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TROPICAL FOREST CHANGE DETECTION OVER THE LAST 25 YEARS IN XISHUANGBANNA, YUNNAN, CHINA, BASED ON THE CLASLITE MODEL

Rafael Antonio Chaparro,[1] Wang Jinliang[2] and **Li Jia[3]**
[2]Professor, [1, 3]College of Tourism & Geographic Sciences, Yunnan Normal University, Chenggong, Kunming, Yunnan, China.
Email: wang_jinliang@hotmail.com

Abstract: *The development of sophisticated and accessible approaches to monitoring deforestation and forest degradation is central to assessing changes in ecological processes such as carbon storage, biodiversity, biomass and many others in tropical regions. CLASlite is an automated satellite mapping model used to identify deforestation and forest degradation, especially in tropical forest regions. In this paper, we used the CLASlite model to analyses deforestation and forest disturbance from 1990 to 2015 in Xishuangbanna, situated in the southern part of Yunnan Province. We found that the highest rate of forest change was 23% between 1995-2000, followed by 0.64% during the period 1990-1995 and 2.81% during the period 2000-2005. The overall rate of forest change in the last five years is 2.18%. By means of geographic information system processes, the forest changes detected were compared with the land uses and protected areas of the study area. Most of the change to forest area corresponds to crops and plantations, mosaics of vegetation and natural forest. The deforestation within environmentally protected areas was 285.2 km², 6.53% of the total protected area. Xishuangbanna is one of the few regions in China with a significant tropical forest area, but, as the results illustrate, these areas are at serious risk of disappearing. We consider it important to continue monitoring this region conscientiously, especially in its protected areas. Advanced remote sensing approaches play an important role in attaining the objective.*

Key words: CLASlite, Landsat, deforestation, tropical forest, Xishuangbanna.

1. Introduction

According to the WWF estimations in the last 25 years, the world lost some 129 million ha of forest (WWF, 2011). A big part of that loss belongs to the tropical forests cover, they although are less than 6% of the surface of the planet, but are home to approximately half of all living species on Earth (WWF, 2006), tropical forests apart from being home to the richest biodiversity on the planet, are a source of fuel and sustenance to human inhabitants, in addition to storing massive amounts of carbon that would otherwise accelerate global warming (CLASlite Team, 2013). In the last decades China's forest cover have experimented important changes, the rapidity of the country's development has affected its natural resources, during the 1970s to 1990s, with weak forest protection laws and enforcement, the annual deforestation rate reached a value of 3.0% (Li S & Yang Q, 2000; Zhu H, Chai, S. et al., 2015), that contributed to severe water and wind erosion of soil. By 1990s, approximately 38% of China's total land area was considered badly eroded, particularly, in Yunnan and Sichuan provinces (Ren et al., 2013), however, according to recent Chinese government statistics, the country's forests have been recovering over the past three decades, this thanks to one of the largest forest conservation and restoration programs in the world “The Natural Forest Conservation Program (NFCP)”. Lowland tropical forests once covered a large portion of tropical southern China, but currently have a reach of 633,800 ha, mostly in Xishuangbanna in the southern area of Yunnan province (Cao Zou, Warren, & Zhu, 2006, H Zhu, H Wang and SS Chou, 2010). The forests of Xishuangbanna are habitat to a biodiversity that is essential both nationally and globally; this region is included amongst the Indo-Burma biodiversity hotspots and includes over 5000 species of vascular plants, comprising 16 percent of China’s total plant variety (Myers et al., 2000; Zhou, 2010).

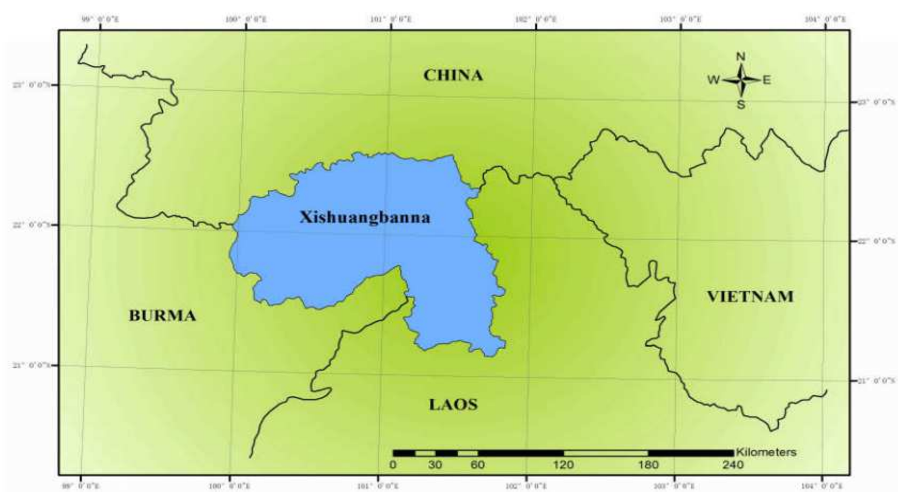
Historically, the Xishuangbanna region would have had almost total forest cover, predominated by subtropical evergreen broad leaf forest, mountain rainforest and tropical seasonal rainforest. These forested areas have mostly been replaced by rubber plantations, shifting cultivation and scrublands (Li, Ma, Aide, & Liu, 2008; Zhu, H, 2017).Monitoring deforestation is central to assessing changes in carbon storage, biodiversity and important ecological processes such as biogeochemical cycling, energy flow, community dynamics, species interaction and biological movement (McQuillan et al, 2009). Satellite remote sensing is the most accurate and cost-effective way of monitoring changes in forest cover and degradation over vast geographical areas (Asner, 2009). Global satellite mapping of vegetation coverage has greatly improved over time and may be considered routine for calculating estimates of deforestation (Achard et al., 2007). However, these mapping approaches currently require expert maintenance and often miss millions of small forest clearings that occur at a small scale, thus discounting a large portion of forest degradation (Zhu, H, 2017). But several other higher resolution regional mapping approaches have also been developed (Hansen et al., 2008; Huang et al., 2008), The Carnegie Institution for Science developed the Carnegie Landsat Analysis System or CLAS. CLASlite is a software package specifically designed to support forest monitoring for REDD “United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation” (Asner, 2009; UN-REDD, 2016), this method was designed for highly automated identification of deforestation and forest degradation, including monitoring at < 0.1 ha spatial resolution (Asner, 2011).

CLASlite has become a very reliable and sophisticated model adopted by official organizations and governments in South American countries and some African and Asian regions with tropical forests for deforestation monitoring (Asner, G, 2014). This model is not very familiar in China yet, so in this study, we applied CLASlite to monitoring forest changes in the tropical region of Xishuangbana. More specifically, we studied forest change over the last 25 years (1990–2015) using satellite images provided by Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (OLI-TIRS). Here, we combine CLASlite and spatial analysis to compare the rates of deforestation with land uses and protected areas. Firstly, we identified deforestation and disturbance pixels through CLASlite's sub-pixel analysis processes (Radiometric calibration, atmospheric correction, masking of Clouds, water and shadows, decomposition and classification of the imagery into forest cover, and mapping of deforestation and disturbance), then, by multi-image analysis calculate the forest change in the last two decades, secondly, we used ArcGIS 10 to compare the CLASlite results, analyze the relation between deforestation and land uses, and calculate the deforestation in the protected areas.

2. Study Area

Xishuangbanna is situated in the province of Yunnan in southwest China, bordering Laos and Burma (Fig. 1). Xishuangbanna has an area of 19,125 km^2 and the altitude varies from 517 to 2415Meters above sea level (Guardiola, Claramonte et al., 2010; Zhu, H. Y. Chai, S. et al, 2015). The average temperature is 20–22.5 °C, with the average highest temperature of 25–27 °C occurring in May–June. The wet season lasts from May to October during which 90% of the rainfall occurs and the average precipitation is 1200–1800 mm per annum (Guardiola et al., 2010). Xishuangbanna lies in the transition zone from sub-tropical to tropical climates and lies within the zone from the Eastern Himalaya flora and fauna to the biota of mainland Southeast Asia (Yi et al., 2014). There are over 5000 flowering plant species, accounting for approximately 35% of all of Yunnan's higher plants, including 153 endemic species and 56 endangered species (Yi et al., 2014). The region contains China's largest area of diverse types of mature tropical forest, which mainly belongs to the Xishuangbanna Biosphere Reserve. This reserve features 8 vegetation types and 12 sub-types, including tropical rain forest, tropical monsoon forest and sub-tropical monsoon evergreen broadleaf forest (Zomer, Trabucco, Metzger, & Oli, 2013; Zomer et al., 2014). The population of Xishuangbanna is approximately 1.1 million and includes 13 distinct ethnic minorities (Sturgeon, Janet C, 2012), included among which are the Dai (Tai Lue), Hani (Akha), Jinuo and Miao (Hmong). Traditionally, all minorities were hunter-gatherers and kept livestock (Sturgeon & Menzies, 2006). In more recent times, however, a large socio-economic shift in household income has occurred across all ethnic groups, with rubber monoculture and terrace tea becoming increasingly important (Cannon, Chen, Ye, & Swetnam, 2014).

Fig. 1. Location of Xishuangbanna in the southern part of Yunnan province of China.



2.1. Data sources

Images from Landsat satellites (Landsat 5-TM, Landsat 7-ETM+, and Landsat 8-OLIT-TIRS) covered the study area. The images selected were taken during the driest period of the year (January to March) as there is a relatively low cloud coverage (<10% cloud cover). In total we used 28 images obtained from the NASA and the US Geological Survey online service http://earthexplorer.usgs.gov (USGS, 2015).

The basic geographical information was obtained from the following sources:

- Raster data: Global land cover data of ESA-GlobCover-2009, resolution of 300 meters, format TIFF, (Gscloud.cn, 2015).
- Boundary line vector data (shape-files): Geo-spatial data cloud www.gscloud.cn (Gscloud.cn, 2015).
- Protected Areas shape-files: UNEP-WCMC, United Nations Environment Programme, World Database on Protected Areas, Cambridge, UK (UNEP-WCMC, 2015).

3. Method

CLASlite is a software package developed by an expert team at the Department of Global Ecology of the Carnegie Institution for Science (Asner, 2009). It was designed specifically for highly automated identification of deforestation and forest disturbance using remotely sensed satellite imagery (CLASlite Team, 2013). The CLASlite technology has evolved in the last 8 years, it has been mainly used to monitor important amazon areas in South America (Brazil, Peru, Bolivia, Colombia) (Cabrera et al., 2011) Also, regions of Asia and Africa, have implemented CLASlite's model to evaluate deforestation, carbon emissions, and illegal logging (Claslite.edu, 2016). CLASlite model provides an automated satellite mapping approach to determine important components of tropical forest structure: fractional cover of vegetation canopies, dead vegetation, and bare surfaces. These covers are core determinants of ecosystem composition, physiology, structure, biomass, and biogeo-chemical processes (Feng, M. C, Huang. et al., 2013). CLASlite through a fractional cover analysis allows for rapid forest monitoring with error tracking, we processed 28 Landsat scenes using CLASlite-version 3.2. In order to detect forest change across the time, CLASlite method integrates a series of processes that take raw satellite imagery and produces forest cover change images. These processes include (Radiometric calibration, Masking, Decomposition of image pixels into fractional surface covers, Forest Cover Classification and Forest Change Detection) as detailed below.

3.1 Radiometric calibration and atmospheric correction of satellite data.

Radiometric calibration consists in linking pixels intensities to a physical parameter. Its main goal is to allow comparisons of spectra from different origins and also measurements of important physical parameters (Buil, C, 2013). For radiometric calibration, CLASlite uses conversion factors (gains and offsets). The result of radiometric calibration is an image in units of radiance, also known as the energy measured by the satellite-based sensor. The radiometric data obtained contain information about both the Earth’s surface and its atmosphere. Thus, to work with vegetation (surface data), it is necessary to minimize the contribution of the atmosphere to the values of each pixel in the satellite image. The process of *atmospheric correction* minimizes the effect of water vapor (humidity), aerosols (from dust, volcanoes, etc.), and other factors. To apply atmospheric correction, CLASlite uses the 6S radioactive transfer mode (Vermote et al., 1997), which simulates the Earth’s atmosphere in each satellite image. 6S models the effect of the atmosphere on sunlight as it passes through the atmosphere, interacts with the land surface, and returns through the atmosphere to the satellite sensor. The raw image is then “corrected” by removing the estimated model of the atmosphere, resulting in an image of surface reflectance, which shows the fraction of incoming solar radiation that is reflected from Earth's surface.

3.2 Cloud, Water and Shadow Masking.

Mapping with optical satellite sensors (Landsat, SPOT, etc.) requires radiance data to determine the reflectance of each pixel, which is the information required to extract information about vegetative cover. No satellite sensors can collect this radiance information on the land surface through clouds, in darkened shadow areas under clouds, or in shadows caused by steep terrain. Thus, clouds and cloud shadows, terrain shadows, as well as bodies of water must be masked, or excluded from the image analysis. CLASlite has two masking steps: The first is in step 1 for image calibration, and the second is in step 2 for the fractional cover map. The masking that occurs in step 1 eliminates clouds, cloud shadows, topography shadows, and water. The second eliminates MCU errors based on the RMSE values [the seventh band product] in the fractional cover image.

3.3 Decomposition of image pixels into fractional surface covers, Monte-Carlo spectral unmixing algorithm-AutoMCU.

Different types of Earth surface covers have different reflectance properties (spectral signature). From these spectral signatures, it is possible to derive information on each pixel in a reflectance image. The traditional land cover classification techniques assign a whole pixel to a class (i.e., forest, rock) based on the spectral signature in the pixel (Weng et al., 2011). This type of thematic classification is useful for land-cover mapping, but it often has reduced sensitivity to small variations and changes in forest cover that occur at the sub-pixel, or within-pixel, scale. Since we want to map deforestation and forest degradation occurring at the sub-pixel scale, we must use a different approach.

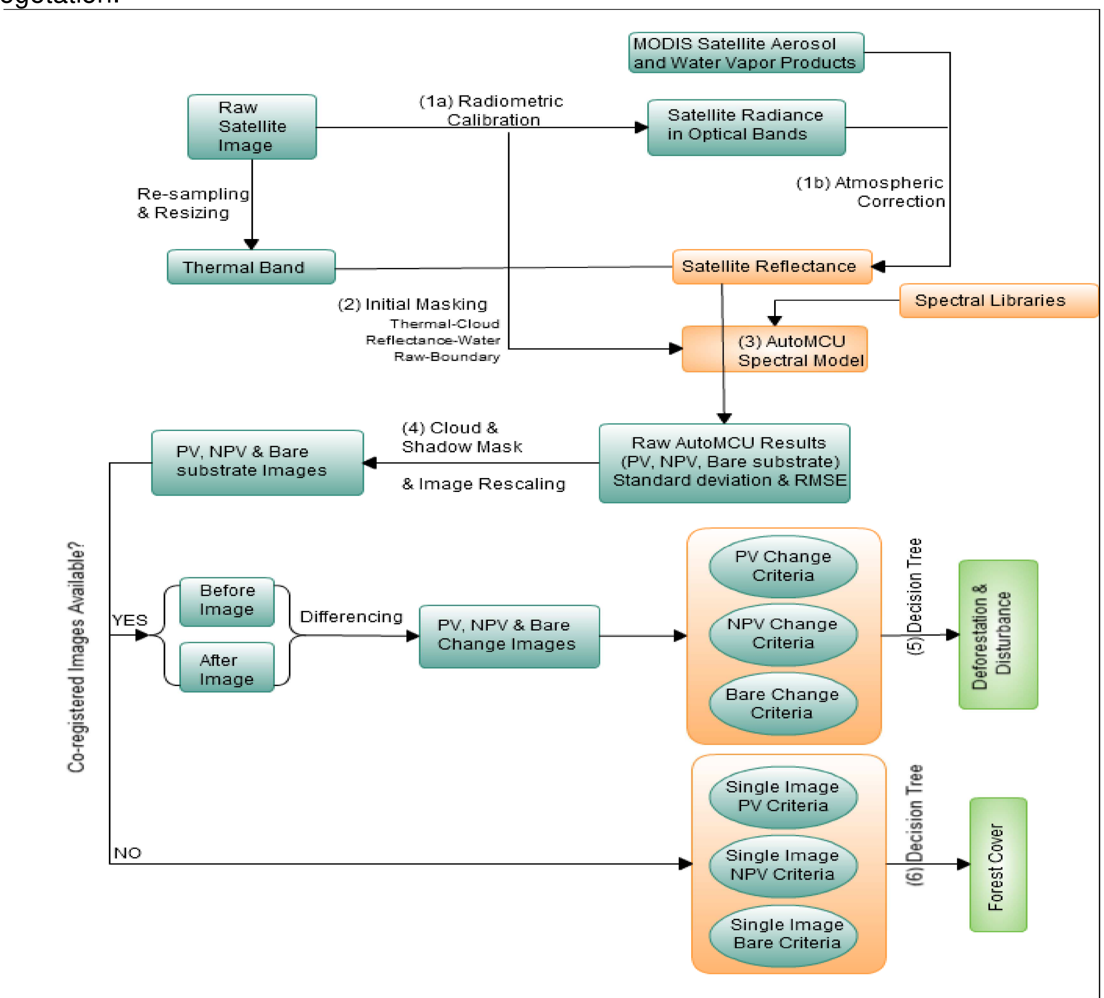
The AutoMCu, or Automated Monte Carlo Unmixing (Asner and Heidebrecht 2002, Asner et al. 2004), provides quantitative analysis of the fractional or percentage cover (0-100 %) of live and dead vegetation, and bare substrate within each satellite pixel (within each 30×30 m pixel in a Landsat image). Live vegetation is technically referred to as Photosynthetic Vegetation (PV) because live vegetation maintains unique spectral properties associated with leaf photosynthetic pigments, canopy water content, and the amount of foliage in the canopy. The dead or senescent vegetation fraction is termed Non-photosynthetic Vegetation (NPV). Which is expressed in the spectrum as bright surface material with spectral features associated with dried carbon compounds in dead leaves and exposed wood. Finally, bare substrate is often dominated by exposed mineral soil, but can also be rocks and human-made infrastructure.

The method requires “libraries” of spectral end members for each of three relevant surface cover types: bare substrate, photosynthetic vegetation, and non-photosynthetic vegetation. End members are reference spectra that are chosen as pure representatives of a given surface material, and they are intended to encompass the spectral variability within that surface material (Carnegie Institution, 2014) (a). These libraries, derived from extensive field databases and satellite imagery, are used to decompose each image pixel using the following linear equation:

$$\rho(\lambda)\ \text{pixe} = \sum [\, C_e \bullet \rho(\lambda)_e \,] + \varepsilon = [\, C_{pv} \bullet \rho(\lambda)_{pv} + C_{npv} \bullet \rho(\lambda)_{npv} + C_{substrate} \bullet \rho(\lambda)_{substrate} \,] + \varepsilon \quad (1)$$

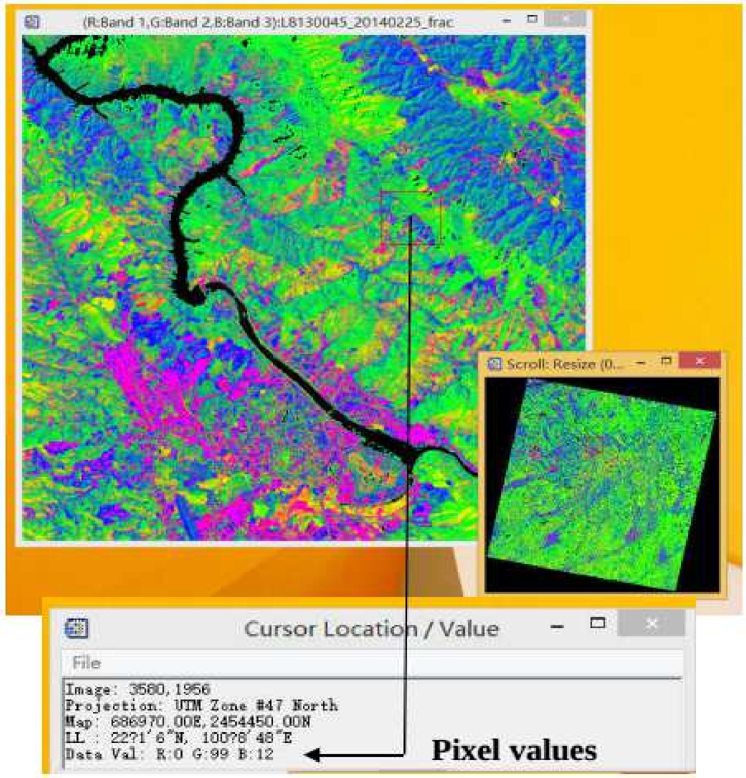
Where $\rho(\lambda)_e$ is the reflectance signature library (e) at wavelength λ and ε is an error term. Solving for each sub-pixel cover fraction (C_e) requires that the satellite observations ($\rho(\lambda)_{pixel}$) contain sufficient spectral information to solve a set of linear equations, each of the form in equation (1) but at different wavelengths (λ).
The tropical forest spectral libraries provide the spectral reflectance signatures required by the AutoMCU sub-model: $\rho_{pv}(\lambda)$, $\rho_{npv}(\lambda)$and $\rho_{subtrate}(\lambda)$.

Fig. 2. CLASlite 3.2 processing stream. Major processes are numbered 1-6. (CLASlite Team, 2013) (b); Asner, 2009(c)). PV: photosynthetic vegetation, NPV: No Photosynthetic vegetation.



The output from AutoMCU process is a 7-band image containing information about fractional cover of PV, NPV, and bare substrate, uncertainty estimates for each cover fraction, and total error for each pixel in the image.

Fig. 3. Image Landsat 8-2014 of Xishuangbanna after Sub-pixel analysis process "Decomposition of image pixels into fractional surface covers"



3.4 Forest Cover Classification.

A simple decision tree is used to convert the single-image AutoMCU results to an estimate of forestcover.Forest:PV≥80ANDS<20Non-forest:PV<80ORS≥20 where PV is photosynthetic vegetation cover fraction in the pixel, S is the bare substrate fraction in the pixel, this S term is included to eliminate non-forest regrowth (successional vegetation, grasses, and some agriculture which may contain high PV fractions) from the forested class. These regrowth cover types usually have higher S levels than are found in neighboring intact forest. This simple decision tree for forest cover, based on a default S setting of 20, is sufficiently general to allow the algorithm to accommodate a broad range of tropical forests.

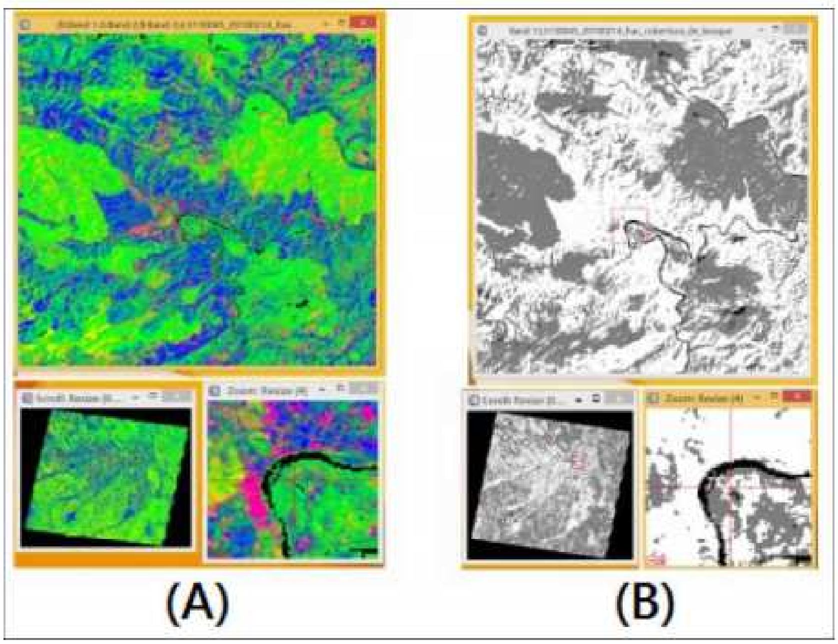
3.5 Forest Change Detection.

Multi-image analysis is the most accurate approach for detection of forest loss (deforestation), gain (secondary regrowth), or degradation (areas of persistent forest disturbance), "forest disturbance" refers to events such as forest fire, harvesting, wind-throw, insect and epidemics, and forest flooding that cause large pulses of CO_2 to be released into the atmosphere through combustion or decomposition of resulting dead organic matter (Pickett and White, 1985).

To map forest change, CLASlite applies the following decision trees to each pair of images, where the subscripts 1 and 2 indicate images from one year to the next. In this study, we compared five periods consisting of five years each from 1990 to 2015. (Table 1)

Deforestation:
$(((PV_1–PV_2)\geq$[PV decrease captures most deforestation] OR $((S_1 \leq 5)$ AND $((S_2 - S_1) \geq 15))$ [S increase captures deforestation followed by early regrowth] OR $((PV_2< 80)$ AND $((NPV_2 - NPV_1) \geq 20)))$[NPV increase]
Forest Disturbance:
$((((NPV_2 - NPV_1) \geq 10)$ AND $((PV_1 - PV_2) > 10))$ OR $((S_1 \leq 5)$ AND $((S_2 - S_1) > 10)$ AND $(S_2 \leq 15)))$ PV: is photosynthetic vegetation cover fraction in the pixel
S: is the bare substrate fraction in the pixel
NPV: is Non-photosynthetic vegetation cover fraction in the pixel
The masked pixels (water, cloud rings, cloud shadows, and topography shadows) are excluded from the forest change analysis [to eliminate the detection of false positives].

Fig. 4. Image Landsat 5-2010 of Xishuangbanna (A) before and (B) after Forest Cover Classification.



After performing all of the CLASlite processes on the images, by ArcGis software we took the obtained maps of forest change and delimited them to the study area, then, were measured theirs correspondent areas, in the same way, we compared this results with layers of land use and protected areas.

4. Results

The results indicate changes in forest cover, deforestation and forest disturbance during five periods. In addition, they show forest change within protected areas and land use units that have likely replaced former forested areas. We found that the largest total amount of forest change was observed during 1995-2000 with 197.32 km^2 of forest disturbance (0.8% of the total area) and 885.60 km^2 (3.97%) of deforestation, followed by 1990-1995 with 0.64% of disturbance and 2.95% of deforestation and then 2000-2005 with 0.34% and 2.81% respectively. During the last two periods (2005-2010, 2010-2015) the rate of forest change was over 2.1% (> 500 km^2 approximately), and the last five years presented the largest percent of forest disturbance (0.67%, >149 km^2 approx). (Table 1, Fig. 5).

Fig. 5. Map of deforestation 2005 -2015 across study area.

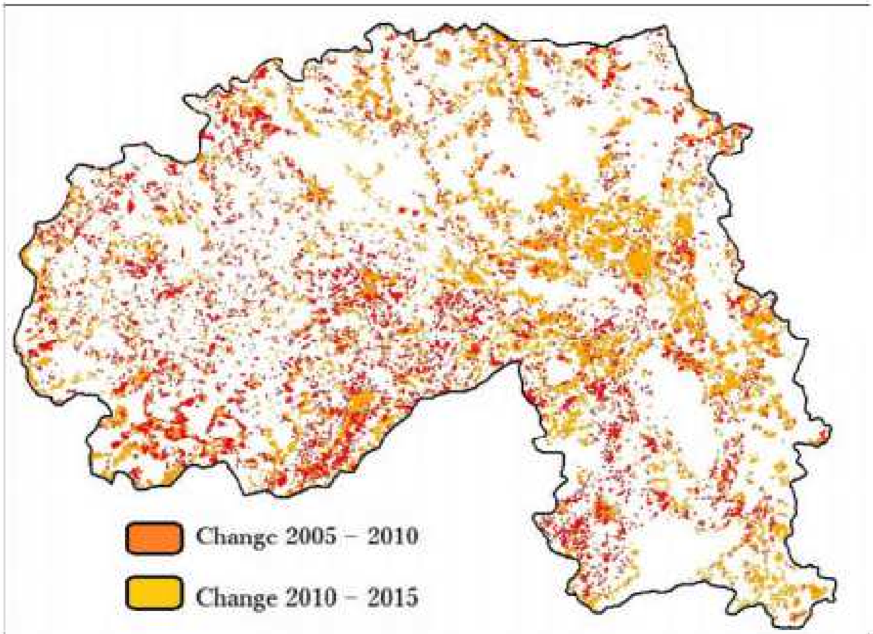
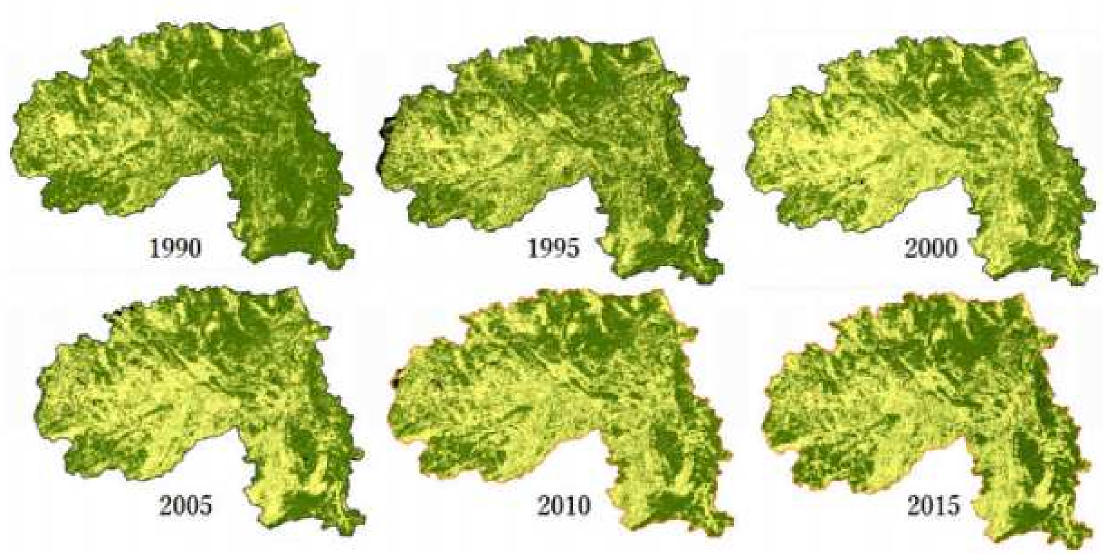


Table 1. Change per period. Forest change is the sum of disturbance and deforestation.

Era	Disturbance		Deforestation		Forest change	
	total	%	total	%	total	%
1990-1995	144.12 km^2	0.64%	657.70 km^2	2.95%	801.82 km^2	3.59%
1995-2000	179.32 km^2	0.80%	885.60 km^2	3.97%	1064.92 km^2	4.77%
2000-2005	76.64km^2	0.34%	626.97km^2	2.81%	703.61 km^2	3.15 %
2005-2010	90.62 km^2	0.40 %	543.59 km^2	2.44%	634.21 km^2	2.84%
2010-2015	149.36 km^2	0.67%	336.40 km^2	1.51%	485.76 km^2	2.18%

The total deforested area during the last 15 years in the study area was of 3050.26 km^2 and the disturbance was 640.06 km^2. the result maps show that besides the current protected areas, most of the others forest sectors were clearly altered.

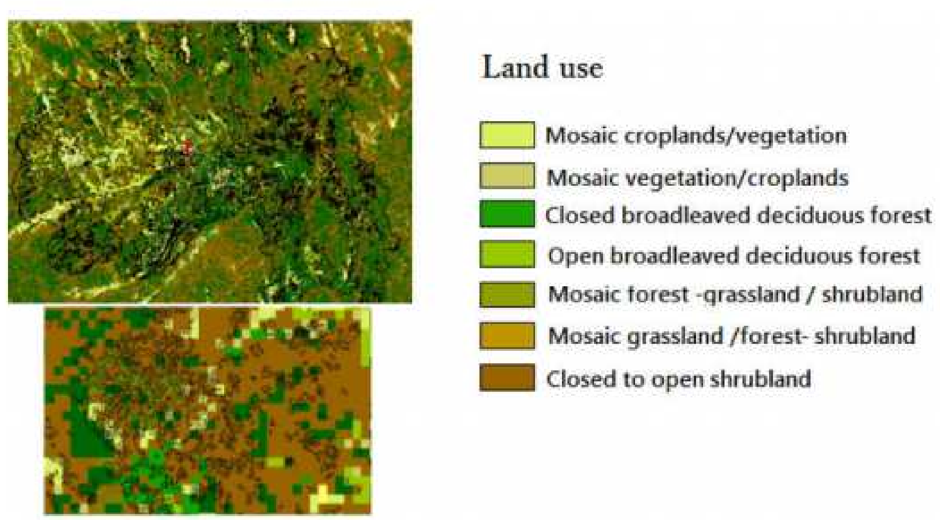
Fig. 6 Change forest cover from 1990 to 2015 on of Xishuangbanna, green areas represent forest cover.



After applying overlay and intersection functions to the CLASlite results, maps of land use in 2009 (Gscloud.cn, 2015) and protected areas of Xishuangbanna (UNEP-WCMC, 2015), we found that:

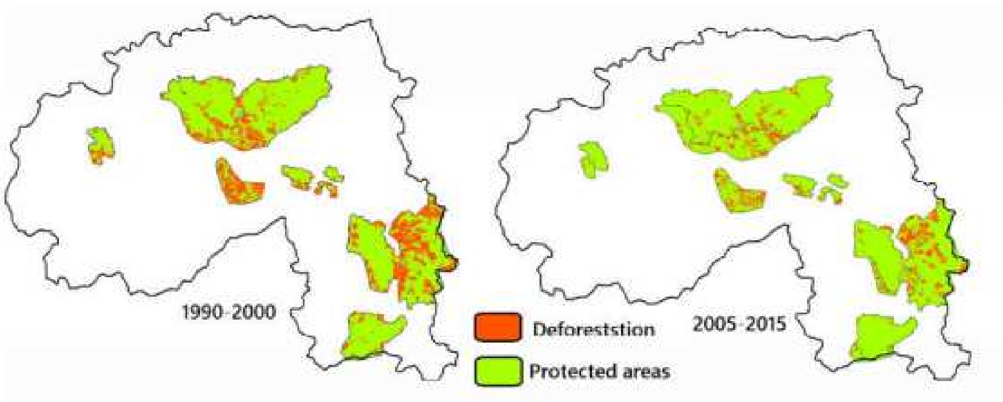
A) The majority of the change found in forested areas correspond to land uses related to crops and plantations, mainly rubber plantations. In 2010, rubber crops occupied 4242 km^2, 22% of the total area of Xishuangbanna, while farmlands occupied 2194 km^2, 11% of the area of Xishuangbanna (Zomer et al., 2014). In the same way, there are current areas of deforestation and disturbance that before were some mosaics of vegetation and natural forest, (mosaic croplands/vegetation, mosaic grassland /forest/ scrubland, closed broadleaved deciduous forest, closed to open scrubland)

Fig. 7. Overlay between deforestation areas and land uses 2009.



B) The deforestation in environment protection areas until 2000 year was of 202.48 km², this area represents the 4.64% of total in protected areas, and from 2005 to 2015 the deforestation was 82.72 km² (1.89%).

Fig. 8. Deforestation on protected areas of Xishuangbanna.



5. Discussion

The results obtained in this study show the forest change in the Xishuangbanna area over the last 25 years. These changes were measured according to the rates of deforestation and forest disturbance in the area. Although we found that the highest rates of forest change were between 3.5 and 4.5% from 1990 to 2000, previous studies indicate that historically the Xishuangbanna region would have had almost total forest cover, dominated by tropical seasonal rainforest (21%), mountain rainforest (23%) and subtropical evergreen broad leaf forest (57%). By 1976, forest cover had been reduced to 70% and by 2003 to 50% (Li, Ma, Aide, & Liu, 2008). The estimates of forest change in the 2000-2005 period was 140.7 km^2 per annum, which are very similar to the results obtained by Li et al. (2008), who estimated a deforestation rate of 137.2 km^2 per annum in the same time period. The forest change is attributable principally to the massive cultivation of rubber (Ahlheim, Börger, & Frör, 2015; Zhai, Xu, & Dai, 2015), scrublands and shifting cultivation (Zomer et al., 2014), other factors such as climate change and accelerated development in the region have also had influence. Southern China has experienced an increase in average temperature in the last decade (Zomer et al. 2013). Also, the increase in urban infrastructure, and changes in local socio-economic dynamics have assisted the transformation of the landscape. These abrupt changes have led to the occupation of territory that was once natural forest. After overlapping the deforestation and land use layers (2009), we confirmed that most of the areas that suffered deforestation corresponded to land uses related to crops and plantations (Fig. 7).

A decrease in the annual rate of forest change can be observed over the last decade. Between 2005 and 2010, the change was 2.8% (Fig. 4, 5). The forest recovery observed during this period was possibly as a result of the reforestation programmes carried out by government, Green Programme (Chen, Zhang, Zhang, & Wan, 2009) and National Forest Protection Program (Ren et al., 2013), Over the 2000-2010 period, around 1.6% (157,315 km2) of China's territory displayed a significant gain in percent tree cover (Vina et al., 2016). The change rate was around 2% in 2015, which is the lowest rate in the last two decades, but it is still a notable degree of forest disturbance. In this study we combined CLASlite methodology with the GIS process to calculate the accumulated deforestation inside environment protection areas, which represent the largest part of tropical rainforest within Xishuangbanna. Until 2000, an area of 202.48 km^2 suffered deforestation, 4.64% of the total area of environment protection areas. In 2015, this rate decreased to 1.89%. XIshuangbanna's tropical forest and rubber plantations have been object of study in the last years, by mean advanced methods of remote sensing, such as Phenology-Based Vegetation Index Differencing (Fan et al., 2015) and Multi-Spectral Phenological Metrics from MODIS Time Series (Senf et al., 2013), although these research results are focused in the rubber plantation detection, also as this study they showed a similar change forest tendency. Due to CLASlite has developed a special technique to tropical deforestation mapping, in recent years it has been used to detection and monitoring of deforestation in important tropical forest regions (Brazilian, Peru, Bolivia and Colombian Amazon, in Madagascar Rain forest and some South-Asia tropical countries, like Malaysia and Indonesia.) (Carnegie Institution, 2016). Here we show how remote sensing tools such as CLASlite can provide an objective and long-term view of trends in both small scale disturbance and deforestation, complementing policy and management needed to safeguard forests in protected areas. CLASlite was specifically designed to measure tropical forest change; therefore it is important to note that Xishuangbanna also has different kinds of forestation that can also be affected by deforestation. So, according to the present results, we suggest the continuation of subsequent research in a specific rainforest area (for example, nature reserves) over a shorter period of time, in this way rendering the CLASlite process more efficient and precise.

6. Conclusions

After we modeled and mapped the change in Xishuangbanna's forestation, our study highlights the continuation of the rate of deforestation, which reached a total of 3690.32 km^2 in the last 25 years. It is evident that forest change patterns in Xishuangbanna changed rapidly between 1995 and 2000 (1064.92 km^2). The lowest deforestation rate (2.18%) was observed over the last five years 2010-2015. Nevertheless, this period presented the largest rate of forest disturbance (0.67%). In this period the results show an increase in forest area as well. This highlights an important and persistent problem of lost forest within the Xishuangbanna region. Despite nominal protection, support and financing from national and international organisations during the last years (Zhu. H, 2017), the rate of deforestation has remained within notable proportions. Although the main cause of Xishuangbanna's deforestation is rubber plantations, other factors such as climate change, economic development and urban expansion are also important causes of landscape alteration and deforestation. Thus, in order to protect and recover tropical forest and its ecological functions, it is fundamental to strengthen and enhance the strategies and programmes established by authorities as well as the participation and compromise of the Xishuangbanna community. CLASlite provides an objective and long-term view of trends in disturbance and deforestation of tropical forests. Tropical forests are on the decline in China, so it is vitally important to preserve the remaining forests. Remote sensing approaches are good tools to complement the authorities' conservation and protection work, so, in order to monitor in a more accurate and detailed manner, we suggest the continuation of research in specific rainforest areas (nature reserves) by using CLASlite and high resolution images.

References

1. Achard, F., DeFries, R., Eva, H., Hansen, M., Mayaux, P., & Stibig, H. (2007) Pan-tropical monitoring of deforestation. *Environ. Res. Lett.*, *2*(4), 045022. http://dx.doi.org/10.1088/1748-9326/2/4/045022
2. Ahlheim, M., Börger, T., & Frör, O. (2015) Replacing rubber plantations by rain forest in Southwest China—who would gain and how much?. *Environmental Monitoring And Assessment*, *187*(2). http://dx.doi.org/10.1007/s10661-014-4088-8
3. Asner, G. (2014). Satellites and psychology for improved forest monitoring. *Proceedings of the National Academy of Sciences*, *111*(2), 567-568. http://dx.doi.org/10.1073/pnas.1322557111
4. Asner, G. (2011) Painting the world REDD: addressing scientific barriers to monitoring emissions from tropical forests. *Environ. Res. Lett.*, *6*(2), 021002. http://dx.doi.org/10.1088/1748-9326/6/2/021002
5. Asner, G. (2009) Automated mapping of tropical deforestation and forest degradation: CLASlite. *Journal of Applied Remote Sensing*, *3*(1), 033543. http://dx.doi.org/10.1117/1.3223675
6. Asner, G. (1998) Biophysical and Biochemical Sources of Variability in Canopy Reflectance. Remote Sensing Of Environment, 64(3), 234-253.http://dx.doi.org/10.1016/s0034-57(98)00014-5
7. Asner, G., Keller, M., Pereira, Jr, R., Zweede, J., & Silva, J. (2004) CANOPY DAMAGE AND RECOVERY AFTER SELECTIVE LOGGING IN AMAZONIA: FIELD AND SATELLITE STUDIES. Ecological Applications, 14(sp4).
8. Asner, G. & Heidebrecht, K. (2002) Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: Comparing multispectral and hyperspectral observations. *International Journal Of Remote Sensing*, *23*(19), 3939-3958. http://dx.doi.org/10.1080/01431160110115960
9. Cabrera, V., IDEAM, Ordoñez, M., Vergara, P., Rubiano, J., Giraldo, P., & Garcial, G. (2011) Memoria técnica de la cuantifi cación de la deforestación histórica nacional – escalas gruesa y fi na (1st ed.). Bogotá D.C., Colombia: Instituto de Hidrología, Meteorología, y Estudios Ambientales-IDEAM.
10. Cao, M., Zou, X., Warren, M., & Zhu, H. (2006) Tropical Forests of Xishuangbanna, China1. *Biotropica*, *38*(3), 306-309. http://dx.doi.org/10.1111/j.1744-7429.2006.00146.x
11. Carnegie Institution,. (2014) CLASlite Forest Monitoring Technology, Version User Guide (1st ed., p. 6). Stanford, CA: Carnegie Institution For Science Department Of Global Ecology.
12. Chen, A. (1991) Main models of existing agroforestry systems in Xishuangbanna. *Journal Of Central South University Of Forestry & Technology*, *1*(2), 174–181.
13. Chen, X., Zhang, X., Zhang, Y., & Wan, C. (2009) Carbon sequestration potential of the stands under the Grain for Green Program in Yunnan Province, China. *Forest Ecology And Management*, *258*(3) 199-206. http://dx.doi.org/10.1016/j.foreco.2008.07.010
14. Carnegie Institution, (2016) CLASlite Forest Monitoring, Carnegie Institution for Science. [online]Claslite.carnegiescience.edu.Availableat:http://claslite.carnegiescience.edu/en/index [Accessed 26 Jul. 2016].
15. Claslite.ciw.edu, (2016) Success Stories from the CLASlite Community, CLASlite Forest Monitoring. *Claslite.ciw.edu*. Retrieved 20 December 2016, from http://claslite.ciw.edu/en/success/index.html
16. CLASlite Team, (2013) *CLASlite Forest Monitoring | Carnegie Institution for Science*. *Claslite.carnegiescience.edu.* Retrieved 31 December 2015, from http://claslite.carnegiescience.edu.

17. EarthExplorer,USGS. (2015) U.S. Department of the Interior U.S. Geological Survey Retrieved 1 September 2015, from http://earthexplorer.usgs.gov/
18. Fan, H., Fu, X., Zhang, Z. and Wu, Q. (2015) Phenology-Based Vegetation Index Differencing for Mapping of Rubber Plantations Using Landsat OLI Data. *Remote Sensing*, 7(5), pp.6041-6058.
19. Feng, M., Sexton, J., Huang, C., Masek, J., Vermote, E., Gao, F., Narasimhan, R., Channan, S., Wolfe, R. and Townshend, J. (2013) Global surface reflectance products from Landsat: Assessment using coincident MODIS observations. Remote Sensing of Environment.
20. GOFC-GOLD, (2008) *Reducing greenhouse gas emissions from deforestation and degradation in developing countries: a source-book of methods and procedures for monitoring, measuring and reporting*. Alberta, Canada: GOFC-GOLD Project Office, Natural Resources Canada.
21. Gscloud.cn, (2015) *Geo-espatial data cloud*. *Gscloud.cn.*. Retrieved 1 November 2015, from http://www.gscloud.cn.
22. Guardiola-Claramonte, M., Troch, P., Ziegler, A., Giambelluca, T., Durcik, M., Vogler, J., & Nullet, M. (2010) Hydrologic effects of the expansion of rubber (Hevea brasiliensis) in a tropical catchment. *Ecohydrol.*, *3*(3), 306-314. http://dx.doi.org/10.1002/eco.110
23. Hansen, M., Roy, D., Lindquist, E., Adusei, B., Justice, C., & Altstatt, A. (2008) A method for integrating MODIS and Landsat data for systematic monitoring of forest cover and change in the Congo Basin. *Remote Sensing Of Environment*, *112*(5), 2495-2513. http://dx.doi.org/10.1016/j.rse.2007.11.012
24. Huang, C., Song, K., Kim, S., Townshend, J., Davis, P., Masek, J., & Goward, S. (2008) Use of a dark object concept and support vector machines to automate forest cover change analysis. *Remote Sensing Of Environment*, *112*(3), 970-985. http://dx.doi.org/10.1016/j.rse.2007.07.023
25. Jianchu, X., Fox, J., Vogler, J., Yongshou, Z., Lixin, Y., Jie, Q., & Leisz, S. (2005) Land-Use and Land-Cover Change and Farmer Vulnerability in Xishuangbanna Prefecture in Southwestern China. *Environmental Management*, *36*(3), 404-413. http://dx.doi.org/10.1007/s00267-003-0289-6
26. Jiaq, Z. (2013) The Impacts of Rubber Plantation on the Eco- environment in Xishuangbanna of Yunnan Province. *China Population, Resources and Environment*.
27. Li, H., Ma, Y., Aide, T., & Liu, W. (2008) Past, present and future land-use in Xishuangbanna, China and the implications for carbon dynamics. *Forest Ecology And Management*, *255*(1), 16-24. http://dx.doi.org/10.1016/j.foreco.2007.06.051
28. Li, SC., Yang, QY. (2000) Socioeconomic factors determining China's deforestation rates. Geographical Research (in Chinese with English abstract) 19(1):1J7.
29. Liu, J. (2013) Forest Sustainability in China and Implications for a Telecoupled World. *Asia & the Pacific Policy Studies*, 1(1), pp.230-250.
30. MINAM. (2011) El Peru de los Bosques (1st ed., pp. 122,123). Lima: Ministry of the environment and the Ministry of Agriculture of Peru.
31. Myers, N., Mittermeier, R., Mittermeier, C., da Fonseca, G., & Kent, J. (2000) Biodiversity hotspots for conservation priorities. *Nature*, *403*(6772), 853-858. http://dx.doi.org/10.1038/35002501
32. Pickett, S. and White, P. (1985) The ecology of natural disturbance and patch dynamics. 1st ed. Orlando, Fla.: Academic Press.
33. Ren, G., Young, S., Wang, L., Wang, W., Long, Y., Wu, R., Li, J., Zhu, J. and Yu, D. (2013) The Effectiveness of China s National Forest Protection Program and National-level Nature Reserves, 2000 to 2010.
34. Senf, C., Pflugmacher, D., van der Linden, S. and Hostert, P. (2013) Mapping Rubber Plantations and Natural Forests in Xishuangbanna (Southwest China) Using Multi-Spectral Phenological Metrics from MODIS Time Series. *Remote Sensing*, 5(6), pp.2795-2812.

35. Sturgeon, Janet C. (2012) The Cultural Politics of Ethnic Identity in Xishuangbanna, China: Tea and Rubber as “Cash Crops” and “Commodities”, in: Journal of Current Chinese Affairs, 41, 4,109–131.
36. Sturgeon, J. & Menzies, N. (2006) IDEOLOGICAL LANDSCAPES: RUBBER IN XISHUANGBANNA, YUNNAN, 1950 to 2007. *Asian Geographer*, *25*(1-2), 21-37. http://dx.doi.org/10.1080/10225706.2006.9684131
37. UNEP-WCMC, (2015) *Protected Planet*. *Protectedplanet.net.*. Retrieved 13 November 2015, from http://www.protectedplanet.net.
38. UNFCCC, (2006) *Issues relating to reducing emissions from deforestation in developing countries and recommendations on any further process*. Geneva: United Nations-UNFCCC.
39. Vermote, E., El Saleous, N., Justice, C., Kaufman, Y., Privette, J., & Remer, L. et al. (1997) Atmospheric correction of visible to middle-infrared EOS-MODIS data over land surfaces: Background, operational algorithm and validation. Journal Of Geophysical Research: Atmospheres, 102(D14), 17131-17141. http://dx.doi.org/10.1029/97jd00201
40. Vina, A., McConnell, W., Yang, H., Xu, Z. and Liu, J. (2016) Effects of conservation policy on Chinas forest recovery. *Science Advances*, 2(3), pp.e1500965-e1500965.
41. Weng qi hao, Du shi hong, and Li pei jun., (2011) Remote Sensing and GIS Integration, Theories, Methods, and Applications. 1st ed. Bei jing.
42. Willson, A. (2006) Forest Conversion and Land Use Change in Rural Northwest Yunnan, China. *Mountain Research And Development*, *26*(3), 227-236. http://dx.doi.org/10.1659/0276-4741(2006)26[227:fcaluc]2.0.co;2
43. Xie, J. (1989) *Study on the productivity of an artificial rubber-tea community in tropical China* (Master). Kunming Ecological Institute, Chinese Academy of Sciences.
44. Yi, Z., Cannon, C., Chen, J., Ye, C., & Swetnam, R. (2014) Developing indicators of economic value and biodiversity loss for rubber plantations in Xishuangbanna, southwest China: A case study from Menglun township. *Ecological Indicators*, *36*, 788-797. http://dx.doi.org/10.1016/j.ecolind.2013.03.016
45. Yi, Z., Wong, G., Cannon, C., Xu, J., Beckschäfer, P., & Swetnam, R. (2014) Can carbon-trading schemes help to protect China's most diverse forest ecosystems? A case study from Xishuangbanna, Yunnan. *Land Use Policy*, *38*, 646-656. http://dx.doi.org/10.1016/j.landusepol.2013.12.013
46. Zhai, D., Xu, J., & Dai, Z. (2015) Forest transition in Xishuangbanna, Yunnan. *Plant Diversity And Resources*, *37*(1), 93-99.
47. Zhang, J. & Cao, M. (1995). Tropical forest vegetation of Xishuangbanna, SW China and its secondary changes, with special reference to some problems in local nature conservation. *Biological Conservation*, *73*(3), 229-238. http://dx.doi.org/10.1016/0006-3207(94)00118-a
48. Zhou, B. (2010). Revising the Yunnan Key Protected Wild Plants List. *Acta Botanica Yunnanica*, *32*(3), 221-226. http://dx.doi.org/10.3724/sp.j.1143.2010.09255
49. Zhu, H. (2017). The Tropical Forests of Southern China and Conservation of Biodiversity. The Botanical Review, 83(1), pp.87-105.
50. Zhu, H., B. G. Li, S. S. Zhou & J. H. Zhang. 2015a. Studies on the forest vegetation of Xishuangbanna. Plant Science Journal 33(5): 641–726
51. Zhu, H., H. Wang & S. S. Zhou. (2010) Changes in species diversity, floristic composition and physiognomy in a rain forest remnant over 48 years in southern Yunnan, China. Journal of Tropical Forest Science 22(1): 49–66.
52. Zomer, R., Trabucco, A., Wang, M., Lang, R., Chen, H., & Metzger, M. et al. (2014) Environmental stratification to model climate change impacts on biodiversity and rubber production in Xishuangbanna, Yunnan, China. *Biological Conservation*, *170*, 264-273. http://dx.doi.org/10.1016/j.biocon.2013.11.028