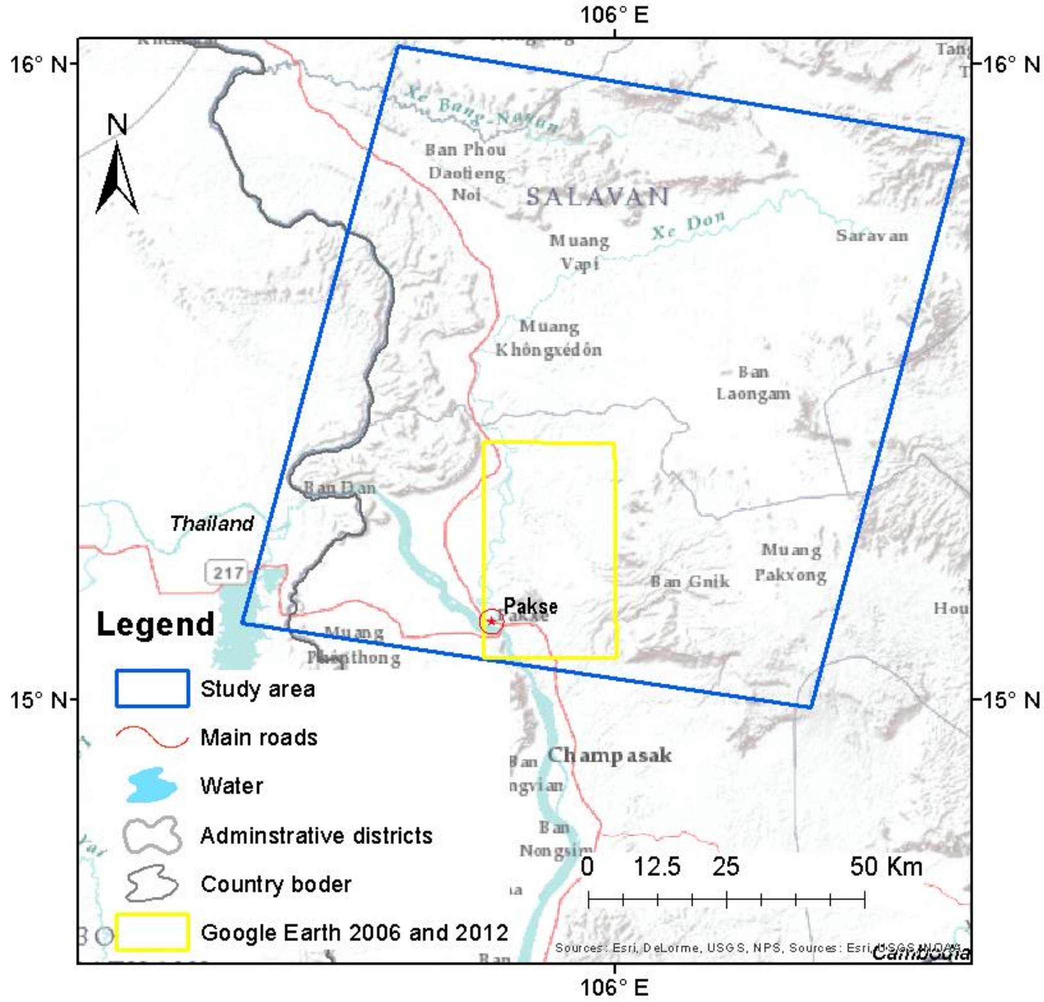


Figure 5.1. The study area, located in Champasack and Salavan Provinces, in the south of Lao PDR. (*Source: Data i.e. roads, water, administrative district and national boundaries were provided by Faculty of Forestry Sciences, National University of Laos*)

5.2.2 Data analysis

The research comprised four main steps as shown in Figure 5.2: (1) dataset and image pre-processing; (2) principal component analysis (PCA) to detect changes in vegetation cover, (3) accuracy assessment of cover change and (4) monitoring of temporal changes in rubber plantations. More details are explained in following subsections.

5.2.3 Dataset and image pre-processing

Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery was used in this research. Landsat imagery provides the most appropriate remotely sensed spatial

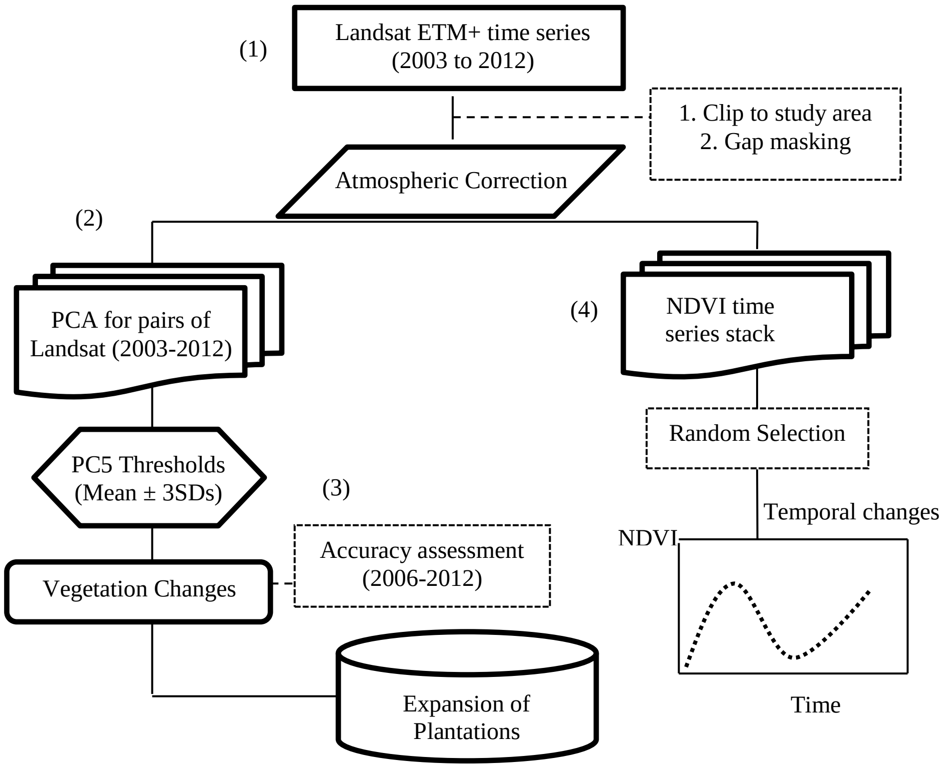


Figure 5.2. Research Flow

resolution for forestry dynamics monitoring. Data has been applied successfully in a number of studies in various environments including tropical forests (Hilker et al. 2012; Vogelmann et al. 2012; Zhu et al. 2012; Main-Knorn et al. 2013; Sexton et al. 2013). The free Landsat imagery is acquired every 16 days, with spatial resolution of 30 meters. Since May 2003 approximately 22% each Landsat ETM+ SLC-off scene contains missing lines due to the scan line corrector (SLC) failure. This caused all later Landsat ETM+ images to have line gaps (The United States Geological Survey 2012). However, these remotely sensed data are useful and essential for worldwide researchers. However, a complete temporal record of land cover change through Landsat images is almost impossible in tropical regions, due to interference by clouds and aerosols (Dong et al. 2012; Thapa et al. 2013; Zhu et al. 2014). Therefore, we used Landsat ETM+ data captured annually at a similar time of the year to avoid effects from phenology and sun angle, and to select a period of minimum cloud cover. These effects have been shown to add noise in previous studies of longer-term change (Kennedy et al. 2010; Main-Knorn et al. 2013).

The MODIS observations in the study area (in Chapter 4), indicated that there was a massive clearance for plantations in from 2004 to late 2007 and an increase in plantation canopies in 2011. In addition, there were noticeable changes in forest and land use following introduction in 2004 of government policy on foreign direct investment in forestry and agriculture, along with land leases and concessions. Therefore, Landsat images corresponding to these pre- and post events were considered as the most suitable to investigate spatial changes in forest cover in more detail. The three year time interval between imagery was chosen to allow observation of significant spatial change within study areas. In addition, fuller time series of Landsat data were available due to cloud cover. Therefore, we acquired the Landsat ETM + images from December - February for the years between 2003 to 2012 (Table 5-1). Only images with 0-5% cloud cover from 2003, 2006, 2009 and 2012 were used. The images were accurately geo-referenced to WGS84, UTM zone 48N and co-registered and further rectification was not needed. The Chavez (1996) atmospheric correction model was applied before we used principal component analysis algorithm.

Table 5-1. Acquisition dates of Landsat 7 ETM+ data used in this research (path 126 and row 49 of the world reference system (WRS)).

Image Date	Image Date
22 Jan 2003	21 Dec 2008
22 Dec 2003	22 Jan 2009
26 Dec 2004	10 Feb 2010
14 Jan 2006	30 Dec 2011
02 Feb 2007	16 Feb 2012

5.2.4 Principal component analysis (PCA)

Principal component analysis was applied to detect areas of significant vegetation cover change in the study area. PCA is often used for change detection in remote sensing image analysis (Singh. 1993; Rigina and Rasmussen 2003; Sheen 2004; Lasaponara 2006; Miranda-Aragón et al. 2012). We used the standardized PCA which computed data based on the correlation matrix, providing an equal weight to each element within the original data series. We applied PCA to a composited stack of six bands from a pair of Landsat image dates (2006 and 2012) to highlight vegetation patterns and change between those two dates. In total 12 principal components were computed for this two-date Landsat stack. One of the principal components was interpreted as showing vegetation cover change between the two dates, and was classified into three classes (vegetation stable, vegetation increase and vegetation loss) using a threshold. The threshold was determined by mean and ±3 standard deviations (SDs) of PC band. Any values ≤ mean and (-) 3SDs were assigned into a vegetation increase class. Values ≥ mean and (+) 3SDs were assigned into a vegetation loss class. The rest was classified as vegetation remains stable. We assessed the accuracy of the 2006 – 2012 PC classification prior to applying this approach to three other temporal of Landsat 7 ETM+ stacks: 2003 and 2006; 2006 and 2009; and 2009 and 2012.

5.2.5 Accuracy assessment

Field data to validate the accuracy of classification maps of each period of change (2003-2006, 2006-2009 and 2009-2012) was not available. Consequently the accuracy of the PCA vegetation change classes for the 2006-2012 PC classification was assessed by comparison with high resolution colour Google Earth ™ imagery. To provide reference data we digitised two dates of Google Earth imagery in 2006 and 2012 with coverage of 2,500 km^2, and produced a vegetation cover change map with three classes: vegetation stable, vegetation increase, and vegetation loss. Their definitions are: (1) 'vegetation increase' refers to areas that show an increase in vegetation cover such as a transition from mixed wooded/cleared areas or bare land to plantation or to native forests, or transformation of agricultural areas to plantation; (2) 'vegetation stable' describes areas that appear to exhibit little or no change between two periods (2006 and 2012); and (3) 'vegetation decrease' means areas which experienced the clearance or loss of vegetation, e.g. a transition of primary forest to plantation, mixed wooded/cleared areas or to agricultural land. Any indication of loss of vegetation cover was assigned in this class, including change from plantation to agriculture and from mixed wooded/cleared areas to agriculture. Our digitizing was focused on native forests, plantation, mixed wooded/cleared and agriculture. We used 1,240 random pixel samples to compare the Landsat vegetation change classes with the reference change map. The resultant error matrix was used to calculate summary accuracy measures.

5.2.6 Temporal changes in rubber plantations

The temporal change in plantations is key indicator to allow us to understand the planted tree conditions. This helps us to evaluate the development stage of plantations since land clearance. We calculated and used annual averages of normalized vegetation index (NDVI) of Landsat to investigate the historical temporal changes in rubber plantation areas. The NDVI is commonly used to study photosynthetic activity and to measure vegetation dynamics in a wide range of forest ecosystems. Our interpretation of the Google Earth imagery suggested that areas of vegetation increase were mostly associated with establishing rubber plantations. These areas of vegetation increase or rubber plantations were identified by the classification of PC5 band from a stack of Landsat data of 2006 and 2012. The accuracy assessment using 1,240 samples provided us with confidence about locations and areas of rubber plantation. Then, we mapped and extracted only polygons of rubber plantations and used these to generate 400 random pixel samples within these areas. These samples were used to extract Landsat NDVI values for each year from 2003-2012. Extracted NDVIs were averaged for each year. The annual averages of NDVI time series were expected to allow us to observe temporal changes in rubber plantations over time. This was to indicate the times when there were increases or decreases in vegetation cover over the ten-year study period.

5.3 Results and discussion

5.3.1 Forest cover change detection

The result from PCA transformation of the two-date Landsat ETM+ images (2006 and 2012) shows that the first PC highlights areas or locations of dense vegetation and least vegetation in our study area. PC2 of our analysis shows additional information on vegetation cover density (low and high). However, its loading value indicates opposite to PC1. A low value of PC2 shows high vegetation cover, whereas a high value shows less vegetation. Cloud also appears visible in PC2. Water is highlighted strongly in PC3 (low value). Both water and cloud are captured in PC4, but vegetation pattern is not visualized.

PC5 of Landsat stack captured less than 2% of variation in the data, however it contained significant information related to changes in vegetation cover. Figure

5.3 shows the result of the classification of PC5 indicating areas of vegetation increase, loss and remaining stable in 2006 and 2012 within the study area. Vegetation increase was classified by thresholds of the mean and (-) 3SDs (dark green), while vegetation loss was classified by mean (+) 3SDs of PC5 (red). The remains of PC5 values were assigned to unchanged vegetation or remaining stable (white). The rests of PCs represent less than 2.7% of variability and their information content was unclear. These can include sensor artifacts and noise.

5.3.2 Accuracy assessment

Table 5-1 presents a summary of the accuracy of the classified PC5 in detecting vegetation cover change for the 2006-2012 image comparison. The overall accuracy was 87.02 % with a kappa value of 0.8 (Table 5-2 and Figure 5.4 and 5.5). Vegetation increase had the highest producer's accuracy (92.0%), but the lowest user's accuracy (79.8%). Vegetation loss had the lowest producer's accuracy (82.0%), but the second highest user's accuracy (88.7 %). The user's accuracy and producer's accuracy for prediction of the areas that remained stable were also relatively high (97.5 % and 86.0 %, respectively). Evidence from field information and the Google Earth images allowed us to conclude that the vegetation increase is a consequence of expansion of rubber plantations. Figure 5.4 shows areas of rubber plantations detected by PC5 (using Landsat data acquired in 2006 and 2012) on high resolution Google Earth images. Figure 5.5 illustrates photos of rubber plantations from some validated field locations in the study area.

Table 5-2. Error matrix for the change detection analysis, from 2006-2012.

Google Earth Images (2006 and 2012)	Vegetation Increase	Vegetation Stable	Vegetation Loss	Total	User's Accuracy
Vegetation Increase	439	43	68	550	79.82
Vegetation Stable	4	312	4	320	97.50
Vegetation Loss	34	8	328	370	88.65
Total	477	363	400	1240	Overall accuracy
Producer's Accuracy	92.03	85.95	82.00		87.02

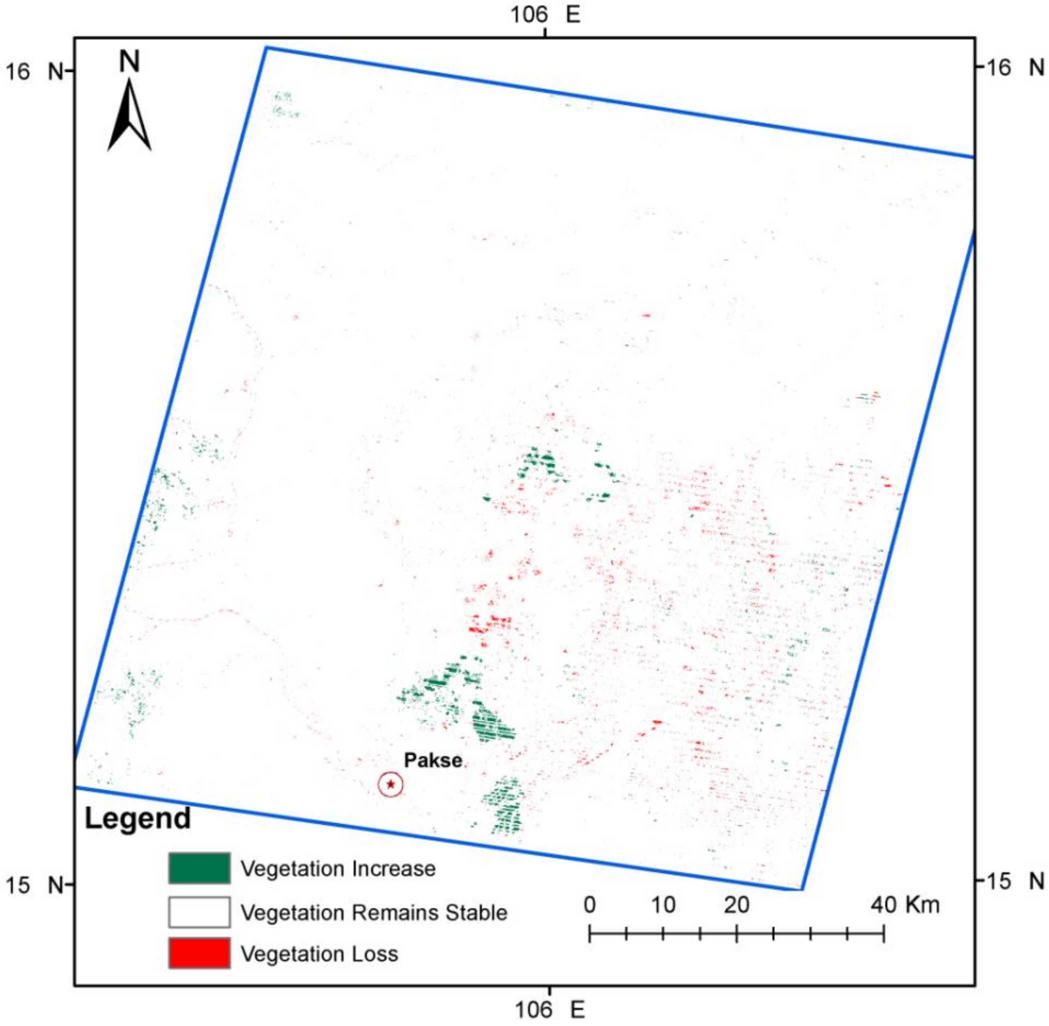


Figure 5.3. The classification of PC5 showing areas of vegetation increase (green), loss (red) and remaining stable (white) in 2006 and 2012 within the study area. A large area of vegetation increase appears near the Pakse city center and the north of province as well as an opposite side of Mekong River. Vegetation clearance is mostly found near the national protected areas; Xepieng and Dong Houa Soa.

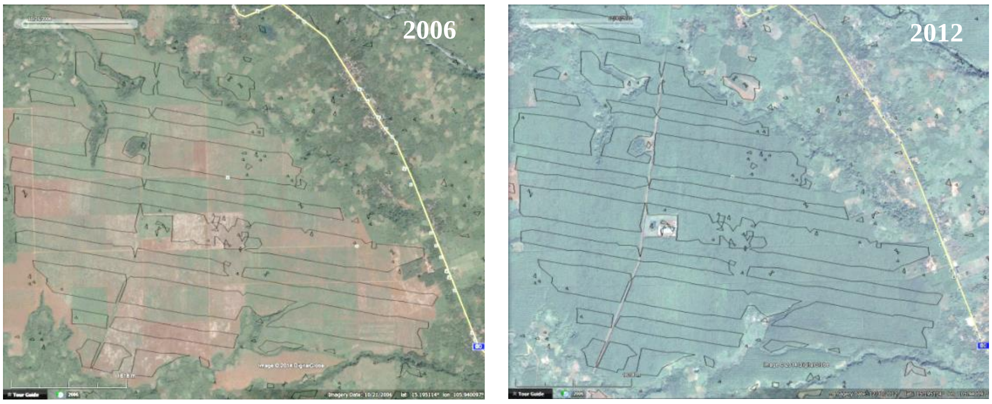


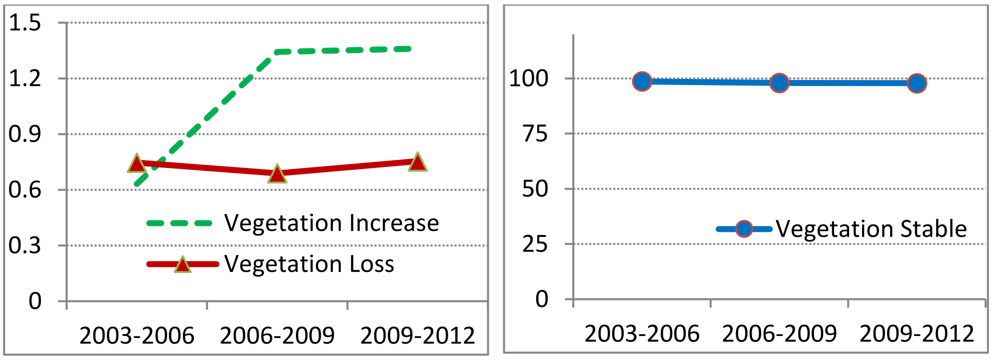
Figure 5.4. Rubber plantations in the Google images 2006 and 2012. Black polygons are rubber plantations detected by PC5 using Landsat data in 2006 and 2012. Gaps are due to missing Landsat 7 data. The Google Earth imagery indicated forest removal occurred by the first date and was replaced by rubber and regrowth by 2012. Rubber plantations show distinctive patterns and spacing of tree canopies.

Figure 5.5. Photos of rubber plantations from a field visit to the areas mapped in Figure 5.4 above (Photos: C. Phompila).

5.3.3 Vegetation cover changes from 2003-2006, 2006-2009 and 2009- 2012

The spatial change in vegetation covers over the periods 2003-2006, 2006-2009 and 2009- 2012 is shown in Figure 5.7. Overall there had been larger areas of vegetation increase than vegetation loss from 2003 to 2012. The majority of vegetation loss areas were replaced by vegetation increase areas which are rubber plantations. Between 2003 and 2006, a large area of vegetation was cleared (in red), but only small area of vegetation increase was found (dark green). The natural colour composited band of Landsat image shows vegetation loss areas as forests in 2003 (author interpretation, not shown). Then, information from the Google Earth image depicts the clearance in 2006. From 2006 and 2009, there is an increase in vegetation in none-forest areas, however more expansion of vegetation loss appears. Our interpretation is confirmed by evidence from the Google Earth image in 2006 and original Landsat data in 2009. It indicates there are re-planting activities as well as more forest clearances are being implemented in this period. Finally, a large area of vegetation increase or rubber plantation occurs between 2009 and 2012. This is also confirmed by the Google Earth image in 2012 (Figure 5.4). A little vegetation loss is detected in this period. These rubber plantations are found largely in the Barjieng and Patumphone districts, which are close to the national protected areas and Pakse central.

Figure 5.6a and 5.6b indicates the percentage of mapped pixels that shows the proportion of changes in vegetation covers from 2003 to 2012. About 22 % of the Landsat scene is not mapped due to missing scan lines. There is a small proportion of vegetation increase and loss but the majority of vegetation remained stable during this period. The percentage of vegetation increase goes up from 2003-2006 to 2006-2009 and remains stable in 2009-2012 (0.63% to 1.34% respectively). However, the rate of vegetation loss and stable appears to be relatively stable over the periods. There is roughly 0.69% - 0.75% of vegetation loss and 98.6%-97.9% of vegetation stable. The forest clearance seems to be less than expansion of rubber plantations. By the estimation, approximately 137.3 km^2 of total study area (12,350 km^2) has an increase in vegetation cover and about 90.1 km^2 of the area experienced a loss of vegetation cover from 2003 to 2012.



(a) (b)

Figure 5.6.An estimation of forest cover changes from 2003-2006, 2006-2009 and 2009-2012; (a) the percentages of vegetation increase and loss, (b) the percentage of vegetation remaining stable. This approximate estimation excludes missing data of Landsat 7.

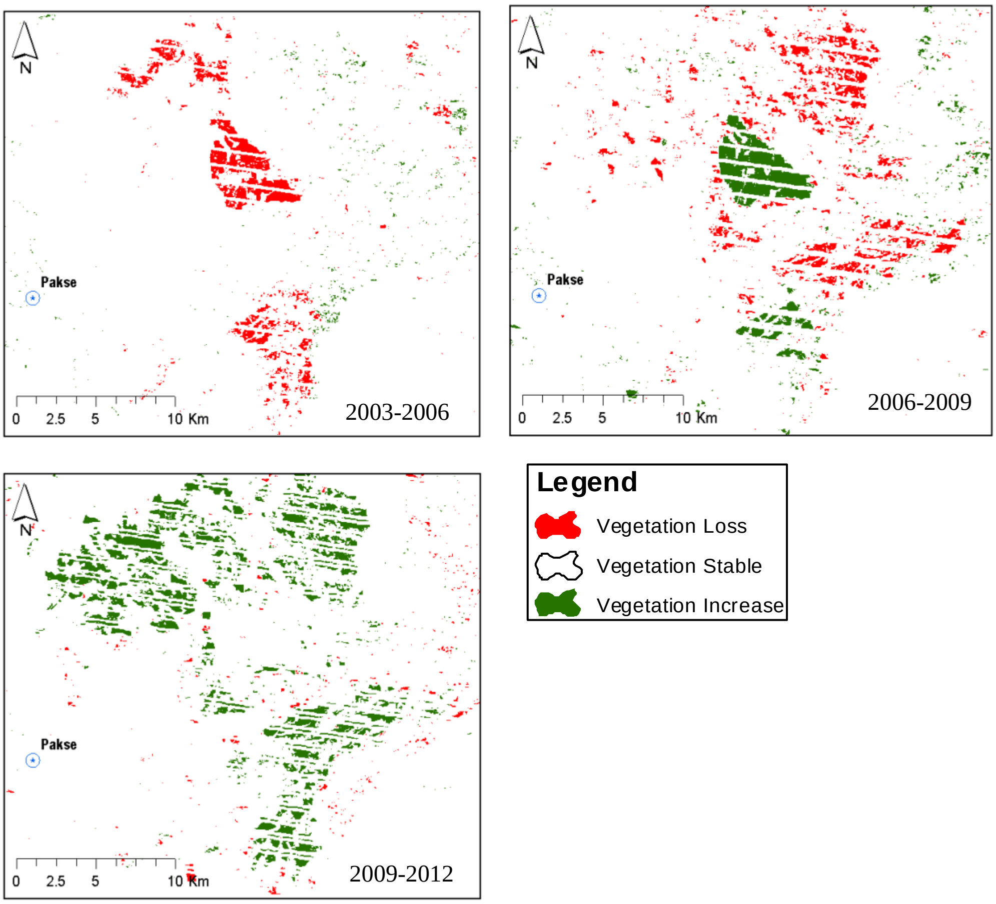


Figure 5.7.An example of PC5 detecting an increase and decrease in vegetation between 2003 and 2006, 2006 and 2009, and 2009 and 2012 in the study area. The white linear features are due to missing Landsat 7 data.

5.3.4 Temporal changes in rubber plantations

The temporal behavior of annual averages of NDVI for plantations extracted from Landsat ETM+ data from 2003 to 2012 is shown in Figure 5.8. This tracked historical changes when there were increases or decreases in vegetation cover within rubber plantation. From 2003 to 2012 there is a considerable fluctuation in NDVI. This fluctuation could be associated with vegetation cover changes or due to variation in climatic factors such as temperature and rainfall. From 2003 to 2006, there is a small fluctuation in NDVI from year to year. During this period, these areas were forested. However there is a dramatic decrease in NDVI in 2007 to a value of less than 0.1, indicating bare soil. This plunge is related to intensive vegetation clearance in late 2006, as seen in the Google Earth imagery. Post clearing, plantation canopy growth results in steadily increasing NDVI values, until maximum of 0.6 is reached in 2011. Healthy rubber plantations display in the image of 2012 (Figure 5.4).

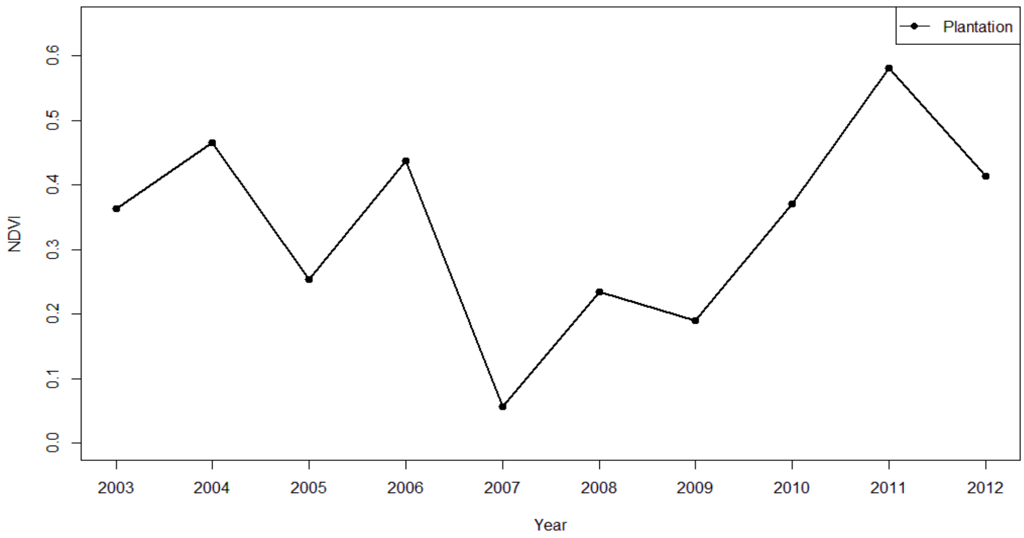


Figure 5.8. NDVI changes in rubber plantations from 2003 to 2012.

Figure 5.8 provides more information on when there was increase or decrease in vegetation cover within in rubber plantations. For example, Figure 5.7 showed that from 2006 and 2009, there was increased expansion of vegetation clearance. This was confirmed by high resolution of the Google Earth image in 2006 and original Landsat data in 2009. Additionally, Figure 5.8 suggested there was a noticeable drop in NDVI during 2006 and 2009.

5.4 Conclusions

The objective of this study was to demonstrate and evaluate a simple remote sensing approach with freely available Landsat ETM+ data to detect spatial changes in vegetation cover. We attempted to map expansion of rubber plantations and observe their temporal changes. We applied PCA transformation to pairs of Landsat images from 2003 to 2012. We also used annual averages of NDVI for observing historical temporal changes in rubber plantation areas. It was evident that PCA was useful in the analysis of forest cover change. This technique detected areas of vegetation cover change (both vegetation increase and loss) with high overall accuracy (87%). PC1 captures most of the variation in the data contrasting areas with the highest and lowest cover of vegetation. The most dense vegetation was found mostly within the national forest protected areas, whereas less vegetation appeared in agricultural and urban areas near the Mekong River. PC5 of each image pair demonstrates significant information that can be used to detect expansion of rubber plantations in our study area. Large areas of forests were cleared and then converted into rubber plantations. Overall, this study provides an example of the use of free Landsat ETM+ data and PCA to detect and map vegetation cover changes due to rubber plantations in the Lao PDR. This method should be transferable to other areas experiencing similar landscape change. However, the specific PC containing the temporal change component is expected to vary, and would need to be determined on a case-by-case basis.

5.5 Acknowledgements

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Chapter 6. Vegetation Cover Changes in Lao Tropical Forests: Physical and Socio-Economic Factors are the Most Important Drivers

Phompila, C., Lewis, M., Clarke, K., and Ostendorf, B. (2016). “Vegetation cover changes in Lao tropical forests: physical and socio-economic factors are the most important drivers”. *Forest Policy and Economics. (Under review)*

Abstract

Lao People’s Democratic Republic has been experiencing significant forest depletion since the 1980s, but there is little evidence to demonstrate the major causes and underlying drivers for the forest cover changes. In this study, we investigated the relationship between vegetation decrease and increase in the south of Lao PDR between 2006 and 2012 and selected physical and socio-economic factors. We used a map of the vegetation cover changes derived from analysis of Landsat ETM+ imagery in 2006 and 2012, together with socio-economic and physical data from the national authorities. The study area has experienced noticeable forest cover changes: both forest decreases and increases were unevenly distributed throughout the region. Logistic regression models were used to test relationships between vegetation cover decrease or increase and selected socio-economic factors. Forest clearance was associated strongly with elevation, distance to main roads and shifting cultivation practices. Meanwhile, vegetation increase was more likely to correlate with rubber plantations. Native forest and shifting cultivation lands were vulnerable to being converted into rubber plantations. This research can provide key information on which to base forestry policy and decision making to minimize and prevent current deforestation, as well as manage potential risks in the future.

Keywords: Lao tropical deforestation, vegetation cover change, Landsat ETM+, associated factors, driving forces, logistic regression analysis.

6.1 Introduction

Lao PDR used to be one of the countries with the richest biodiversity in Southeast Asia. However the country has undergone profound forest and land cover changes over the last few decades. Deforestation has been become a crucial issue in the country. The deforestation rate has increased alarmingly since the 1980s (Robichaud et al. 2009). Forests covered nearly 50% of the country in 1982, but dropped to 41% in 2002, before gradually decreasing to 40% of the total land area by 2010 (Department of Forestry 2011; Vongsiharath 2008). This 40% of forest cover can be mixed with secondary forests, plantations and bamboo, as indicated by a rapid assessment in 2010 (Forest Carbon Partnership Facility 2014), and the share of primary forest within this estimation is unclear. To address this forest decline, the government of Laos has set an ambitious target to increase forest cover up to 70% by 2020 through afforestation, reforestation and stabilization of shifting cultivation (Ministry of Agriculture and Forestry 2005). Meanwhile, foreign direct investment in forestry and agriculture, along with land leases and concessions, has been promoted (The National Land Management Authority 2004). Despite this, the country has recently been experiencing forest and land use transformation to plantations, resulting in controversies about the decrease in the area of native forests. Phimmavong et al. (2009) suggested that between 1990 and 2007 the area of plantations, especially rubber plantations, increased dramatically from 1,000 ha to over 200,000 ha. In addition, shifting cultivation practices, or mountainous agriculture, are considered as a critical environmental issue for forest resources. Approximately 6.5 million ha of forest areas were replaced by shifting cultivation during the 1990s (Messerli et al. 2009; Sovu et al. 2009).

There is growing concern over the depletion of the area of tropical forests in Laos. Its forests have been declining at an alarming rate, although the causes or factors associated with this depletion are poorly understood and the responses of tropical forests to environmental changes remain unknown. Both socio-economic and physical factors have important influences on forest depletion. Lao PDR has made rapid progress in its national socio-economic development (Organisation for Economic Cooperation and Development 2013; Asian Development Bank 2015); however, much remains unclear in regard to the relationship between this development and forest cover changes in the country. This has increased the nation's efforts to explain the causes of deforestation and conversion of forests to other land uses.

Understanding these spatial relationships and complexities can offer insight into the effective maintenance of forest resources. Identifying driving forces for forest cover changes is essential, as this would allow policy and decision makers to understand ongoing land use management and forest cover change processes and their effects on the country as a whole (Meyfroidt et al. 2013; Vu et al. 2014b). This research will provide key information on which to base forestry policy and decision making to minimize and prevent deforestation, as well as manage potential risks in the future. Vu et al. (2014a) suggested that understanding the links between socio-economic and physical factors and forest cover changes at a national level is important for cause-targeted strategies when planning policies for combating deforestation. However, these still remain poorly investigated in the Lao context.

Worldwide, several studies have been undertaken to identify the drivers or associated factors of forest cover changes (Casse et al. 2004; Bhattarai et al. 2009; Pineda Jaimes et al. 2010; Ryan et al. 2014; Scullion et al. 2014; Vu et al. 2014b; Webb et al. 2014), and are useful in developing predictive deforestation models and suggesting implications for national forest and land management policy. The key factors in changes in vegetation cover are often physical factors, such as elevation and slope, as illustrated by studies by Mon et al. (2012) and Bhattarai et al. (2009). In addition, socio-economic factors at local and national levels also can also influence patterns of tropical deforestation. For example, it was found that deforestation in China was associated with rivers and roads (Gao and Liu 2012) and with village locations (Mon et al. 2012; Du et al. 2014).

In Lao PDR, as in many developing countries, identifying and understanding the primary causes of these changes remains challenging. There is little evidence to understand the causes and underlying drivers of forest cover changes. Detailed and in-depth study is still limited and the issue needs to be investigated urgently. Therefore, the primary objective of this research was to investigate the relationship between the changes in the spatial patterns of forest cover and physical and socio-economic factors that have taken place in the south of the Lao PDR. This study can be useful for providing research-based indicators of appropriate actions and future management for Lao PDR's forest resources. This study is an important step in understanding the relationship between socio-economic and physical characteristics and forest cover changes, particularly in Laos, and to illustrate the complex interaction between the human and natural environments at national level.

6.2 Study site

The study region is located in the south of Lao PDR, covering large areas of three provinces: Savannakhet, Salavan and Champasak (Figure 6.1). The area is approximately 23,500 km2, including parts of the Annamite mountains (known as Xai Phou Luang) and borders Vietnam in the east. The altitude within the area ranges from 20-1700 m above sea level, with an average elevation of 300 m.

The biggest river in the area is the Mekong River. It serves as a significant transport channel and essential food source for the Lao people. In addition, there are several other important rivers in this region including Xe Bang Fai, Xe Nou and Xe Bang Hieng in Savannakhet territory. The Se Don River flows through the Salavan province and eventually joins the Mekong River at Pakse, Champasak province.

The main road is Route No. 13, which connects the north to the south. There are also four important roads, including Routes 9, 15, 16 and 20, which cross the region from west to east. These connect within the provinces, and extend to the Vietnam border. A large population is settled closely along the roads. There are a total of 1363 villages within the study area.

The study area covers four national protected areas (NPAs): Dong Phou Vieng, Xe Bang Nuan (located in Savannakhet and straddling the border with Salavan Province), Phou Xieng Thong (located between Salavan and Champasak), and Dong Houa Sao (situated in Champasak). These NPAs are rich in forest and wildlife species. The forests located in these areas are evergreen, dry dipterocarp and mixed deciduous and are important natural habitats for wildlife. However, a majority of forest areas has been the target of heavy logging since the 1980s.

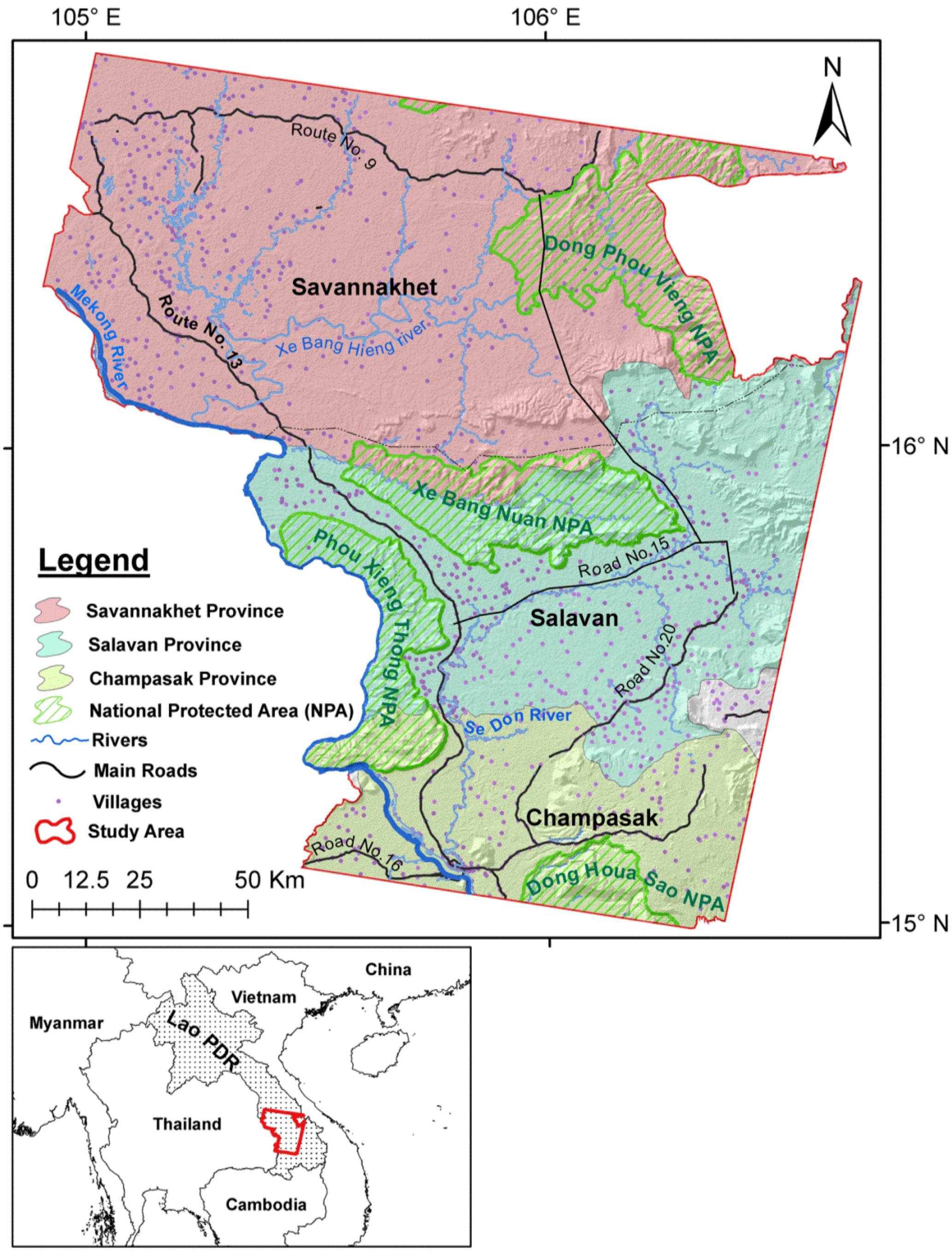

Figure 6.1. The location of the study area in the south of Lao PDR, showing provincial boundaries, national protected areas, rivers, roads and village locations.

6.3 Data and methods

6.3.1 Vegetation cover change between 2006 and 2012

We used a map of vegetation cover changes between 2006 and 2012 presented in Phompila et al. (2014). This vegetation cover change map covered approximately 23,500 Km^2 across 24 districts of three provinces: Savannakhet, Salavan and Champasak. The map was derived from Landsat ETM+ images in 2006 and 2012 using Principal Component Analysis (PCA) and was evaluated using high-resolution Google Earth™ images from the same years. The map identified areas of vegetation decrease and increase as well as areas where vegetation cover appeared unchanged. The overall accuracy of this map was 87%, Kappa = 0.8 (Phompila et al. 2014). The accuracy was evaluated by high resolution images (2006 and 2012) from Google Earth using 1,240 random samples over 2,500 km^2. The details of this accuracy assessment are shown in Table 5-1 in Chapter 5.

The map was classified into three vegetation types: vegetation increase, vegetation stable and vegetation decrease. Their definitions are: (1) 'vegetation increase' refers to areas that show an increase in vegetation cover such as a transition from mixed wooded/cleared areas or from bare land to plantation or to native forests, or agricultural areas transformed to plantation; (2) 'vegetation stable' defines areas that appear to exhibit little or no change between two periods (2006 and 2012); and (3) 'vegetation decrease' means areas which experienced the clearance or loss of vegetation, i.e., a transition of primary forest to plantation, mixed wooded/cleared areas or agricultural land. Any indication of loss of vegetation cover was assigned in this class, including transition from plantation to agriculture and from mixed wooded/cleared areas to agriculture.

6.3.1.1 Physical and socio-economic factors

Given the availability of data in our study area, we investigated a total of eight physical and socio-economic variables, as shown in Table 6-1. Information on elevation and slope can provide an indication of access to forest and land use. Vu et al. (2014a) suggested that forest areas located on steep slopes or high elevations can create difficulties in access for people utilizing forest resources or transforming land into agricultural areas. Thus, we investigated whether elevation and slope influence population pressure on the forest.

Another key element to facilitate access to the forest resources is improved infrastructure development, such as road networks and river routes. Many studies have found that these factors can increase pressure on forest and land use (Gao and

Liu 2012; Du et al. 2014). Therefore, we examined whether distances from main roads and rivers influence vegetation cover changes.

Protected areas are rich in biodiversity. We assumed that the abandonment of forest resources without a strong protection mechanism could increase the risk of illegal forest timber exploitation. It is essential to examine whether this is a factor associated with deforestation. The location of villages is also important for assessing how people achieve access to forest resources (Bhattarai et al. 2009; Mon et al. 2012; Getahun et al. 2013; Du et al. 2014). Closer distances to the forest resources may increase the rate of deforestation. Thus, we hypothesized that the village locations would have some degree of correlation with a decrease in vegetation cover.

6.3.1.2 Elevation and slope

Elevation data was obtained from the Global Digital Elevation Model (GDEM), derived from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images. This data is under the administration of the Ministry of Economy, Trade, and Industry (METI) Earth Remote Sensing Data Analysis Center (ERSDAC) in Japan and the National Aeronautics and Space Administration (NASA) in America. The data was downloaded from the NASA site in a Geo-referenced Tagged Image File Format (GeoTIFF) (http://earthexplorer.usgs.gov/). The data comes with the 1984 World Geodetic System (WGS84)/1996 Earth Gravitational Model (EGM96) projection. Slope data was generated from this GDEM data using the Spatial Analyst tool in ArcGIS 10.2 software.

6.3.1.3 Distance to main roads, rivers, protected areas and villages

The road and river data was collected from the Research Division, Faculty of Forestry Sciences (FFS), at the National University of Laos. The locations of villages were derived from population census data, distributed by the Lao National Statistic Centre. The population survey was conducted in 2011/2012 by the Department of Forestry (DOF), Ministry of Agriculture and Forestry. Villages were categorized into three groups: villages without rubber plantations or shifting cultivation, villages with rubber plantations and villages with shifting cultivation. A protected area map was also obtained from the DOF. The distances of vegetation increase and decrease to main roads, rivers, protected areas and villages were extracted using the "Near" tool in ArcGIS10.2 from four different GIS layers derived from this data: main roads, rivers, protected areas and village locations. The WGS84, UTM zone 48 North projection was used for these GIS layers.

Table 6-2. A summary of the spatial data used to produce variables for our logistic regression models of factors associated with vegetation increase and decrease in the south of Lao PDR.

Data	Source	Unit
Dependent Variables		
Vegetation increase from 2006 to 2012	Landsat ETM+ (Phompila et al., 2014)	Categorical data (Yes=1 , No=0)
Vegetation decrease from 2006 to 2012	Landsat ETM+ (Phompila et al., 2014)	Categorical data (Yes=1 , No=0)
Independent Variables		
Elevation	NASA	m
Slope	NASA	%
Distance to main roads	FFS	km
Distance to rivers	FFS	km
Distance to villages without rubber plantations or shifting cultivation	NSC	km
Distance to villages with rubber plantations	NSC	km
Distance to villages with shifting cultivation	NSC	km
Distance to protected areas	DOF	km

Sources: NASA = National Aeronautics and Space Administration, NGD= National Geographic Department, NSC=National Statistic Centre, DOF= Department of Forestry, FFS=Faculty of Forestry Sciences

6.3.2 Sampling procedure

We established a random sampling system within the study area using the Random Point tools in ArcGIS 10.2.1, producing a total of 5,000 sample points. To ensure the spatial distribution of samples and minimize the effects of spatial autocorrelation, each sample point was at least 1 km from another. This is similar to the method of avoiding spatial autocorrelation performed by Linkie et al. (2004), Mon et al. (2012) and Vu et al. (2014a). Ultimately 4998 sample points were used due to missing values from the elevation dataset. The attributes of both dependent and independent variables were extracted for each random sample and then analyzed using R scripts and packages in RStudio software.

6.3.3 Data analysis

6.3.3.1 Data transformation

The normal distribution of data is important as the logistic regression model assumes that the variables are normally distributed. Therefore, before we applied the logistic regression analysis, we tested for normality of our sampling data. Variable data was transformed by log10. and then tested for normality through a Chi-squared test using the chisq.test () function in R.

6.3.3.2 Examining collinearity of variables

Several studies suggest that strong collinearity between the independent variables creates a problem when applying a logistic regression model. Midi et al. (2010) suggested that the existence of collinearity inflates the variances of the parameter estimates, and consequently suggests incorrect inferences about relationships between explanatory and response variables. Thus, the collinearity between each independent variable was tested by using Pearson's correlation coefficients using the cor() function in the R software.

6.3.3.3 Logistic regression model

We applied logistic regression models to investigate the relationship between vegetation cover change and the chosen physical and socio-economic factors. Logistic regression allowed us to evaluate the odds (or probability) of membership in one of the groups, based on the combination of the independent variables.

Vegetation increase and decrease between 2006 and 2012 was used as two binary dependent variables, each expressed as two categories: change and no change. We used two separate regression models because we expected different factors contributing to forest clearance or abundance. A total of seven socio-economic variables were used in the analysis including elevation, slope, distance to main roads, distance to rivers, distance to villages without rubber plantations or shifting cultivation, distance to villages with rubber plantations and distance to villages with shifting cultivation. The distance to protected areas variable was excluded due to its non-normal distribution. We noted if there were any outliers in our data using Cook's Distance in R, because outliers can create statistical problems in logistic regression models (Mon et al. 2012). No outliers existed in our data. We examined the levels of statistical confidence in each independent variable in the results. We also used the receiver operating characteristic (ROC) statistics and the Hosmer and Lemeshow test to measure the goodness-of-fit of the logistic regression model, as suggested by recent experts Mon et al. (2012) and Vu et al. (2014a). The ROC curve is constructed by plotting the true positive rate against the false positive rate that is accumulated by the frequencies across a rank ordering. It is shown in the ROC graphical plot, as a value closes to 1 indicates a better fit of a model. In the Hosmer and Lemeshow test, if the p-value of the test is high ($p > 0.05$), it may simply be a consequence of the test having lower power to detect mis-specification. This is indicative of poor fit. Our analysis was conducted using statistical analysis in R software.

6.4 Results

6.4.1 Distribution of changes in vegetation cover between 2006 and 2012

Figure 6.2 is a map from the previous study by Phompila et al. (2014) that shows vegetation cover changes between 2006 and 2012 within the study area. Overall, it appears that a large proportion of the vegetation areas remained stable between 2006 and 2012 (94.6%). However, forest cover in the study area decreased by 2.8% and increased by 2.6%. Vegetation increase is found in all three provinces: Savanakhet, Salavan and Champasak. Noticeable areas of increase are located in Phin, Sepon, Thapanthong and Bachiangchaleunsouk districts. This increase is close to the national protected areas (NPA): Dong Houa Soa and inside the Dong Phou Vieng and Xe Bang Nouan NPA. There are about 37 villages located inside the NPAs that contributed to the increase in forest cover, including 21 shifting cultivation villages. A majority of shifting cultivation areas in these two NPAs was transformed to rubber plantations, resulting increase in forest cover.

However, vegetation decrease is notable in Champasak and Savanakhet provinces. The areas of most significant decrease appear in LaoNgam district, Salavan province and Bachiangchaleunsouk, and Pakxong district near Pakse city centre and the north of Champasak province, as well as in Champhon and Xonbouli district, Savanakhet province.

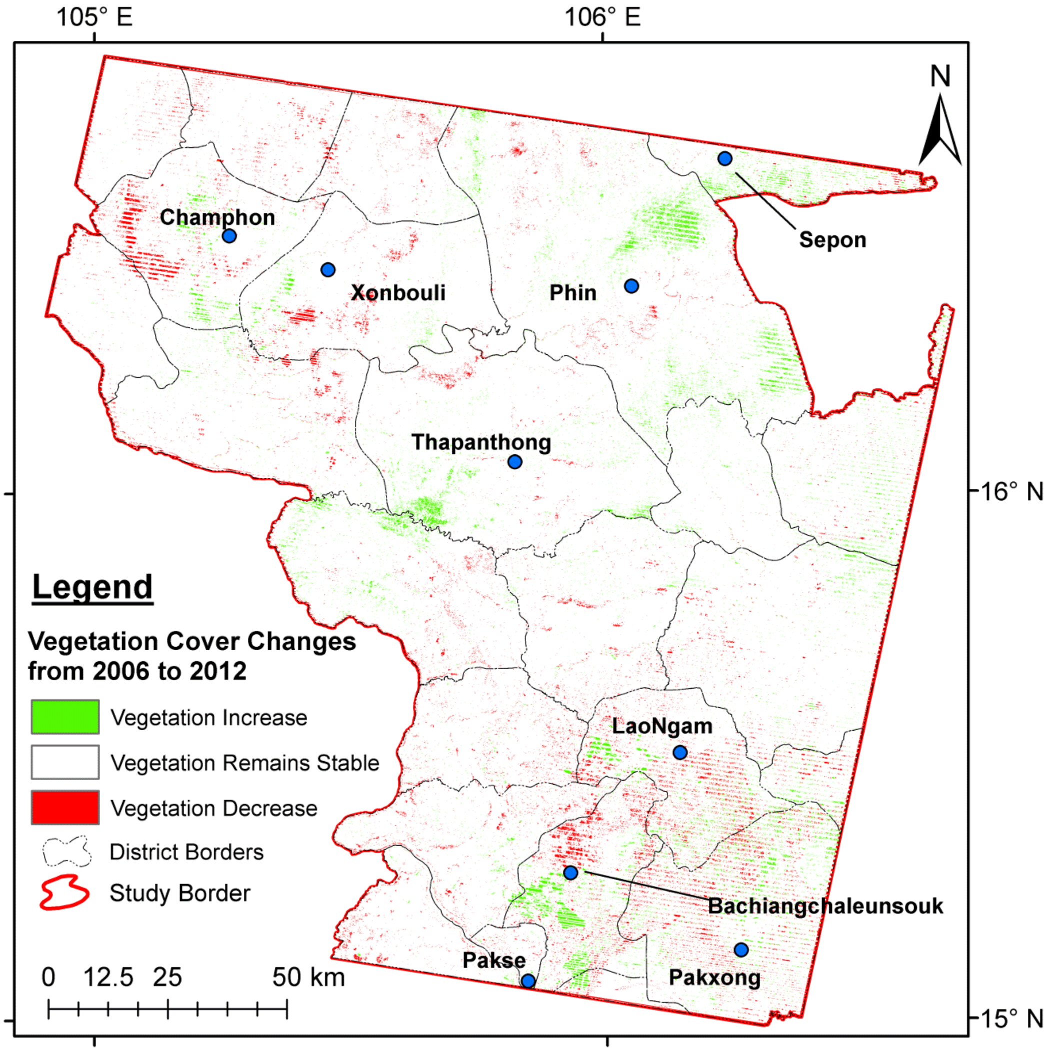

Figure 6.2. Vegetation cover changes from 2006 to 2012 derived from Landsat ETM+ images and evaluated by high-resolution Google Earth TM images: white indicates no change, red indicates vegetation decrease and green indicates vegetation increase (Phompila et al. 2014; Phompila et al. 2015). *Vegetation remains stable* are areas that appear to exhibit little or no change between the images; *vegetation increase* indicates areas that shows an increase in vegetation cover such as the transition from mixed wooded/cleared areas or bare land to plantation; *vegetation decrease* indicates the clearance or loss of vegetation, i.e., the transition of native forest to mixed wooded/cleared areas, shifting cultivation areas, or agricultural land.

Using high resolution Google images in 2006 and 2012, we found that vegetation increase appears to have resulted largely from the establishment of plantations, especially rubber: rubber plantations were recognized by their regular tree canopy patterns and spacing. Forest removal occurred around 2006 and was replaced by rubber and regrowth later (Figure 6.3a, 3b, 3c and 3d). Meanwhile, vegetation decrease was likely to have been derived from forest transformation into shifting cultivation lands or to rubber plantations

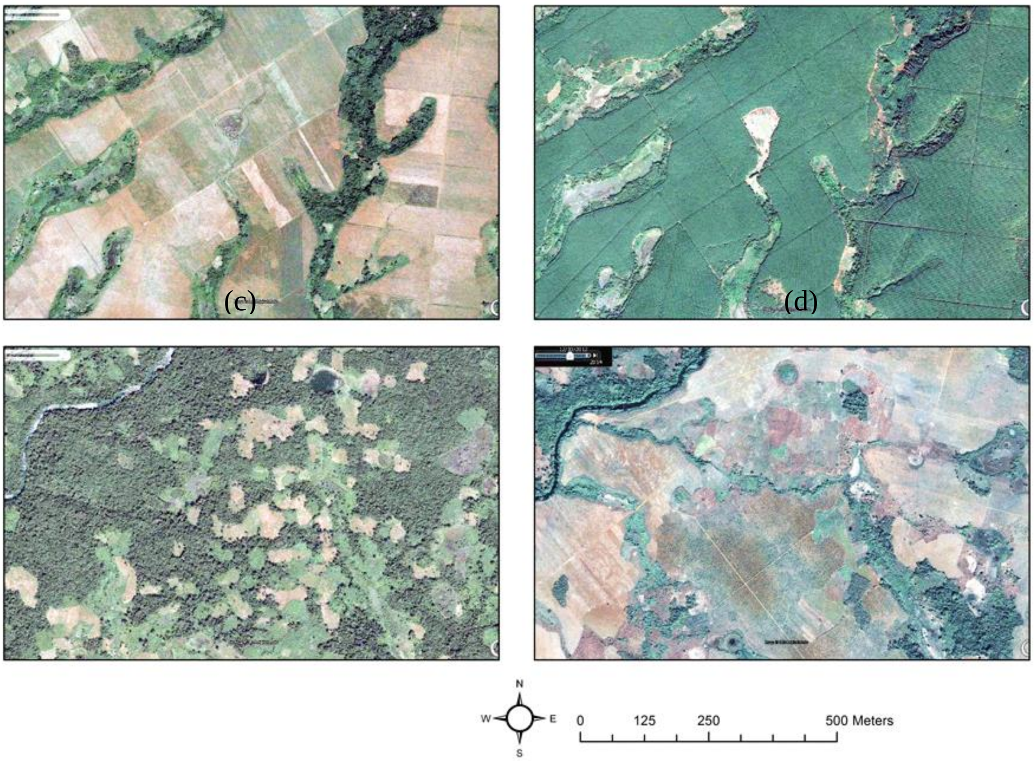

Figure 6.3. Google[TM] Images showing vegetation cover changes from 2006 to 2012 in two locations: (a) land preparation in 2006, (b) full canopy of rubber plantations in 2012, (c) forest and shifting cultivation areas in 2006, and (d) massive forest and land clearances apparent in 2012.

6.4.2 Collinearity of independent variables

The existence of collinearity in independent variables can cause unstable estimates and inaccurate variances which affect the confidence intervals and hypothesis tests in statistical models (Hosmer and Lemeshow 2000; Midi et al. 2010; Mon et al. 2012; Vu et al. 2014a). It has been suggested that the level of collinearity of the independent variables must be below an acceptable threshold of

0.7 (Mon et al. 2012; Vu et al. 2014a). Results of the simple procedure of examining paired independent variable correlation values are shown in Table 6-2.

In our case, none of our independent or explanatory variables exceeded this collinearity level. Only three pairs of variables showed a moderate degree of collinearity: elevation and distances to villages without rubber plantations or shifting cultivation ($r = 0.41$), distance to main roads and distance to villages with shifting cultivation ($r = 0.40$), and elevation and distance to rivers ($r = 0.32$). Thus, all the variables were considered to be acceptable for use in the logistic regression analysis.

Table 6-3. Collinearity of the seven predicted variables used in the logistic regression analyses.

Elevation						
0.24	*Slope*					
0.14	0.09	*Distance to main roads*				
0.32	0.07	-0.03	*Distance to rivers*			
0.41	0.17	0.21	0.20	*Distance to villages without rubber plantations or shifting cultivation*		
-0.09	0.02	0.15	0.00	-0.04	*Distance to villages with rubber plantations*	
0.08	0.04	**0.40**	-0.09	0.11	0.11	*Distance to villages with shifting cultivation*

**The bold figures in the table indicate the highest collinearity found among seven predicted variables*

6.4.3 Factors associated with vegetation cover changes

Table 6-3 shows the result of a logistic regression used to investigate the probability of vegetation decrease between 2006 and 2012 and its correlation with the seven variables.

Three physical and socio-economic variables have significant effects on the spatial extent of vegetation cover decrease, including elevation, distance to main roads, and distance to villages with shifting cultivation. These were the most important predictors of vegetation decrease in the periods 2006 and 2012. The logistic regression model showed that elevation was significantly correlated with the likelihood of vegetation decrease in the study area ($p < 0.01$; and highest Wald value, Table 6-3). This positive correlation revealed that land at higher elevations was more likely to decrease in vegetation cover, especially in the south of the study area. The vegetation decrease was found to correlate negatively with distances to main roads ($p < 0.05$): there was more disturbance to native forests closer to roads. In addition, the distances to villages with shifting cultivation was the third strongest influential factor for forest depletion ($p < 0.05$). Forests located at a closer distance to these villages were more likely to be disturbed. However, other variables were not significant in the logistic regression analysis, including slope, distance to rivers, distance to villages without rubber plantations or shifting cultivation, and distance to villages with rubber plantations.

Both the Hosmer and Lemeshow and ROC tests indicate the results of the model are acceptable. The goodness-of-fit test statistics are acceptable, according to the criteria of Mon et al. (2012) and Vu et al. (2014a), whilst the Hosmer and Lemeshow test provides a non–significant value (p = 0.589). The area under the ROC curve (theoretically ranging from 0.5 to 1.0) was used as the basis for evaluating the model's performance (Vu et al. 2014a). In our case, the area values of 0.848 (p > 0.001) demonstrate excellent performance.

Table 6-4 shows the results of a logistic regression used to investigate the correlation of vegetation increase between 2006 and 2012 with the seven variables. The logistic regression model indicated that the probability of forest cover increase in the study area from 2006 to 2012 was significantly correlated to distances to villages with rubber plantations and distances to villages with shifting cultivation variables used in the regression model ($p < 0.05$ *and* $p < 0.1$ respectively; Table 6-4). We found that these variables were negatively associated with an increase in vegetation cover. A closer distance to these villages was related to a greater increase in vegetation cover. However, in our analysis, the following factors were not significantly associated with vegetation increase: elevation ($p = 0.369$), slope ($p = 0.929$), distance to main roads ($p = 0.369$), distance to rivers ($p = 0.929$), and distance to villages without rubber plantations or shifting cultivation ($p = 0.929$).

The Wald statistics also indicated that distances to villages with rubber plantations was the most important variable (highest negative value) for forest increase in the study area during 2006-2012, followed by distances to villages with shifting cultivation. Similar to the logistic regression model for deforestation, the value of the Hosmer and Lemeshow test (*P = 0.50*) and Area under ROC = 0.817 (*p < 0.001*) indicated that the model fit was acceptable.

Table 6-4.Results of regression analyses for identifying associated factors of vegetation decrease between 2006 and 2012 in our study area.

Variables	**B**	**S.E**	**Z-value**	**p-Value**	
Elevation	3.578	0.917	3.903	0.000	***
Slope	-2.209	1.954	-1.130	0.258	
Distance to main roads	-0.781	0.374	-2.086	0.037	**
Distance to rivers	-0.623	0.432	-1.443	0.149	
Distance to villages without rubber plantations or shifting cultivation	0.142	0.671	0.212	0.833	
Distance to villages with shifting cultivation	-1.030	0.519	-1.987	0.047	**
Distance to villages with rubber plantations	0.216	0.501	0.431	0.667	
(Intercept)	-4.265	3.824	-1.115	0.265	

Null deviance= 260.76 on 4997 degrees of freedom
Residual deviance=223.71 on 4990 degrees of freedom
AIC= 239.71
n = 4998; B= coefficient; S.E.=standard error; Z-value= Wald z-statistic
Nagelkerke $r^2 = 0.15$
Hosmer and Lemeshow test= X-squared = 6.5256, df = 8, p-value = 0.589
Area under ROC = 0.848 ($p < 0.001$)

Note: * Statistical significance at 90% ($p < 0.1$).
** Statistical significance at 95% ($p < 0.05$).
*** Statistical significance at 99% ($p < 0.01$).

Table 6-5.Results of regression analyses for identifying associated factors of vegetation increase between 2006 and 2012 in our study area.

Variables	B	S.E	Z-value	p-Value	
Elevation	-0.820	0.915	-0.896	0.370	
Slope	-0.161	1.950	-0.082	0.934	
Distance to main roads	-0.051	0.427	-0.119	0.905	
Distance to rivers	0.670	0.521	1.285	0.199	
Distance to villages without rubber plantations or shifting cultivation	1.055	0.708	1.491	0.136	
Distance to villages with shifting cultivation	-0.905	0.502	-1.802	0.072	*
Distance to villages with rubber plantations	-1.512	0.487	-3.104	0.002	**
(Intercept)	0.025	3.595	0.007	0.995	

Null deviance= 293.43 on 4997 degrees of freedom
Residual deviance=262.98 on 4990 degrees of freedom
AIC= 278.98
n = 4998; B= coefficient; S.E.=standard error; Z-value= Wald z-statistic
Nagelkerke $r^2 = 0.11$
Hosmer and Lemeshow test= X-squared = 7.3362, df = 8, p-value = 0.5008
Area under ROC = 0.817 ($p < 0.001$)

Note: * Statistical significance at 90% ($p < 0.1$).
** Statistical significance at 95% ($p < 0.05$).
*** Statistical significance at 99% ($p < 0.01$).

6.5 Discussion

The results indicate that the areas of decreased vegetation were associated with higher elevations, shifting cultivation and main roads within our study area. The flat areas had less deforestation whilst high elevation areas were more likely to suffer higher deforestation. Although there are a greater number of human settlements on the lower land when compared with those on high elevation mountainous areas, the impact of human activities was mainly found in high elevation areas. This finding differs from a number of studies, which suggest that the likelihood of vegetation decrease is greater at a low elevation (Fox et al. 2000; Mas et al. 2004; Gao and Liu 2012; Mon et al. 2012). In those cases, expansion of the cultivated land was associated with the distance to towns in low elevation areas which provide better accessibility and ease of access to markets. Our analysis suggests that forest clearance in mountainous areas in southern Lao PDR was associated with shifting cultivation. The majority of shifting cultivation land is located in mountainous areas, whereas permanent agricultural lands are largely found in lowland areas. In these areas, infrastructure is better developed and little forest remains to be cleared. Slash-and-burn agriculture or shifting cultivations are widely practiced and important food production systems for the minority ethnic groups in Laos (Shi 2008; Sovu et al. 2009; Inoue et al. 2010). Shifting cultivators rely completely on the availability of the upper farming land and forests for their income and self-subsistence due to their poverty. Thus, we infer that population increases can simultaneously lead to an increase in forest and land use, which in turn leads to expansion in forest clearance. The shifting cultivation practice is recognized as a serious threat to biodiversity (Geist and Lambin 2002; Rasul and Thapa 2003; Li et al. 2014).

Our study suggests that roads are also a very important factor associated with vegetation decrease during 2006-2012 in the southern part of Laos. The area of greatest deforestation is found where the land is easily accessible with good road systems nearby. Logging activities frequently happen when markets and timber saw factories are easily accessible. The improved road networks create greater ease for travel: this can lead to a relative increase in the transportation of timber. As a result, forests located at close distances to roads are more likely to be disturbed. This was similar to several studies which report that deforestation has a link with distance to roads (Ali et al. 2005; Etter et al. 2006; Bhattarai et al. 2009; Gao and Liu 2012; Du et al. 2014). However, other studies suggest that there is no link between deforestation and ease of road access (Deng et al. 2011).

Our results also reveal that distances to villages with rubber plantations are an important factor related to an increase in vegetation cover. We assume that most of the vegetation increase is a result of the establishment of rubber plantations in these villages. In recent decades, investment in rubber plantations had been promoted by the Lao Government, which aims to stimulate greater foreign investment in the country in order to reduce poverty, while managing natural forest resources and land use (Shi 2008; Phimmavong et al. 2009). However, this can potentially increase rates of forest and land use change, due to massive land preparation and clearance, when governance is ineffective and monitoring systems are insufficient. There are a number of concerns related to rubber investment promotions, including the destabilization of rubber prices in the international market, and environmental issues due to large areas of natural forest being converted to rubber plantations, which leads to a loss of biodiversity and wildlife displacement (Sirirak Ara Trakorn et al. 2006; Beukema et al. 2007; Yi et al. 2014). Furthermore, another factor associated with vegetation increase was distance to villages with shifting cultivation areas. There are two potential hypotheses for this: firstly, it was assumed that after a harvest, the cultivated area would be left untouched, which would create an opportunity for vegetation recovery. Secondly, shifting cultivation areas in these villages were converted into rubber plantations due to high demand for rubber products in this region.

6.6 Conclusions

In this research, we investigated the relationship between the physical and socio-economic factors in terms of vegetation decrease and increase from 2006 to 2012 in the south of Lao PDR. We used vegetation cover change maps derived Landsat ETM+ imagery, together with physical and social-economic data from the Lao Government, in a logistic regression model. There are noticeable changes in forest cover within the study area, with regional and local patterns of vegetation decrease and increase. Key findings in this research showed that vegetation decrease was associated with both physical and socio-economic components, including elevation, access to roads and shifting cultivation practices. Meanwhile, vegetation increase was more likely to be linked with rubber plantation investments in the southern region. Native forest and shifting cultivation lands were vulnerable to transformation into rubber plantations when rubber prices were booming. The goals of poverty alleviation and eradication of shifting cultivation through foreign investments requires more attention in order to reduce potential pressures on forest and land use. Our study should be useful for obtaining a greater understanding of socio-economic and physical drivers of forest cover change at a local level. This should also be helpful in ensuring the effectiveness of the land management policies being implemented on uplands, especially where such policies are created in response to the natural and socio-economic conditions of this region.

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6.7.1 Conflicts of Interest

The authors declare no conflict of interest.

Chapter 7. Conclusions and Recommendations

7.1 Introduction

Native forests around the globe are under imminent threat from deforestation, especially in developing countries in tropical regions. There are many forms of tropical deforestation such as slash-and-burn for agriculture, infrastructure and industrial development, urbanization and unsustainable timber extraction. The changes in forest cover have adverse effects on a range of Earth's ecosystems, including global climate change. Appropriate monitoring approaches and tools are urgently required to gain a better understanding of the characteristics and responses of tropical vegetation and to detect these changes at a range of geographic scales in order to achieve positive and effective management of forest resources.

Remote sensing technology has become an essential tool for understanding vegetation's characteristics and responses, along with reliable mapping and monitoring of forest cover changes at different scales. However, the range of limitations and challenges in tropical environments needing to be taken into account is broad. Factors such as atmospheric conditions and geographical constraints (e.g. cloud cover, haze and rough terrain) all impact significantly on applications of remote sensing. As a result, detailed spatiotemporal information on deforestation in developing countries is often unavailable or inconsistent, including for the Lao People's Democratic Republic (PDR). Therefore, improving appropriate remote sensing tools for this context is urgent and essential.

The overall goal of this study was to demonstrate and evaluate remote sensing methods for assessing and monitoring forest cover changes in tropical environments, particularly in the context of the Lao PDR. The objective of this research was to understand tropical vegetation phenology, which can be useful for detecting temporal changes in tropical forests, to explore and test selected parameters (LST and EVI) in a remote sensing approach that can be used to improve the classification accuracy of land covers in tropical environments, to test the use of time series data for detecting spatial and temporal changes in forest cover in tropical environments, to detect and map vegetation cover changes at a high resolution, and finally, to examine the spatial relationship between vegetation cover changes and associated physical and socio-economic factors. These objectives have been addressed in the papers and chapters that comprise this thesis. The key contributions of this research to mapping and monitoring forest cover changes in a tropical region are summarized below.

7.2 Key research contributions

7.2.1 New information on monitoring of forest phenology for different land covers, improving accuracy of land cover classification in a tropical region

The exploration and use of MODIS LST and EVI time series data has provided valuable understanding of the seasonal characteristics and temporal responses of tropical forests and land covers involved in deforestation and land-use conversion. The use of these indices to improve the classification accuracy of land cover in tropical environments was presented in "*MODIS EVI and LST Temporal Response for Discrimination of Tropical Land Covers*"; Chapter 2. This knowledge is essential for improving remote sensing approaches for land use inventory and detecting deforestation in tropical regions.

This study reveals the distinguishing characteristics and temporal responses of LST and EVI within and across tropical forests and three different types of land cover associated with deforestation and replacement land-uses. Each land cover shows distinctly different intra-annual LST and EVI variations. For example, native forests have the highest EVI, and the lowest LST throughout the year, as opposed to agriculture which has the lowest EVI and highest LST throughout the year. The monthly transition of LST/EVI for partially cleared forests, agricultural lands and rubber plantations demonstrated recognizable seasonality, while by contrast, LST/EVI of native forests varied little throughout the year.

The results show that, by using long-term means of these two indices, we can classify the four land covers with high overall accuracy (86%). EVI contributed the most to the discrimination of cover types, with LST made a much smaller contribution. When used in combination with LST, EVI provided detailed information on the characteristics and temporal responses of the four land covers. The outcomes of this study thus contribute to improving our understanding of tropical vegetation seasonal growth characteristics and responses to climatic conditions. This study is a pathfinder towards providing an improved option for detecting and monitoring land cover changes in tropical regions. It indicates that there is scope for use of these MODIS indices, EVI in particular, for broadscale mapping and inventory of land cover and land use in these environments.

7.2.2 A new application and evaluation of remote sensing approaches for monitoring of spatiotemporal changes in Lao tropical forests

Spatiotemporal information on the changes in tropical land cover is essential for monitoring the global terrestrial ecosystems for carbon, climate and biosphere exchanges, and land use management. Using the richness of time series data for monitoring this change has rarely been applied and evaluated in tropical environments. The demonstration and evaluation of a remote sensing model, the disturbance index (DI) was implemented in a Lao tropical forest and presented in "*Applying the Global Disturbance Index for Detecting Vegetation Changes in Lao Tropical Forests*"; Chapter 3.

In this chapter, MODIS EVI and LST time series data (from 2006–2012) were used to test whether this DI is useful for detecting spatial change in different land covers. Whereas the initial demonstration of DI averaged EVI and LST over two years to provide 'baseline' conditions against which changes in cover were detected (Mildrexler et al. 2007), I used seven years of MODIS data. This longer term incorporated more inter-annual variability in defining the characteristic EVI/LST signals, and hence provided a firmer basis for detecting significant changes. Areas of land cover change identified by the DI model were evaluated against high-resolution images from Google Earth™. It was found that the DI was capable of detecting spatial changes in vegetation cover with high overall accuracy (82%). However, it showed forest clearance was not well detected (about 42% accuracy). The areas of forest clearance within my study area are often small and fragmented, caused by shifting cultivation and small-scale agriculture, which may not be detected at the MODIS resolution (1km). This limitation in detecting localized forest harvesting was also noted by Coops et al. (2009) in an application of the DI across Canada. My study suggested that implementation of the DI model is straightforward and that it can be used for rapid assessment of broad-scale land cover changes in the tropics. However, it may not be suitable for detecting small or fragmented deforestation areas when high accuracy is required. A limitation of the model is the use of an annual maximum composite index for comparison with the longer-term mean (Mildrexler et al. 2007; Coops et al. 2009). This makes it sensitive to annual fluctuations or noise in the MODIS signal, and possibly unable to accommodate short-term intra-annual tropical forest changes, as noted by Coops et al. (2009).

Time series data from MODIS EVI alone was used to detect temporal changes in tropical land covers across the study area in southern Lao PDR. The paper titled "*Monitoring temporal vegetation changes in Lao tropical forests*" forms Chapter 4. Here the Breaks For Additive Season and Trend (BFAST) model was applied in a new context: tropical forest environments. It was found that the BFAST analysis of MODIS EVI is a promising tool for assessing tropical forest cover changes. Abrupt temporal changes in vegetation in the tropical forests were well captured; for example, the model indicates the time when large areas of mixed wooded or cleared areas were converted into plantations. This study is of practical use and contributes significantly to efforts in monitoring deforestation in Lao PDR, while the DI and BFAST models may also be more widely applicable in other tropical regions.

7.2.3 New, updated information on forest clearances in the south of Lao PDR

Three sets of Landsat data were used to detect forest cover changes within a 12,000 km^2 study area spanning two provinces in southern Lao PDR. The paper entitled *"Monitoring expansion of plantations in Lao tropical forests using Landsat time series*" was included in Chapter 5. Lao PDR has recently been experiencing forest and land use transformation to plantations and shifting cultivation, resulting in controversies about the decrease in the area of native forests. However, precise and up-to date information on the forest cover changes is unavailable in many parts of the country. This study provides new knowledge of vegetation cover and patterns, trends and rates of change, which is crucial for management purposes and can help to evaluate the success of forest and land use management. A standard remote sensing method, principal component analysis (PCA), provided good results in identifying areas of change during 2003-2006, 2006-2009 and 2009-2012.

Overall accuracy in mapping vegetation changes from 2006-2012 (the period for which independent validation data was available) was 87%. User's classification accuracy for areas of vegetation loss was 89%, while that for vegetation increase was 80%. The findings suggested that although a majority of forest areas remained stable over the study periods, some areas have experienced increases and decreases in vegetation covers. There was a decrease of approximately 90.1 km^2 of forest area, and 137.3 km^2 of vegetation cover increase from 2003 to 2012 in the 9,360 km^2 of the study area covered by non-missing data in the Landsat 7 scene. This area of vegetation increase largely resulted from new rubber plantations. To our knowledge, this was the first and the most recent objective documentation of forest cover change implemented at local level in Laos.

7.2.4 Improving understanding of underlying drivers of forest cover changes in the south of Lao PDR

The spatial relationships between local physical and socio-economic factors and forest cover changes were investigated within a 23,500 km^2 study area spanning three provinces in southern Laos. The paper entitled "*Vegetation cover changes in Lao tropical forests: physical and socio-economic factors are the most important drivers*" was included in Chapter 6.

The depletion of the area of tropical forests in Laos has been increasing significantly. However, the causes or factors associated with this depletion are poorly understood. The underlying drivers of changes have yet to be assessed, at both local and national levels. Thus, the causes and factors influencing deforestation and conversion of forests to other land uses require identification.

This chapter provides basic understandings of ongoing land use management and land cover change processes. The key result suggests that elevation, distance to main roads and shifting cultivation practices are the main factors associated with forest clearance in the study region. In contrast, rubber plantations are the major contributors to the increase in vegetation cover. Native forest and shifting cultivation areas were more likely to be converted into rubber plantations. This study provides key information for policy and decision makers to use in order to minimize deforestation and deal with potential risks to land covers. Additionally, understanding of the drivers of vegetation cover changes can also be useful for developing predictive deforestation models.

7.3 Recommendations for future applications and research

Changes in forest cover are a serious problem and growing concern in Lao PDR as well as throughout the global community. Appropriate tools are required to combat tropical deforestation, such as understanding forest characteristics and responses, approaches for mapping and monitoring the spatial and temporal changes in forest cover over time periods and at different scales (regional, national and local), and investigations of underlying causes or associated factors of the changes to create better management of the forest and land use, thereby preventing further deforestation. Such monitoring tools were evaluated and demonstrated in this thesis. The following are recommendations for future applications and development of this research.

This study has used MODIS EVI and LST data to improve our understandings of tropical forest seasonal growth characteristics and phenology phases of four different land use types: native forest, rubber plantation, mixed wooded/cleared areas and agriculture. This study and approach should be expanded to other land use types or sub-classes associated with tropical deforestation and land-use conversion, such as savanna, secondary forest, bamboo and built-up areas. This would provide more understanding of the remote sensing responses of a wider range of land use and land cover types associated with tropical regions undergoing deforestation and development. It is expected that these would also have characteristic EVI and LST seasonal signatures, because of differences in forest canopy or types, tree density, composition of species, and rock and soil background. Such a task was not implemented in this research due to the lack of reference data, and remains to be completed in the future. In addition, although the use of LST and EVI provided information on the characteristics and temporal responses of these land covers, a comparison of LST and EVI alone, or with other vegetation and land cover indices for monitoring of forest cover change in tropics requires further investigation.

This study showed that accurate classification of these four land cover types was possible using MODIS EVI and LST averaged over seven years. However, in an environment where land cover is changing rapidly, it would be desirable to use shorter time averages of these indices for classification and mapping. Consequently further research is needed to determine classification accuracies for discrimination of the land cover classes with other temporal samples of the MODIS data, for example annual means. In addition, use of the distinctive seasonal signatures for land cover classes may improve classification accuracies. Lack of time-specific ground reference data prevented these investigations in this research.

Applying MODIS time series data in the global disturbance index model has shown good results at continental scale (Mildrexler et al. 2007; Coops et al. 2009; Mildrexler et al. 2009). However, my study suggested that this model has low accuracy in predicting fragmented deforestation in tropical regions. While mean EVI with some contribution from LST was shown to be able to discriminate some of the predominant land covers in the southern Laos tropical forests (Chapter 2), the most effective use of these indices as time series data to detect deforestation in tropical forests requires further research. Thus, there is scope for further testing or modification of the model in tropical contexts.

In our research, applying the BFAST analysis was useful to detect rapid temporal changes in vegetation in the tropical forests. There was an abrupt change in time series signals when mixed wooded/cleared areas were largely converted into plantations. In our analysis, 250 random samples were averaged to represent each land cover, in order to encompass variations in land cover response. However, the approach may be applied to targeted study areas or single pixels to capture detailed changes in the time series for smaller or more specific geographic areas. This requires further investigation, and an automated interpretation approach needs to be developed for this task. Moreover, near-real time detection of significant deforestation and land use change using BFAST may be possible to implement in tropical regions, but will rely on adequate ancillary or supporting data, and remains to be conducted in the future. In addition, MODIS 16 day composite time series was used across the decade, although meteorological data at the same temporal resolution was not compared to this data. As a result, a comparison between trends and breaks of spectral response and rainfall and temperature time series was not fully investigated in my research, and requires future investigation.

In Chapter 5, the use of Landsat 7 data to detect changes in forest cover showed considerable success. The utilization of freely available of Landsat 7 data provided the data-rich satellite imagery for this research. However, there are some limitations, including cloud-free data availability and scan-line errors in the Landsat EMT+ sensor, and therefore the data has to be compiled along with that from other sensors such as Landsat 8 in order to complete the time series. The USGS provides freely available, calibrated Landsat 8 time series data. This will also enable the wider application of this approach. Recently, the first high-resolution global map of forest cover and its changes from 2000 to 2014 has been made freely available through the University of Maryland's webserver (Hansen et al. 2014). This is one step towards high-resolution monitoring of forest cover changes at global scale, which will benefit developing countries, including Laos. However, this product still needs to be evaluated for local contexts and integrated with national and local forest cover assessments or analysis. Comparison of this product with the forest mapping and change conducted in my research would be a valuable focus of future research.

An investigation of the spatial relationship between the changes in forest cover and physical and socio-economic factors was carried out locally in the south of the Lao PDR (Chapter 6). Our results provide better understandings of socio-economic and physical drivers of forest cover change at a local level, which is useful for policy makers to ensure the effective management of land use and forest resources. Expanding the social and environmental factors (e.g. income and timber species) included could improve the analysis and provide deeper understanding of factors driving forest clearance, but is dependent on availability of suitable data. Additionally, there is scope to apply this model in different geographic areas in Laos, which may provide insights into the underlying causes of deforestation in contrasting locations and populations. This is desirable for further research.

A limitation to my study was the availability of adequate reference data, especially recent and historical data from the Government of Laos. Adequate ground reference data is needed to validate the selected remote sensing approaches and any further application of them in this region. This drawback limited the extent of my study areas as well as the timing and duration of study periods. The approach adopted throughout this research was to use true colour satellite images from selected dates available through Google Earth. These very high resolution images allowed visual discrimination and digitizing of relevant land cover classes as a source of independent information to validate the other MODIS and Landsat derived maps of forest cover change. This source of information provided adequate details of land cover to achieve this purpose, although it limited the location and size of study areas. As more such high resolution, free satellite imagery becomes available, there will be scope to use it for wider validation of broad scale remote sensing products.

At present, producing up to date, reliable data on land use and ground cover is becoming more feasible due to developing technologies such as unmanned aerial vehicles (UAV). UAV mapping techniques have been applied recently in many aspects of conservation and mapping projects in tropical and other regions (Koh and Wich 2012; Anderson and Gaston 2013; Dandois et al. 2015). Although UAVs can only cover relatively small areas, they may be useful to capture high resolution, cloud free observations of current field conditions, for inaccessible areas or areas where there is an absence of reference data. Such technology may provide detailed spatiotemporal information on the characteristics of vegetation and quantify vegetation conditions at finer scales. This approach shows promise for further research and experiment in the future.

Satellite radar data such as ALOS PALSAR are now freely available. This may be integrated with Landsat images to overcome cloud cover problems in tropical environments, and requires further evaluation. In addition, a recent remote sensing technique, called “CLASlite” has been demonstrated as a successful model for estimating deforestation from 2000 to 2011 in Amazon forests, Peru (Asner et al. 2009). This model is in an initial stage of development for tropical forests, thus it is still required further investigation and a comparison to my results.

Finally, given the state of depletion of forest cover in Lao PDR, improved spatial and temporal mapping and monitoring of changes is urgently required. However, there are still several challenges for the country to overcome. These include the limited national experience in assessment of vegetation conditions and low existing capabilities to detect forest cover changes. Availability of cloud free remote sensing data is limited and reference data is out of date or non-existent for most of the country. To overcome these challenges, improving capacities of national institutions and organizations, and collecting and further developing existing data are necessary. It is essential to strengthen better coordination among them to engage their monitoring activities to avoid any duplication, and to share and develop existing ecological data. This data sharing can be done through internet platforms, such as open access datasets which is important and require development. Effective development of these pathways will be keys to improve mapping and monitoring of forest resources in Lao PDR.

7.4 Conclusions

This research thesis contributes to the development and evaluation of remote sensing methods that can be used for assessing and monitoring forest cover changes in tropical forests. This task was carried out specifically in the context of the Lao People's Democratic Republic (PDR). One of the major challenges of applying remote sensing in Lao tropical forests is cloud cover. While microwave remote sensing has the advantage to overcome this issue due to its capability to penetrate the atmosphere in any conditions, optical satellite images were chosen for this research because of the suitability of their spatial, spectral and temporal resolutions and availability of data for the relevant time periods.

Understanding of tropical forest characteristics and phenology was an essential first step for this research. This is an important pathway for the use of remote sensing to identify and track changes in forest cover. Applications and evaluation of the global disturbance index and the BFAST models for detecting spatial and temporal changes in Lao tropical forests are considerable achievements in the thesis. The former model may be suitable for wide application of regional and/or national monitoring of land cover, whereas the latter model can be applied either locally or nationally. The DI uses the resolution of 1 km of MODIS LST and EVI, while the BFAST uses the higher resolution (250m) of MODIS EVI alone. The BFAST may be suitable for small targeted or specific geographic areas. Moreover, free Landsat data and a standard image analysis approach (PCA) were applied to capture detailed changes at a local scale. This technique detected areas of vegetation cover changes with high overall accuracy (87%). Finally, factors associated with forest cover change in the study area were investigated. This final output assists with evaluating on going land cover change processes and land use management. This knowledge can be useful for policy and decision makers and ecologists to deal with current deforestation issues and prevent potential threats to forest resources in the future.

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APPENDIX

The appendix contains scripts and steps for implementing software used by author to derive some results of this research. Key steps and scripts are explained briefly in the following sections.

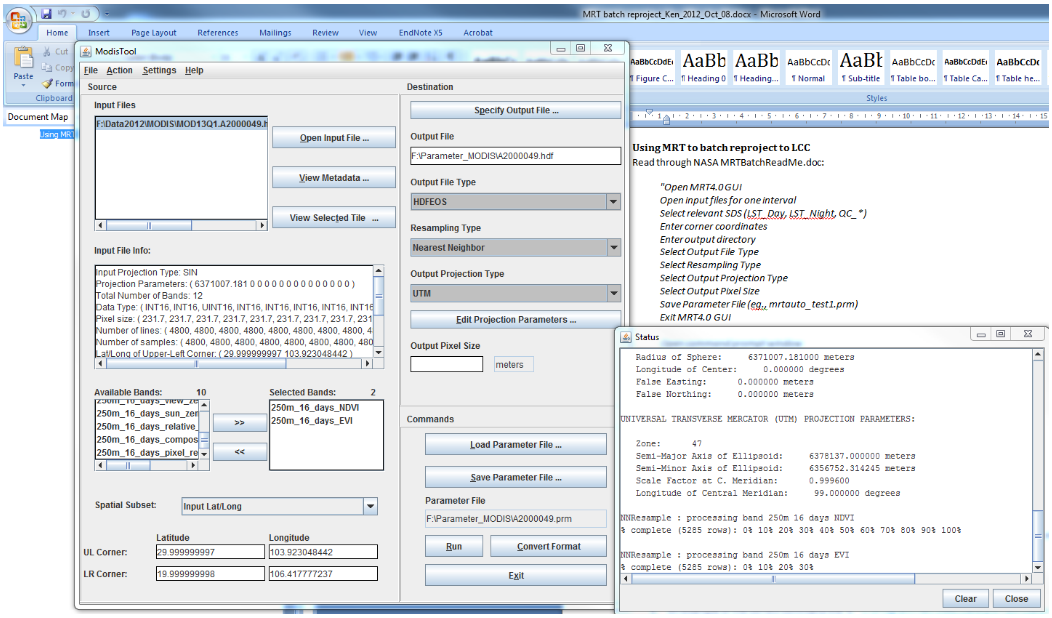
1. Performing geographic transformation/re-projection of MODIS data time series

The MODIS Reprojection Tool (MRT) was used to reproject and subset the MODIS data time series in this research project. After MRT installation, three main steps are implemented to prepare the MODIS data's projection: creating a parameter file, creating MRT batch file, and running a batch command. More details are found in MRT user manual:

https://lpdaac.usgs.gov/tools/modis_reprojection_tool

1.1. Creating a parameter file

1. *"Open MRT4.0 GUI*
2. *Open input files: selecting .hdf file that we want to reproject/subset i.e. MOD13Q1.A2000049.hdf*
3. *In selected bands: choose only file that we need: NDVI & EVI*
4. *Leave corner coordinates as default, if subset is not required*
5. Change other parameters if necessary, for example: Output Files : .hdf or .TIF
6. Select Output Projection Type : UTM, then
7. Save a parameter file in output directory: (E:\Test_Chittana\Para\)
8. Leave Output Pixel Size default
9. Save Parameter File (jit.prm) in : E:\Test_Chittana\Para\
10. Run the test and wait until finish & Exit MRT4.1 GUI



1.2. Creating a MRT batch file

In order to create a MRT batch file, we require Java software in window or Mac. After completing the Java installation, these steps were followed:

1. Copy Java.exe into the MRT installed directory, i.e. D:\MODIS_Tool\bin where there is MRTBatch.jar file
2. Then creating the MRTBatch.bat by type:

   java –jar MRTBatch.jar –d input_directory –p parameter_directory\ input_parameter_file

Where

input_file_directory is the directory in which all input files are placed (e.g., E:\Test_Chittana\Test_MODIS); parameter_file_directory is the directory where the parameter file created using the GUI (i.e. E:\Test_Chittana\Para\jit.prm) was saved earlier.

To create a MRT batch file, we used the below script in command prompt in Window. In command prompt, please type:

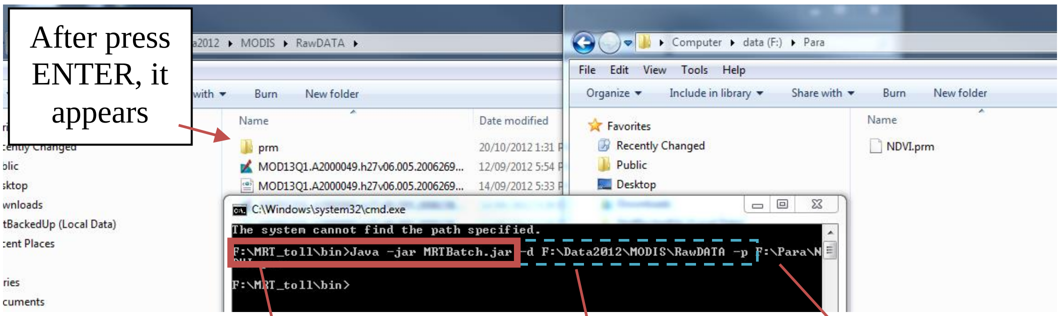
1. An example of the correct command line is " D:\MODIS_Tool\bin\Java –jar MRTBatch.jar -d E:\Test_Chittana\Test_MODIS -p E:\Test_Chittana\Para\jit.prm "
2. Then, press **Enter**
3. Now, this writes a file, mrtbatch.bat in the D:\MODIS_Tool\bin directory

1.3. Running a batch command

After creating a MRT batch file, now we ready to run the batch scrip. Follow these steps:

1. Navigate to D:\MODIS_Tool\bin, then execute “mrtbatch.bat” by double click
2. Now, wait for results. This batch execution can takes up to two days, depending on a volume of dataset. This was tested 20th Oct 2012, it works!

3. Output files will be located in a subdirectory of the input files, such as "\prm" in E:\Test_Chittana\Test_MODIS. *Example:*



java –jar MRTBatch.jar –d input_directory –p parameter_directory\ input_parameter_file

2. Masking MODIS time series data

Masking MODIS time series data was to exclude unwanted pixels or noises in each data scene. In this project, we selected only good quality of pixels data, thus unwanted pixels were masked. There are two steps (implemented in R-studio software): firstly creating QA mask layers and secondly masking QA and raw data of MODIS, as follows:

2.1. Creating QA mask layers

```
>>setwd("E:\\TEst")          # setting working directory in a local hard drive
>>library(rgdal)             # using rgdal and raster library
>>library(raster)

>>files <- list.files(pattern="*pixel_reliability")        # listing files from a working directory
>># files                                                   # if you want to see whether all files are
listed

>> for(i in 1:length(files)){                               #Creating a loop of command
   file <- readGDAL(files[i])                               #Read all files from a list
   rast <- raster(file)                                     #Creating a raster file for a list
   qa1 <- rast                                              #Renaming a file
   qa1[qa1 != 0] <- NA                                      #Assigning a new value, any value differs to
                                                            0 are NA
   qa1[qa1 == 0] <- 1                                       #Assigning a new value, any value equals to
                                                            0 are 1
   filename <- as.character(paste("QA_", files[i]))         #Giving new name for each new raster
   writeRaster(qa1, filename, format="GTiff", overwrite=TRUE)}          # Saving a raster as .tiff
                                                                        file, finished!
```

<u>Note:</u>

```
##########################################################################
# Using MOD13A2 Pixel Reliability & Selecting ONLY Good Data /Use with confidence (0):
#Codes:
# -1     Fill/No Data       Not Processed
# 0      Good Data          Use with confidence
# 1      Marginal data      Useful, but look at other QA information
# 2      Snow/Ice           Target covered with snow/ice
# 3      Cloudy   Target not visible, covered with cloud
##########################################################################
```

3. Masking QA and raw data of MODIS

```
>>setwd("E:\\TEst")          # setting working directory in a local hard drive
>>library(rgdal)             # using rgdal and raster library
>>library(raster)

>>files <- list.files(pattern="*EVI")                # Listing all EVI datasets
>>maskfiles <- list.files(pattern="^QA_")            # Listing all mask layers
>>head(files) ; head(maskfiles)                      # Checking those files
>>length(files); length(maskfiles)                   # how many files?


>>for(i in 1:length(files)){                         # Masking each pair of files by a loop
function:
   file <- readGDAL(files[i])                        #Read all files from a list
   ras.file <- raster(file)                          #Creating a raster file for a list
   mask <- readGDAL(maskfiles[i])                    # Read all mask files from a list
   mask.file <- raster(mask)                         #Creating a raster file for a list of mask files
   r.mask <- mask(ras.file, mask.file)               #Masking each QA and raw data by mask
function
   filename <- as.character(paste("FinalQA_", files[i]))           #Giving new name for each new
raster
   writeRaster(r.mask, filename, format="GTiff", overwrite=TRUE)}       # Saving a raster as .tiff
file, finished!
```

4. Extracting pixel values of MODIS time series data by samples

4.1. Creating a layer stack of rasters

```
## Setting a working directory, where data is located:
>>
setwd("F:\\BFAST_Appraoch\\Pre_pocessing_data\\MOD13Q1_h28_v07_reproject_UTM_z47_C
LIP_EVI")

## Getting raster files & staking them as one layer:
>> require(raster)
>> myfile.list <- list.files()
>> rasStack = stack(myfile.list)

## Checking a stacked raster data
## head(rasStack) ; nlayers(rasStack)
```

4.2. Opening random points shapefile

```
## Getting a point data in "shapefile" format
require(rgdal)   # Using rgdal library

>> wd = "F:\\BFAST_Appraoch\\Extraction_Raw_EVI data"                # Setting a working
directory
>> point.extra <- readOGR(dsn = wd, layer="random")                  # giving path & shapefile
name

## Preforming the raster values extraction by points:
rasValue=extract(rasStack, point.extra)

## Then, combining those points values with its corresponding coordinates:
>> rasValue <- (rasValue) * 0.0001
>> combine.extr=cbind(coordinates(point.extra), rasValue)
>> head(combine.extr[,1:4])

#Save an output file as ".csv"
>> write.table(combine.extr,file="F:\\BFAST_Appraoch\\Extraction_Raw_EVI
data\\Raw_EVI_random.csv", append=FALSE, sep= ",",row.names = FALSE, col.names=TRUE)

>>End !
```

5. Linear Discriminant Analysis Scripts

5.1. Reading .csv file

```
>> data <- read.csv("AllData_discriminantAnalysis_Updated.csv")
>> head(data)
>> summary(data)
```

5.2. Perform the LDA on data by using LDA in Mass package

```
>> require(MASS)

## run lda to discriminate LCs
>> output_discriminant_analysis <- lda(data$Class ~ data$EVI + data$LST, CV= TRUE, data = data)
>> output_discriminant_analysis                                   # Showing an output from running
the LDA
>> prediction <- predict(output_discriminant_analysis, data)    # running a predictoin for our data
>> tab <- table(data$Class, prediction$class) ; tab               # Summarizing them in a table

## This is our prediction of land cover classes based on EVI/LST
>> plot(data[,c(1,2)],col=as.factor(data[,3]),pch=as.numeric(prediction$class))              #
Showed LCs in a plot
>> legend("topright", legend=c("Agriculture", "Native forest", "Mixed wooded-cleared area",
"Plantation"),
    col=c(1,2,4,3), pch=c(1,2,4,3))

## Calculating the percent of prediction classes in a table:
>> PC_prediction <- rbind(tab[1, ]/sum(tab[1, ]), tab[2, ]/sum(tab[2, ]), tab[3, ]/sum(tab[3, ]),
tab[4, ]/sum(tab[4, ]))

## Labelling the table (using land covers' names)
>> dimnames(PC_prediction) <- list(Actual = c("Agriculture", "Forest", "Plantation",
"Wood/Cleareed"), "Predicted (cv)" = c("Agriculture", "Forest", "Plantation", "Wood/Cleareed"))
>> print(round(PC_prediction, 3))                                       # Showed them in 3 digit
numbers
>> prediction.final <- round(PC_prediction, 2) ; prediction.final           # Showed them in 2 digit
numbers
```

5.3. Saving a result

```
>> write.table(prediction.final,file="prediction_save.csv", append=FALSE, sep= ",",row.names = T,
col.names=T)

## Calculating overall accuracy (%) of the prediction
>> table_class <- table(data$Class, prediction$class); diag(prop.table(table_class, 1))
>> sum(diag(prop.table(table_class))) # Overall accuracy (%)

## Showed overlapping of land cover classes (using proportion of trace)
>> plot(output_discriminant_analysis)                                # Showed overlapping of land
cover classes
>> plot(output_discriminant_analysis, dimen=1, type="both")  # Showed overlapping in each land
cover

##pairs(data[c(1,2)], main="My Title ", pch=22, bg=c("red", "yellow", "blue",
"green")[unclass(data$Class)]) #############
```

6. Using BFAST Scripts

6.1. Opening & preparing files

```
>> a <- read.csv("Raw_EVI_Agriculture_random.csv", head=F, sep=",")
>> b <- read.csv("Raw_EVI_BareArea_random.csv", head=F, sep=",")
>> c <- read.csv("Raw_EVI_Built_up_random.csv", head=F, sep=",")
>> d <- read.csv("Raw_EVI_Forests_random.csv", head=F, sep=",")
>> e <- read.csv("Raw_EVI_plantation_random.csv", head=F, sep=",")

# Giving column names for each file then combine them into one matrix:
>> colnames(a) <- paste0("Agr", 1:ncol(a))
>> colnames(b) <- paste0("Bare", 1:ncol(b))
>> colnames(c) <- paste0("Built", 1:ncol(c))
>> colnames(d) <- paste0("Forest", 1:ncol(d))
>> colnames(e) <- paste0("Plant", 1:ncol(e))

##Creating ts objects:
>> a.ts <- ts(a, start=c(2000, 4), frequency=23)
>> b.ts <- ts(b, start=c(2000, 4), frequency=23)
>> c.ts <- ts(c, start=c(2000, 4), frequency=23)
>> d.ts <- ts(d, start=c(2000, 4), frequency=23)
>> e.ts <- ts(e, start=c(2000, 4), frequency=23)

## Average all 250 points over LCs, using row mean function:
>> a.ts.mean <- ts(rowMeans(a.ts), start=c(2000, 4), frequency=23)
>> b.ts.mean <- ts(rowMeans(b.ts), start=c(2000, 4), frequency=23)
>> c.ts.mean <- ts(rowMeans(c.ts), start=c(2000, 4), frequency=23)
>> d.ts.mean <- ts(rowMeans(d.ts), start=c(2000, 4), frequency=23)
>> e.ts.mean <- ts(rowMeans(e.ts), start=c(2000, 4), frequency=23)
```

6.2. Applying BFAST scripts

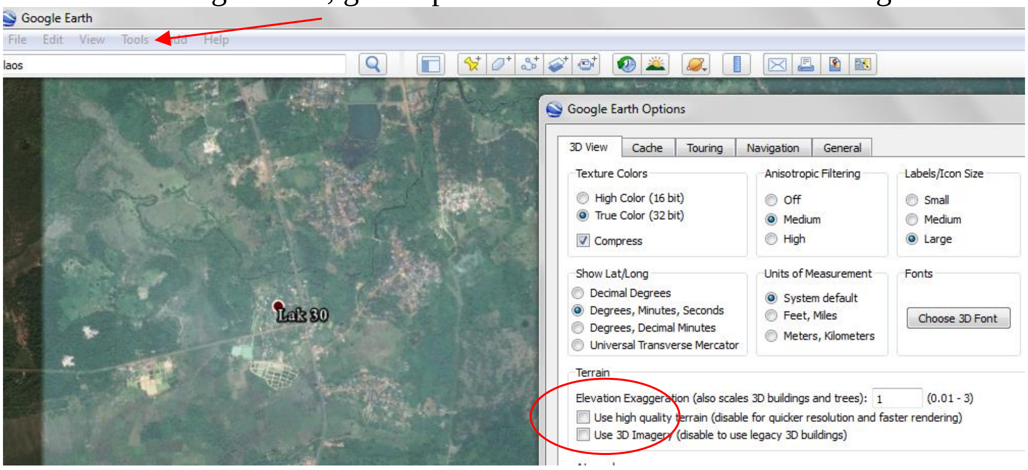
```
require(bfast)                      #using bfast library
## Creating objects to make them easier to read:
>> Agri <- a.ts.mean
>> Bare <- b.ts.mean
>> Built <- c.ts.mean
>> Forest <- d.ts.mean
>> Plantation <- e.ts.mean

##Plotting bfast showing temporal changes in different land covers:
>> plot(bfast(Agri,h=0.15, season="dummy", max.iter=1), main="Agriculture")
>> plot(bfast(Plantation,h=0.15, season="dummy", max.iter=1), main="Plantation")
>> plot(bfast(Forest,h=0.15, season="dummy", max.iter=1), main="Forest")
>> plot(bfast(Bare,h=0.15, season="dummy", max.iter=1), main="Woody")

##Showing one of results:
>> summary(bfast(Bare,h=0.15, season="dummy", max.iter=1))
```

7. Extracting and Geo-referencing Google Earth ™ Images

High resolution images from the Google Earth™ were important for this research, used as reference data. In order to use these images in any GIS software, we geo-rectified these images. To do this, two open source software packages were used: Google Earth and Elshayal Smart Web on Line Software. After installation, these steps were followed:

7.1. Settings in Google Earth program:

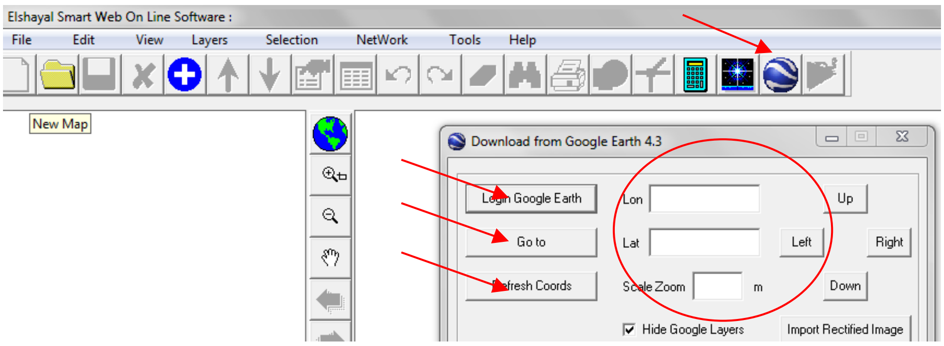
In Google Earth, go to option >> turn off terrain or 3D image



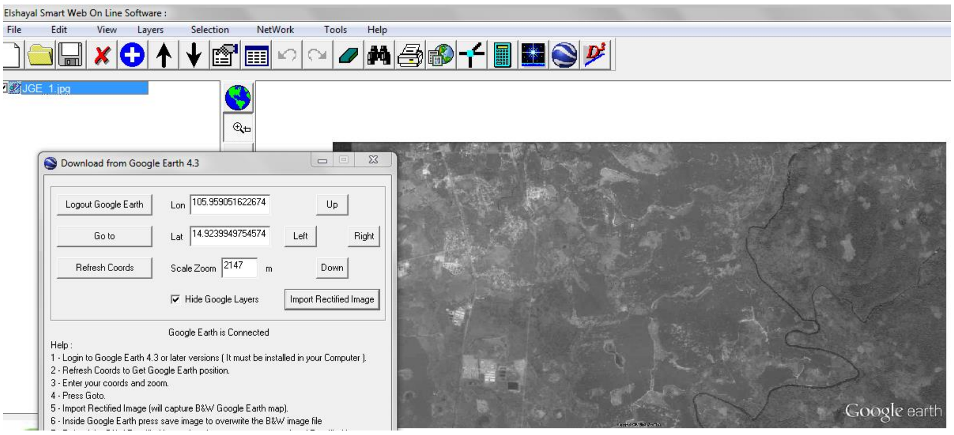
Now, zoom in an area of interests which we want to geo-reference.

7.2. Now, opening the Elshayal Smart Web on Line Software

1. Click on download from Google Earth
2. Login Google Earth, now Google Earth is connected
3. Click on Go to & refresh Coords, Lon & Lat, Scale Zoom values will be appeared.

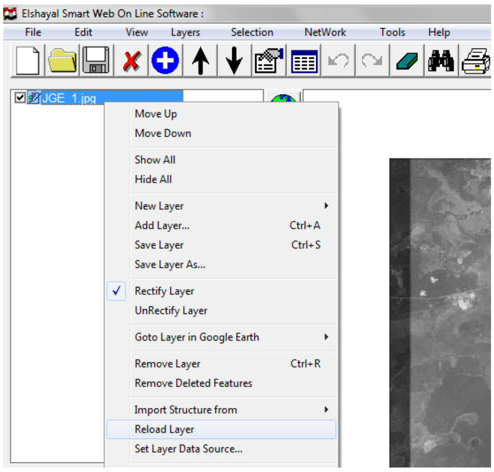


4. Click on Import Rectified Image, and save this image in your favour folder
5. Now, new downloaded image will be appeared in a view of Elshayal Smart Web on Line program



6. Now go back to Google Earth, click on File >> Save >> save image, replace this image to the imported rectified image which we saved earlier.

7. Confirm when you are asked “Do you want to replace it?” Yes
8. Now, go back to the Elshayal Smart Web on Line program, right click on image name >> Reload Layer



9. The output is a colour georectified image suitable for use with other maps.