Recent Co-occurring Expansion of Rubber Tree Plantations and Land Use/Land Cover Change in Luangnamtha District, Northern Laos

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Abstract

Monitoring land use/land cover change at various scales is of foremost importance for the management of natural resources and pivotal to achieve effective environmental governance. The purpose of this study was to classify land use/land cover and to quantify changes in land use/land cover in Luangnamtha district, northern Laos over the past two decades, using remote sensing and Geographic Information System technologies. We used Landsat 5 Thematic Mapper (TM) images from 2000, 2005, 2010 and Landsat 8 Operational Land Imager (OLI) images from 2017. A supervised classification was achieved by applying the maximum likelihood algorithm in the ENVI software. Five land cover classes, namely agriculture, forest, rubber tree, settlement and water were thus identified. The nature and extent of change detected was analyzed on the basis of the land use maps generated for years 2000, 2005, 2010 and 2017. We applied spatial point process theory to analyze spatial relationships between land use classes and with terrain covariables. The overall accuracy of our classifications were 86.8%, 89.3%, 90.4%, and 91.7% for the years 2000, 2005, 2010, and 2017, respectively and the Kappa coefficients were 0.76, 0.85, 0.85, and 0.89, respectively. The results of these classifications indicated that over the 2000 to 2017 period, settled areas increased by 2.35% (5,038 ha), water bodies increased very marginally (0.01% or 20 ha), but that rubber tree cover increased by as much as 7.60% (16,314 ha). During the same period, agricultural land decreased by 0.11% (224 ha) and the forested area shrunk by 9.84% (21,129 ha). Spatial analysis indicates that rubber tree plantations expanded from the lowest part of the landscape, in close spatial association with agricultural land, to increasingly higher locations where it most likely replaced forest. This study confirms that drivers such as government policies for permanent allocation of agricultural land poverty eradication, as well as foreign investments, had a major impact on the expansion of rubber tree plantation in Luangnamtha district from 2000 to 2017.

1. Introduction

The monitoring of land use/land cover change has become a central component of environmental natural resources management. Land use/land cover change is a complex process, resulting from a combination of social, political, economic, ecological, technological, cultural factors (Fox and Vogler, 2005) such as environmental development policies, human activities, and natural disaster at different scales, from local, regional, to global scales (Ram and Kolarkar, 1993, Lambin et al., 2001 and Muttitanon and Tripathi, 2005). Across Southeast Asia, over the past 100 years, natural resources have decreased steadily, due to population growth and conversion of forested land for food production, initially through the expansion of shifting cultivation (Fox, 2000, Sandewall et al., 2001 and Inoue et al., 2010) and subsequently as a result of national land tenure policies and international market pressures (Fox and Vogler, 2005). In Recent decades, Southeast Asia has undergone the highest rate of deforestation in the tropics and sub-tropics (Zhao et al., 2006). For example, in Menglun, Xishuangbanna, the extent of rubber tree plantations increased by 12% while forested areas dropped from 49% to 28% between 1988 and 2006 (Hu et al., 2008). Global externalities of land use change such as tropical forest conversion, shifting cultivation and clearing of secondary vegetation include increased emissions of greenhouse gases in future decades (Fearnside, 2000).

In the uplands of northern Laos, shifting cultivation has played an important role in rural livelihoods for decades (Luangmany and Kanako, 2013). In recent years, farmers have rapidly moved from traditional shifting cultivation to permanent and diversified market-oriented cultivation systems (Thongmanivong et al., n.d., Phanvilay et al., 2006, Thongmanivong and Fujita, 2006 and Vongvisouk et al., 2014), particularly since the market liberalization in 1986 (Phimphanthavong, 2012). Following road network development/improvement and the re-opening of regional borders in the early 1990s, the province of Luangnamtha has undergone accelerated conversion from subsistence cultivation into permanent agriculture, in particular with Chinese investments promoting sugarcane and rubber tree cultivation (Thongmanivong et al., n.d.). This transition from shifting cultivation to other land uses is systematically associated with permanent deforestation, forest degradation, loss of biodiversity, increased weed pressure, decreasing soil fertility and accelerated soil erosion (van Vliet et al., 2012, Castella et al., 2013 and Kim et al., 2017). Therefore, over the past 20 years, the Government of Laos (GoL) has issued several policies such as the Shifting Cultivation Stabilization and Arranging Permanent Occupations Program in 1989; the Village Land Use Planning and Land Allocation Program (LUP-LA) in 1993; and the Participatory Agriculture and Forest Land Use Planning (PLUP) at village and village cluster levels in 2010. Through these policies, the GoL has aimed to convert shifting cultivation to more permanent land use and associated occupations while increasing family income and expanding forest cover (Ministry of Agriculture and Forestry and National Land Management Authority, 2010). As part of this process, the GoL has identified the eradication of poverty as a priority, and has, as such aimed to increase land tenure security in order to encourage farmers to engage into intensive farming and to eliminate shifting cultivation to protect the environment, in a country still rich in forest resources (Ducourtieux et al., 2005). Through this process, the GoL aims to increase trade and market with neighboring countries (mainly China, Vietnam and Thailand) via the production of commodity crops such as watermelon, maize, sugarcane, vegetables and rubber tree (Thongmanivong and Fujita, 2006). In Luangnamtha district, rubber tree planting started in 1994 at Ban Hatyao, which became the first rubber producing village of Laos, with tapping operations starting in 2002. At the time, the trading price of para rubber was high and farmers were getting high income from latex sales. As a consequence, rubber boomed in 2003, promoted by foreign traders and companies, with the official support of government policies (Alton et al., 2005, Manivong and Cramb, 2007 and Shi, 2008). Promoting rubber tree plantation was seen as a means to replace opium cultivation, reduce shifting cultivation, provide permanent occupations, increase family income, protect natural forests, and sustainably eradicate poverty (Vongvisouk and Dwyer, 2017). Consequently, while many farmers initially converted their agrarian and fallow fields to cultivate cash crops such as sugarcane, maize, and cassava, they eventually moved to rubber tree plantations (Alton et al., 2005). The resulting expansion of smallholder rubber tree plantations has been one of the most extensive and rapid land use change in the uplands of northern Laos (Manivong et al., 2003). Awareness and the knowledge of land use/land cover, and of how they vary with time at a range of scales are very important to understand natural resources, their utilization, conservation and management (Nagamani and Ramachandran, 2003). Many studies have used remotely sensed data to classify land use types and analyze, land use/land cover change at different scales in order to develop management strategies for sustainable land resource use (Hu et al., 2008, Rawat et al., 2013, Zhang et al., 2014, Butt et al., 2015 and Liu et al., 2016;). Indeed, quantifying, analyzing and interpreting geographical dynamics such as land cover change is an effective methodology for monitoring, assessing and planning the impacts of land use/land cover change. Understanding land use/land cover type is very important to assess and manage areas of critical concern for environmental control such as flood plains and wetlands, energy resource development and production areas, wildlife habitat, recreational lands, and areas such as major residential and industrial development sites (Anderson et al., 1976). Many publications have discussed that land use and land cover classification is a process that depends on the purpose of study and its scale (Anderson et al., 1976, FAO, 2000 and Hu et al., 2008). While such detailed studied have covered nearby regions of Xishuangbanna (Hu et al., 2008), there is a paucity of studies on recent land use change in Lao PDR, despite reports and ancillary data that indicate the occurrence of extensive land use change across the country (Shi, 2008 and Vongvisouk and Dwyer, 2017). In this perspective, the main objective of this study was to classify the categories of land use/land cover, and to quantify land use/land cover change over the 2000 to 2017 period, in Luangnamtha district, northern Laos, using remote sensing and Geographic Information System technologies. Further to the results of a supervised classification based on applying the maximum likelihood algorithm, we present and discuss land use/land cover change detected as well as some spatial interactions between land use classes and covariables.

2. Materials and Methods

2.1 Study Area

Luangnamtha district is located to the northeast of Luangnamtha province between latitudes 20°45′51″ N and 21°15′22″ N and longitudes 101°09′29″ E and 101°46′35″ E, corresponding to and area of 214,662 ha. The Luangnamtha district shares a border with the People's Republic of China to the North and with the Oudomxay province to the East while Nalae, Viengphoukha and Sing districts of Luangnamtha province lie to its southern and western borders. Elevations range from 472 to 1,993m a.s.l. and approximately 75% of the district is mountainous, 37% with slopes >10°, while 25% is plateau and plain areas. The climate of Luangnamtha district undergoes two seasons: the dry season from November to April, and the rainy season from May to October. The annual rainfall averages approximately 1,420 mm, and the annual average temperature is 25°C (Agricultural Land Research Center, 2008). In 2015, Luangnamtha district had 54,089 inhabitants, equivalent to about 31% of the total population of Luangnamtha province; the population density was of the order of 19 inhabitants per Sq.Km. and the population growth rate was 1.9% (Lao Statistics Bureau, 2015). The main industries of Luangnamtha are agriculture, wood processing, lignite and copper mining, handicraft production, transportation and tourism. Most inhabitants of the study area are engaged in agriculture, planting rice, corn, vegetables, cassava and peanuts. Other important agricultural products include buffalo and other cattle, fish, chicken, rubber, teakwood, watermelon, sugarcane and pepper. Forest products such as bamboo shoots, mushrooms, rattan, cardamom and ginger are also important sources of income for the rural population (Tourism Marketing Department, 2012). Moreover, the study area includes parts of the Nam Ha National Biodiversity Conservation Area (Nam Ha NBCA) established by Prime Minister's (PM) Decree No.164, 29 October 1993, which covers an area of 222,400 ha or 23.85% of Luangnamtha province (MoNRE-IUCN, 2016), 117,709 ha or about 54.83% being located in the Luangnamtha district (Figure 1).

2.2 Data Preparation

In this study, the Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) images were obtained from the U.S. Geological Survey Earth Explorer Website (http://earthexplorer.usgs.gov/). These images have a spatial resolution of 30m. We used images from four different periods, namely, 2000 acquired on 12th February, 6th March and 7th April; 2005 acquired on 16th February and 25th February; 2010 acquired on 7th and 14th February, and 2017 acquired on 5th and 14th March. The period at which these images were acquired was chosen because it corresponds to the period of the dry season during which cloud cover is minimal. However, for the four investigated years, we could not obtain images from the same exact date or within a couple of days due to cloud cover. The season during which these images were acquired overlaps the defoliation (between January to February) and the beginning of the re-foliation phases of rubber trees. The characteristics of these images are described in Table 1. Furthermore, Google Earth imagery acquired at times corresponding to that of Landsat images used for land use/land cover classification was used as an additional source of information to determine sample points in conjunction with the Landsat. The sample points were collated in reference data forms used to conduct field surveys and interview local people.

2.3 Pre-Processing

All Landsat data were geometrically corrected and calibrated to the Universal Transverse Mercator (UTM), Zone 47N, and WGS 84 Datum. We used images without cloud cover for the four different years analyzed. Our study area being located at the boundary of four connected Landsat images scenes, images were preprocessed individually and subsequently mosaicked using ENVI software (Boulder, Colorado USA) to co-register and normalize images from different dates and produce a seamless single image that covers the whole study area (Figure 2). As images from year 2000 were acquired on 12th February, 6th March and 7th April, similar combinations of data dates were used for the other years as indicated in Table 1. Google Earth imagery and sample points from fieldwork were used for both the land use/land cover classification and accuracy assessments.

2.4 Land Use Classification Methodology

The Luangnamtha district presents several physical specificities that led us to conduct a land use classification based on supervised image classification. First, the district is very mountainous with steep slopes with over a third of the landscape corresponding to terrain with slopes > 10°, which is problematic because of variations in the sun illumination angle. Second, agricultural areas are generally small upland plots located along roads, rivers, and valleys which are often smaller than the 30x30 m size of pixels. Finally, access to many areas is difficult and time-consuming in the absence of access roads and due to the rugged nature of terrain, which led us to recourse to the use of high resolution imagery to complement ground-truth field data.

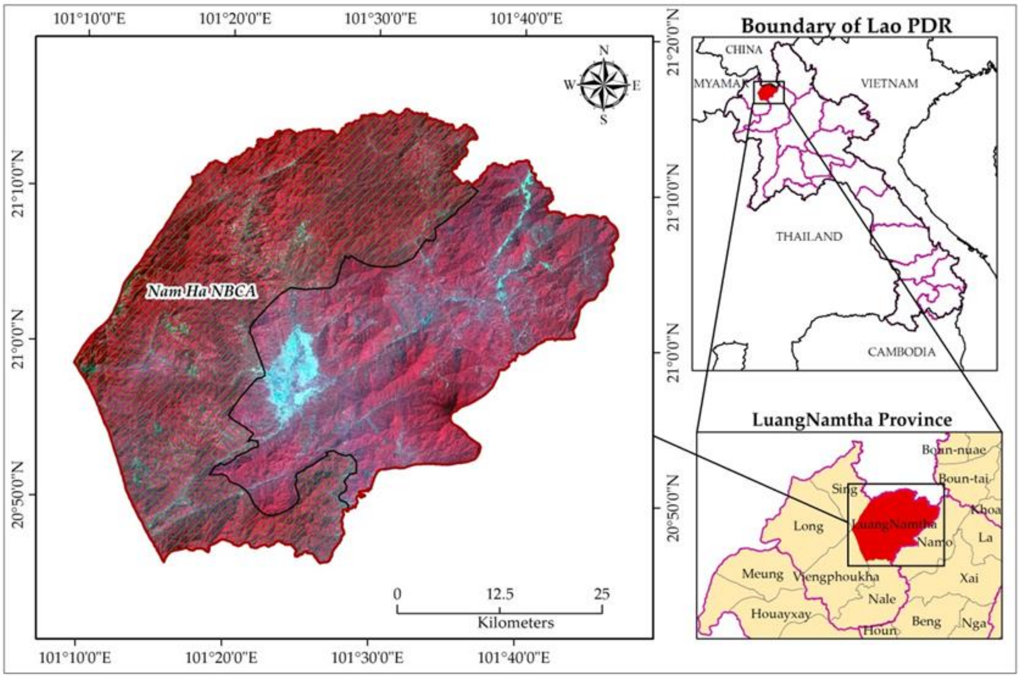

Figure 1: Location of the study area: Luangnamtha District and Province, Northern Laos (The red color line is the boundary of the study area. The black color line and the inner green shading outline the boundary and extent of the Nam Ha NBCA in the study area. The color composite background image uses the near-infrared, red, and green spectral bands of Landsat 8 OLI in 2017)

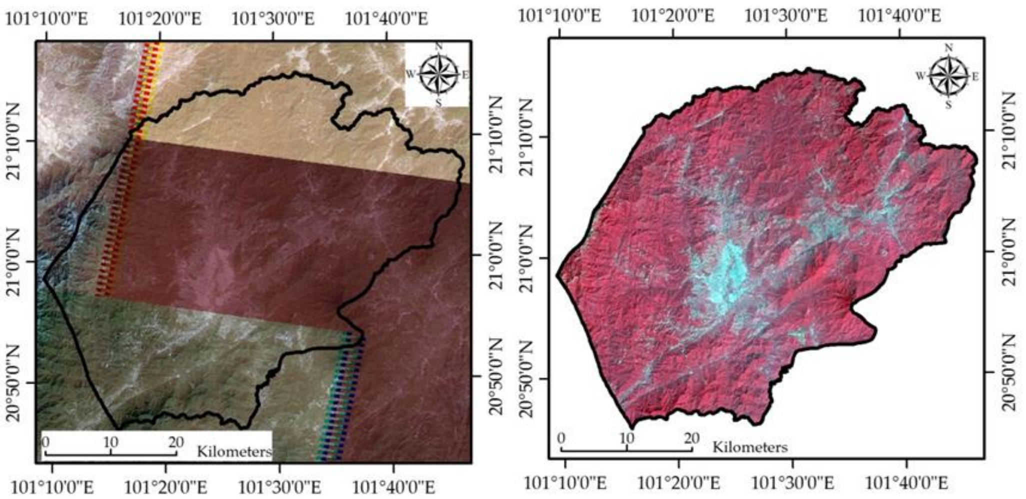

Figure 2: Four connected Landsat images scenes (left) and Landsat image after preprocessing (right)

Table 1: Data characteristics of Landsat images

Years	Path/Row	Date of acquisition	Resolution (m)	Sensors
2000	129/45 130/45 130/45	12 February 2000 06 March 2000 07 April 2000	30 30 30	TM TM TM
2005	130/45 130/46 129/45 129/46	16 February 2005 16 February 2005 25 February 2005 25 February 2005	30 30 30 30	TM TM TM TM
2010	129/45 129/46 130/45 130/46	07 February 2010 07 February 2010 14 February 2010 14 February 2010	30 30 30 30	TM TM TM TM
2017	129/45 130/45	14 March 2017 05 March 2017	30 30	OLI OLI

Unsupervised image classification or hybrid classification (unsupervised followed by supervised) can reportedly yield improved product accuracy than either approach used separately (Rozenstein and Karnieli, 2011 and Ishtiaque et al., 2017), particularly for large and complex areas for which ground-truthing is not possible and ancillary data are lacking. On the other hand, supervised classification can prove superior when ground-truthing is possible and provided training sites are well chosen and classes are spectrally sufficiently distinct. Since we could afford ground truthing, we opted for supervised classification.

A field survey was conducted to validate the land use classification and accuracy assessment. Fieldwork was undertaken from mid- June to the beginning of July, 2017 (i.e. during the cropping period in the rainy season). Sampling points were purposely selected near roads and rivers to ensure convenient access of each land use type, and were marked on the Landsat and Google Earth images (for the years 2000, 2005, 2010, 2017). For older time periods and remote areas, visual interpretation of high spatial resolution images of the Google Earth imagery was combined with interviews of local people. In the field, the coordinates of sample points were recorded using the Geographical Positional System (GPS), and then input into the GPS forms. Google Earth Pro V 7.1.5.1557. (February 21st, 2017. Luangnamtha district and province, Lao PDR. 20°57′40.63′′N, 101°24′01.25′′E, Eye alt 13.01 mi. CNES/Airbus 2017, DigitalGlobe 2017. http://www.earth.google.com [June 5, 2017]). These sampling points were locations where ground truth information was collected in order to improve the land use/land the supervised classification; they were chosen so as to encompass the classes of land use classified, namely agriculture, forest, rubber tree, and settlement, except water, as shown in Figure 3. Field photographs of specific land use patterns (namely agriculture (paddy field and upland rice), settlements (mixed urban), water (pond), rubber tree plantations, and forest) were taken at each ground-truth sampling point as shown in Figure 4.

2.5 Land Use/Land Cover Classification

For this research we selected the closest values of wavelength including Band 4 (NIR), Band 3 (RED), and Band 2 (GREEN) for Landsat 5 TM, and Band 5 (NIR), Band 4 (RED), and Band 3 (GREEN) for Landsat 8 OLI. The sample points of 153, 164, 167 and 167 points was used for the four categories of land use classified in this work (Table 2), for the years 2000, 2005, 2010 and 2017, respectively. Training areas were defined by delineating 60x60 m polygons around representative sites. All sample points were intentionally chosen to be located in the middle of these representative training areas. The supervised classification method with maximum livelihood algorithm was applied in the ENVI software for classification of land use/land cover types. We used the Normalized Difference Water Index (NDWI) to detect surface waters (Xu, 2006, Hui et al., 2008, Rozenstein and Karnieli, 2011 and Ishtiaque et al., 2017). The NDWI is calculated using Equation (McFeeters, 1996).

$$NDWI = P_{GREEN} - P_{NIR} / P_{GREEN} + P_{NIR}$$

Equation 1

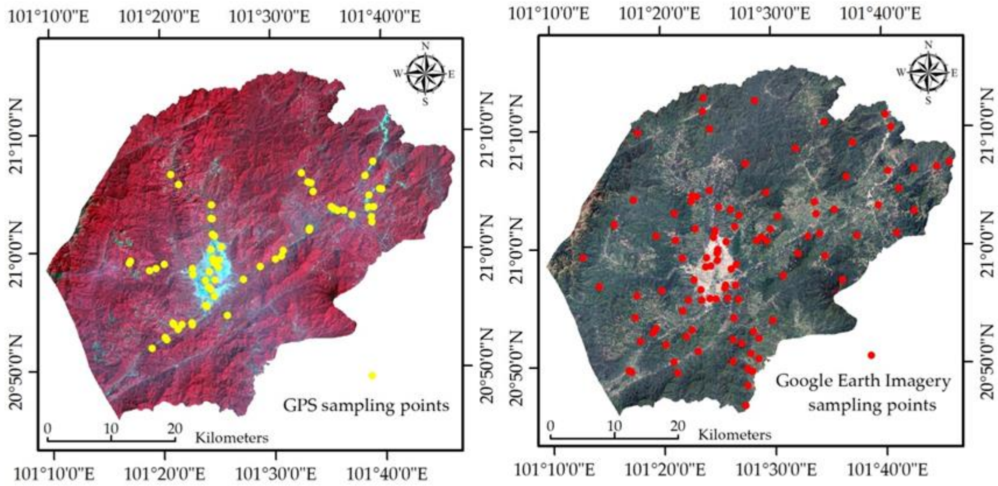

Figure 3: Location of GPS sampling points and background image is the Landsat OLI 8 acquired on 5th and 14th of March 2017 (left), and Google Earth Imagery sampling points and background image is the Google Earth Imagery on February 2017 (right) for image classification in 2017

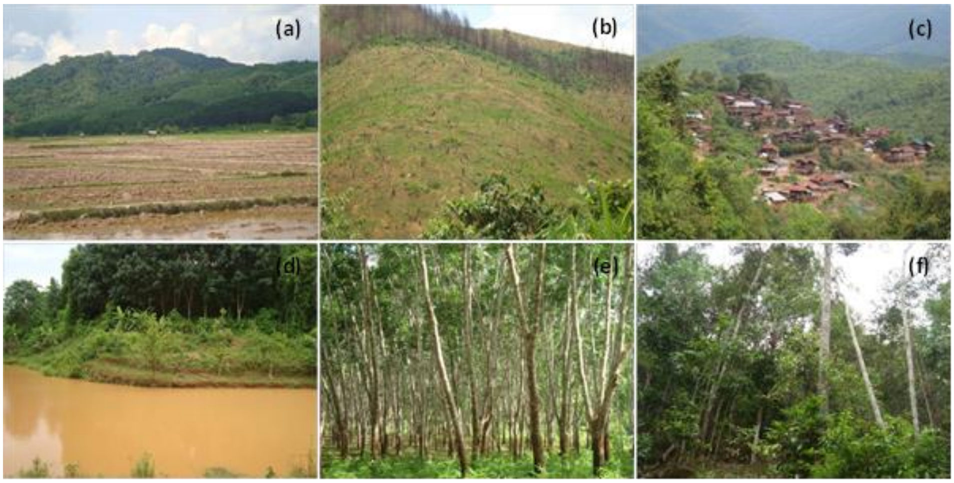

Figure 4: Pictures from ground-truth sampling points in the Luangnamtha district, (a) Paddy field; (b) Upland rice; (c) Mixed urban of Namyang village; (d) Pond ; (e) Rubber planted at Ban HatNgao (1994); (f) Forest; these pictures were taken in June, 2017

Table 2: Land use and land cover classification scheme

No.	Land use/land cover types	Description
1	Agriculture	Paddy rice, upland rice, annual crops and fruit tree
2	Forest	Evergreen forest, deciduous forest, gallery forest, bamboo, savannah and scrub
3	Rubber	Rubber tree plantation
4	Settlements	Residential, commercial, roads, mixed urban
5	Water	Rivers, reservoirs, ponds

Where P_{GREEN} is the TOA green light reflectance and P_{NIR} is the TOA near-infrared (NIR) reflectance. NDWI was calculated for each of the four years (2000, 2005, 2010, and 2017) using the Raster Calculator and Reclassify tools of the Spatial Analyst Extension in ArcGIS. Finally, we combined the resultant water and the result derived from supervised classification together by using the Update tool in the Analysis Tools in ArcGIS, to produce the maps of land use/land cover types from year 2000 to 2017.

2.6 Accuracy Assessment

The quality of information derived from field survey, interview of local people and visual interpretation on Google Earth imagery was determinant for the validation of land use/land cover classification accuracy of years 2000 to 2017 (Figure 5). An independent reference data sample of 152, 159, 188 and 168 points was used for accuracy assessment of years 2000, 2005, 2010 and 2017, respectively. The accuracy assessment was carried out using the overall accuracy, user and producer accuracy and Kappa coefficient (Congalton, 1991 and Congalton and Green, 2009).

2.7 Land Use/Land Cover Change Detection Analysis

Change detection was analyzed over 3 short-term periods, namely between the years 2000-2005; 2005-2010; and 2010-2017 as well as the full time-span of the set of classified images, i.e. 2000-2017 in Luangnamtha district (Rawat and Kumar, 2015 and Tran et al., 2015). Change detection was performed in ArcGIS by overlaying the land use maps of each short-term and long-term period. A change matrix was produced with the help of PivotTable in Excel in order to make a cross-tabulation to produce the land use change for each time period across the study area.

2.8 Assessment of Spatial Relationships between Land Use Classes and Covariables

Additionally, we assessed spatial relationships between the patterns of Settlements, Agriculture and Rubber pixels and variables that putatively represent explanatory variables of these patterns, such as elevation, slope and distance to forest. This was achieved by handling land use classes as point patterns and assessing their density distribution relative to covariates (Baddeley et al., 2012). In this specific application, point data provide the location of objects, i.e. here the coordinates of pixels belonging to a given land use class and are complemented with a categorical mark corresponding to the observation year. The 'rgdal' (Bivand et al., 2018) raster (Hijmans, 2018) and 'spatstat' libraries (Baddeley et al., 2015) for the R environment (R Core Team, 2018) were used for practical handling of GIS files and subsequent computations. We first computed, for each land use in each year the densities of the corresponding point processes on a surface tessellated according to distance classes, namely, <30, 30 to 60 and >60 m to the Forest class in the corresponding year. The same calculation was carried using aggregated datasets of the four observations periods for each land use. Covariate maps of terrain elevation and slope as well as of Euclidean distance to forest pixels (generated with the 'distmap' function of library 'spatstat') were used as an argument to the 'rhohat' function of 'spatstat' to estimate the spatial density of pixels corresponding to the Rubber, Settlement and Agriculture classes in each of the four considered years as a function of these covariates.

3. Results

3.1 Land Use/Land Cover and Accuracy Assessment in Luangnamtha District

The results of our land use/land cover classification of Luangnamtha district for years 2000, 2005, 2010, and 2017 are shown in Figure 6 and Table 3. The results reveal that the overall accuracies of land use/land cover classification and the Kappa coefficients were 86.8%, 89.3%, 90.4% and 91.7%; and 0.76, 0.85, 0.85, and 0.89, respectively for the years 2000, 2005, 2010, and 2017 (Table 4).

3.2 Land Use/Land Cover Change in Luangnamtha District

As shown in Figure 7, the five classified land use/land covers went through various trajectories of change over each of the four time periods considered. We found that forested land steadily declined from 2000 to 2017. Likewise, agricultural land underwent major decrease in the first short-term period (2000-2005) and over the long-term period (2000-2017), but increased marginally over the second and third short-term periods (2005-2010; 2010-2017). In contrast, settlement modestly but steadily increased from 2000 to 2017, while water increased gradually in the first and second short-term periods (2000-2005; 2005-2010) but decreased in the third short-term period (2010-2017). Rubber tree plantations expended massively during each time interval, but this expansion tended to gradually slow down towards the third time interval (2010-2017). Table 5 shows the land use/land cover change matrix of 3 short-term and 1 long-term periods in Luangnamtha district. In the first short-term period, all land cover classes except forest went through a major conversion from the original land cover class to another class. For example, the conversion of agricultural land to forest, rubber, settlement and water was 37.3%, 10.7%, 5.3% and 0.3% in the first period 2000-2005, respectively. Over this period, forested land changed the least with 95.8% of this land cover remaining in the same class. However, the proportion of settlement in the second short-term period (2005-2010) greatly increased, and from agricultural land to other classes in the third short-term and long-term periods (2010-2017; 2000-2017).

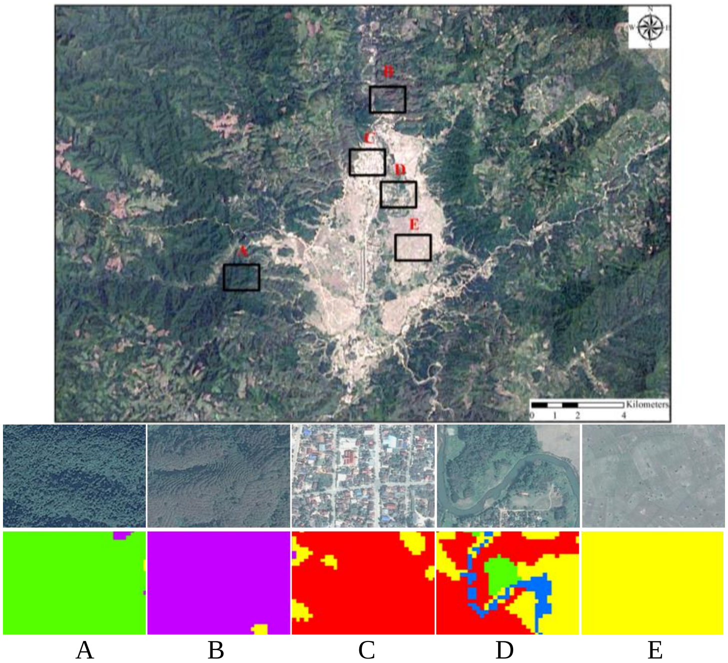

Figure 5: Google Earth Imagery on February 2017 used for accuracy assessment in 2017; (A) natural forest, (B) rubber tree plantation, (C) settlement, (D) water, and (E) Agriculture.

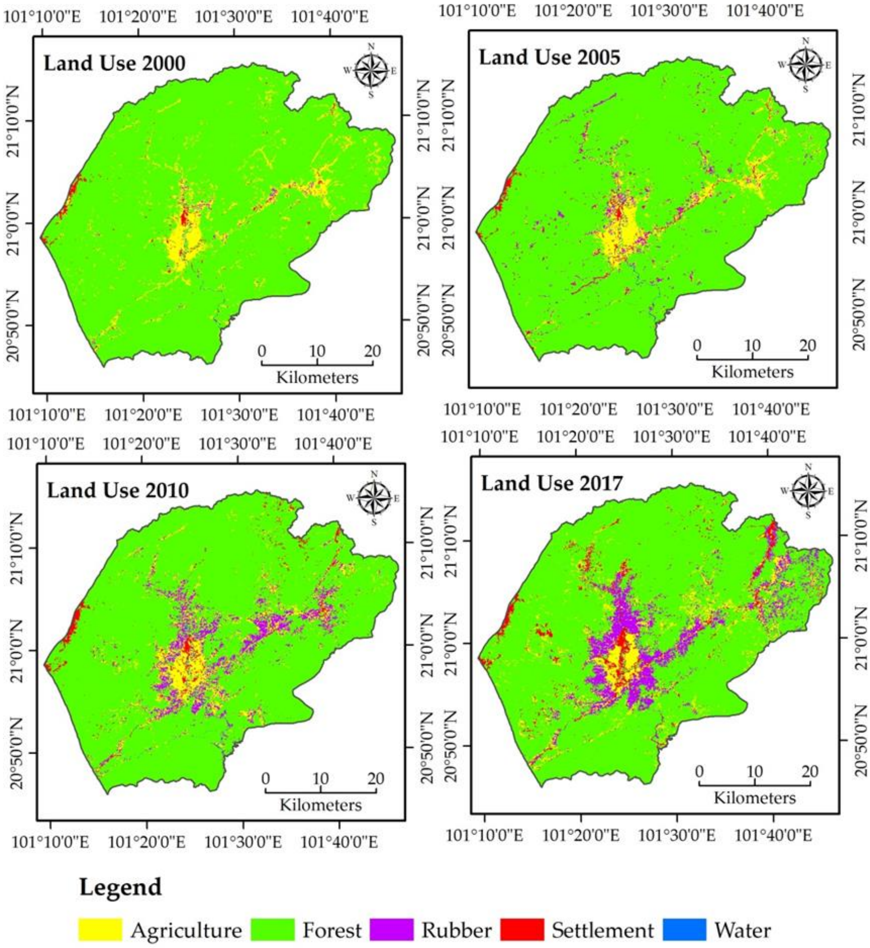

Figure 6: Land use/land cover maps in the Luangnamtha district during 2000 to 2017

Table 3: Land use/land cover types in Luangnamtha district during 2000-2017

Land use types	**2000**		**2005**		**2010**		**2017**		**Change (%) 2000-2017**
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	
1	16,332	7.61	12,829	5.98	15,279	7.12	16,088	7.49	-0.11
2	195,337	91.00	193,972	90.36	183,304	85.39	174,208	81.15	-9.84
3	795	0.37	4,836	2.25	11,650	5.43	17,109	7.97	7.60
4	1,948	0.91	2,683	1.25	3,962	1.85	6,986	3.25	2.35
5	251	0.12	342	0.16	466	0.22	271	0.13	0.01

Table 4: Confusion matrix statistics of land use/land cover (in %) during the years of 2000 to 2017 in Luangnamtha district

Years	**Land use types**	**1**	**2**	**3**	**4**	**5**	**Overall accuracy**	**Overall coefficient**
2000	Producer	80	90	75	86	75	86.8	0.76
	User	71	96	60	80	75		
2005	Producer	92	95	67	85	80	89.3	0.85
	User	85	99	67	88	67		
2010	Producer	82	96	81	88	83	90.4	0.85
	User	77	97	85	92	71		
2017	Producer	95	95	86	89	80	91.7	0.89
	User	91	95	94	86	80		

Table 5: Land use/land cover change matrix (in %) during the 3 short-term periods and 1 long-term period in the Luangnamtha district

Years						
	Period 2000-2005	1	2	3	4	5
2005	1	**46.4**	2.2	54.9	22.2	13.3
	2	37.3	**95.8**	26.7	23.3	8.9
	3	10.7	1.5	**15.6**	5.6	0.6
	4	5.3	0.4	2.6	**47.4**	3.7
	5	0.3	0.0	0.2	1.5	**73.5**
	Period 2005-2010	1	2	3	4	5
	1	**44.9**	3.9	28.0	20.8	9.6
	2	22.4	**91.8**	38.4	19.7	7.9
2010	3	24.1	3.5	**30.5**	12.8	0.4
	4	7.9	0.8	3.0	**45.2**	8.2
	5	0.7	0.0	0.1	1.4	**73.9**
	Period 2010-2017	1	2	3	4	5
	1	**35.6**	4.2	20.3	15.2	9.7
	2	28.7	**90.2**	28.9	28.2	15.4
2017	3	23.5	4.2	**47.4**	6.3	4.1
	4	11.9	1.5	3.3	**49.5**	32.5
	5	0.2	0.0	0.0	0.7	**38.3**
	Period 2000-2017	1	2	3	4	5
	1	**37.2**	4.8	35.1	15.2	10.2
	2	30.6	**86.3**	21.0	18.3	11.9
2017	3	17.9	7.0	**38.8**	7.9	1.6
	4	14.0	1.8	5.0	**57.3**	31.8
	5	0.4	0.0	0.1	1.3	**44.5**

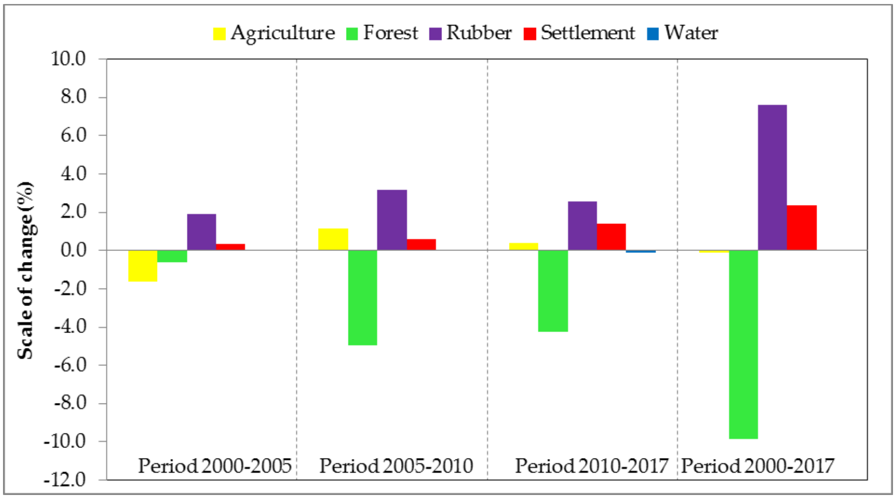

Figure 7: Dynamics of land use/land cover change in percent of the 3 short-term periods and 1 long-term period in the Luangnamtha district

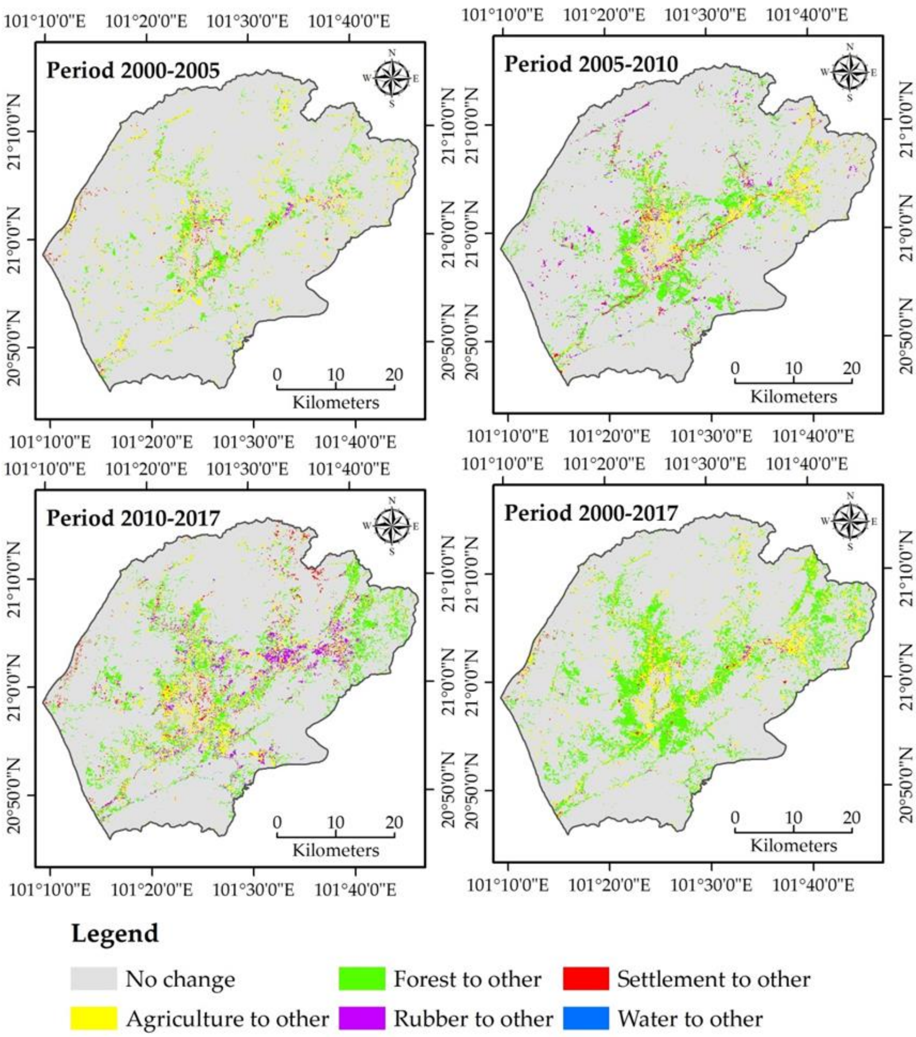

Figure 8: Land use/land cover change maps for short-term periods and long-term periods in the Luangnamtha district

Table 6: proportions of pixels corresponding to the four Land Use classes (Rubber, Settlements, Agriculture and Forest) located at less than 60 m from pixels of Forest class

Land use types	2000	2005	2010	2017	2000-2017
Rubber	0.36	0.53	0.44	0.43	0.94
Settlements	0.35	0.42	0.39	0.37	0.65
Agriculture	0.47	0.37	0.41	0.49	0.73
Forest	1	1	1	1	1

Furthermore, there was a slight change from land use of any given class to another class that can be observed in each time interval in the study area. Figure 8 shows the spatial distribution of change of land use/land cover classes to the other class, from 2000 to 2017 across Luangnamtha district. This figure reveals the locations where both change and no change occurred. Most of Luangnamtha district is mountainous; therefore, we can observe that most of the agricultural/forestry production areas are concentrated along the main roads, rivers or streams, and flat valley bottoms in the northeast, especially around urban centers, which is also where most land use change is observed, for all the time intervals considered in the study.

3.3. Spatial Relationships between Land Uses and Covariables

As Forest covered nearly 91% of the studies area in 2000 and 81% in 2017, we assessed the spatial relationships between the three other classes of land uses considered in this work and forest. Point densities at distances less than 60 m from Forest pixels indicated that, in all years, Agriculture and Rubber were closest to the forest than settlements and that in 2005, more than 50% of rubber pixels were located within a maximum distance of two pixels (60 m) from forest pixels (Table 6). When considering the distances of pixels of the three non-forest land uses of the four considered periods to the forest pixels of the same four periods, it appeared that 94, 73 and 65% of Rubber, Agriculture and Settlement pixels, respectively were located within less than 60 m of Forest pixels (Table 6), suggesting that these three land uses were established over the 17-year time span considered here, at the expense of forest and that the highest proportion of rubber plantations were gained from forest, followed by agriculture and settlements.

The nonparametric estimator of the dependence of a spatial point process on spatial covariate (Baddeley et al., 2012) allowed assessing the spatial density of pixels corresponding to Rubber as a function of the distance to pixels classified as pertaining to other land uses. Overall, as shown in Figure 9a, when comparing the spatial density of pixels classified as rubber in 2017 to pixels corresponding to other land uses, aggregated over the whole 2000-2017 period, it appears that the strongest dependence (besides that of rubber pixels with themselves, data not shown) was observed between Rubber and Agriculture pixels. Spatial dependence of Rubber upon both distance to Settlement and Forest appeared qualitatively similar, with a density peak at less than 200 m from both Settlement/Forest pixels.

When considering these spatial relationships between rubber and other land uses year by year, it appears that they were qualitatively equivalent in all years (data not shown). However, the intensity and spatial range at which rubber was associated with forest changed substantially over the study period (Figure 9b): the density of rubber tree plantations at distances <200 m from Forest pixels of the corresponding year increased regularly throughout the study period, as indicated by increasing ρ values. These strong short range interactions, particularly in 2005 and 2010 are consistent with the results of the analysis based on densities of point processes on distance-tessellated surfaces. Further, it appears that densities of rubber tree plantations at distances > 600 m, which was almost virtually null until 2010 increased dramatically in 2017 as indicated by the major increase in ρ values at distances from Forest pixels > 600 m from 2010 to 2017. Estimates of ρ for the Rubber pixels of each successive year as a function of distance to Forest pixels in 2017 (Figure 10) also indicate that, throughout the study period, the highest densities of rubber tree plantations progressively shifted closer to the edges of forest as they appeared in 2017.

When considering the spatial dependency of land use classes with terrain elevation and slope, it appeared that both Agriculture and Rubber were associated with low elevations (500 to 900 m) while forest was mostly present at intermediate elevations ranging from 900 to 1,600 m. The case of Settlements was different, with strong dependency at both ends of the elevation range (Figure 11).

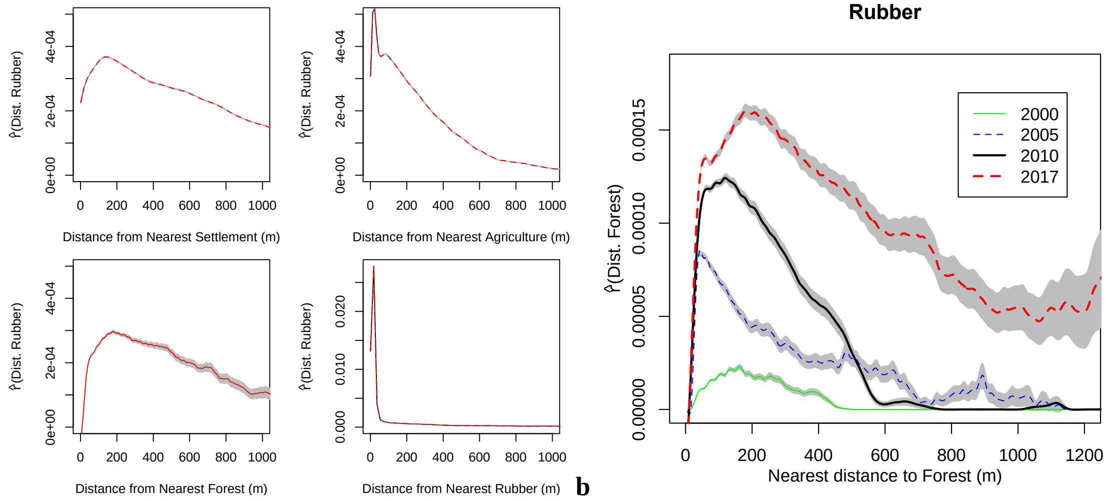

Figure 9: a. From top left to bottom left panel, clockwise: estimates of $\hat{\rho}$ (kernel density estimation of dependence of a spatial point pattern on spatial covariates; Baddeley et al., 2012) for the Rubber pixels from the 2017 classification as a function of distance to nearest Settlement, Agriculture Rubber and Forest pixels (distances computed based on unmarked point processes with all years (2000-2017) aggregated). b. Estimates of $\hat{\rho}$ for the Rubber pixels of each year of the observation period as a function of distance to nearest Forest pixels in the corresponding year. Lines are estimates of ρ. Grey shading indicates ±2 standard deviation (nominally 95% pointwise confidence) intervals

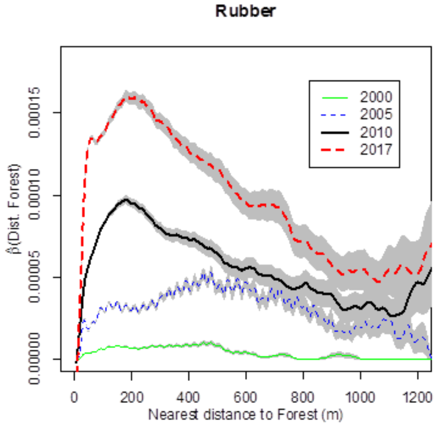

Figure 10: a. estimates of $\hat{\rho}$ (kernel density estimation of dependence of a spatial point pattern on spatial covariates; Baddeley et al., 2012) for the Rubber pixels of each year of the observation period as a function of distance to nearest Forest pixels in 2017. Lines are estimates of $\hat{\rho}$. Grey shading indicates ±2 standard deviation (nominally 95% pointwise confidence) intervals

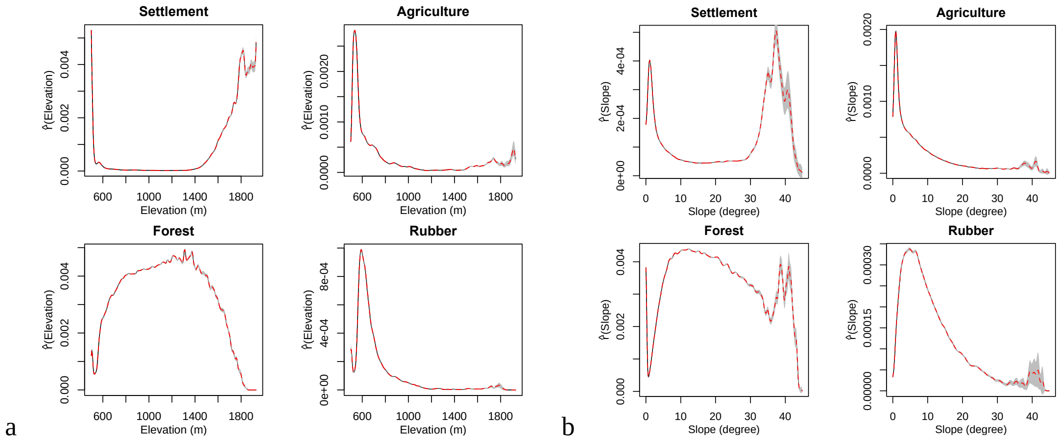

Figure 11: Estimates of $\hat{\rho}$ (kernel density estimation of dependence of a spatial point pattern on spatial covariates; Baddeley et al., 2012) for the four Land Use classes (unmarked point processes, all years aggregated) as a function of a. terrain elevation and b. slope. Dashed lines are estimates of $\hat{\rho}$. Grey shading indicates ±2 standard deviation (nominally 95% pointwise confidence) intervals

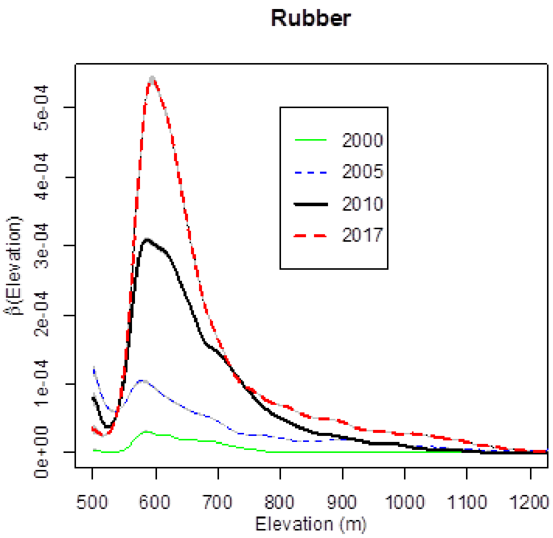

Figure 12: a. estimates of $\hat{\rho}$ (kernel density estimation of dependence of a spatial point pattern on spatial covariates; Baddeley et al., 2012) for the Rubber pixels of each year of the observation period as a function of terrain elevation. Lines are estimates of $\hat{\rho}$. Grey shading indicates ±2 standard deviation (nominally 95% pointwise confidence) intervals

Agriculture appeared more strongly associated with flat terrain (<10 degrees) than Rubber, which displayed a weaker dependency to low slopes. Forest was associated to both gentle and steep terrain while settlements were found in both the flattest and steepest areas of the studied region (Figure 11). Over years, it appears that, while the peak of rubber tree point density remained centered around elevations of about 600 m, rubber tree plantations also became increasingly frequent at higher elevations as indicated by higher ρ values for successive years at elevations > 600 m (Figure 12).

4. Discussion

Agriculture remains a main source of income for the populations that reside in the rural areas of many Southeast Asia countries (Putzel, 2000). The majority of farmers have used their lands for subsistence and commercial production. On the other hand, although they focus on cash production, but they still produce subsistence output because this helps reduce the risks associated with market demand (Manivong, 2007). This research aimed to characterize and analyze land use/land cover change in the Luangnamtha district, northern Laos, from 2000 to 2017, based on remote sensing and Geographic Information System techniques. The overall accuracy of the land use classification presented in this paper ranged from 86.8% and 91.7%, indicating that the classification computed can be accepted in the study area. However, there are limitations related to the collection of some training points, particularly for older time periods and remote areas. To attempt solving such problems, we relied upon information provided by farmers who have knowledge of the areas for which we could not obtain data directly and/or from imagery. In particular, we resorted to this an approach to collect some training points of agricultural land and rubber for year 2000 and 2005. In the study area, the main land use/land cover was forest land which has found to have decreased of about 9.84% from 2000 to 2017. This result is consistent with other studies conducted in Luangnamtha province and northern Laos (Thongmanivong et al., n.d., Phanvilay et al., 2006, Luangmany and Kanako, 2013 and Liu et al., 2016). During the same time interval, agricultural land was reduced, particularly during the 2000-2005, period, but also over the whole 2000-2017 interval. Since 2003, rubber tree plantations have boomed in Luangnamtha province (Shi, 2008), farmers having converted their swidden and fallow forests into permanent agricultural land (Thongmanivong et al., n.d.). From that time on, agricultural land (swidden) has not expanded and many paddy fields have been converted to woodland and construction land in Luangnamtha district (Liu et al., 2016). This narrative is in line with the results of our study which clearly indicate that rubber tree plantations sharply increased over the time span of the study period, while agriculture remained virtually unchanged and settlements expended much more gradually and to a much lesser extent. Overall, the spatial relationships between Land Use classes and terrain covariables that we have assessed in this work suggest that, over the 2000-2017 period, both rubber tree plantations, agriculture and settlements expended at the cost of loss of corresponding forested areas. Rubber tree plantations and agricultural land appeared to be the two land use classes the most strongly spatially associated, which is consistent with the conversion of agricultural land to rubber tree plantations, while rubber was also, while more weakly, spatially correlated to the location of settlements. The results of our analysis of the dependence of the spatial distribution of Rubber pixels on covariates such as terrain attributes and distance to forest boundaries also indicate that, over the course of the study period, rubber tree plantations tended to occur ever closer from the most recent forest boundaries and at regularly increasing elevations, thus suggesting a centrifugal expansion from the lowest, most populated and settled parts of the landscape to increasingly remote areas, at the expense of forest cover. Although our classification procedure resulted in classifying some pixels located in high elevation/slope areas as pertaining to the Settlement class, this most likely correspond to a misclassification, at least for the areas above 1,700 m, which represent only a small fraction (0.2%) of the study area.

The study area is located along the Northern Economic Corridor which connects to Chiang Rai province in Thailand to the South and Yunnan province in China, to the North; along this economic corridor, development has focused on agriculture and rural development, urban development including building industrials, infrastructures, construction of roads to promote the trade and tourism, and social development. All these actions aimed to reduce poverty and economic differences between provinces and regions (Anderson et al., 1976 and MPI, 2011). Likewise, the statistics data of the National Statistics Centre of Laos, indicate that between 2005 and 2015 the population density has increased from 16 to 19 persons per Sq.Km. which represents 17.32% increase (Lao Statistics Bureau, 2015 and National Statistics Centre, 2005). From our classification, although rubber prices have plummeted after 2011 and remain low now with prices of 0.6 to 0.8 US dollars (Vongvisouk and Dwyer, 2017), we can conclude that farmers continued to expand rubber tree plantations until as late as 2017, even though at a lower expansion rate than during the 2005-2010 period, and that they keep maintaining the vast majority of the area planted in rubber trees across the district. Such a choice is probably related to the important investment that conversion to rubber tree plantations represents and to most farmers' expectation that the rubber trading prices will increase in the near future.

5. Conclusions

This research focused on land use/land cover change in Luangnamtha district, northern Laos over the 2000 to 2017 period, based on classification and analysis of Landsat Images, using GIS technologies. Our results revealed major land use change , with a 9.84% (21,129 ha) decrease in forested land largely due to conversion to rubber tree plantations, the area of which underwent a near twenty-fold increase in less than two decades and now distribute along most of the main roads, rivers, and urban areas of the study area. This conversion of forest to rubber tree plantation was accompanied by a 2.35% (5,038 ha) increase in the area covered by settlements, a modest decrease 0.11% (224 ha) in agricultural land and a marginal increase 0.01% (20 ha) of the area covered by water bodies. These changes correspond to population growth and socio-economic development, which resulted in the expansion of built-up areas and commercial infrastructure (roads, factories, tourism places). Moreover, the research methodology presented in this paper can be transferred to governmental research and education agencies as practical tools to monitor and assess land use and land use change.

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