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The Impact of land use change on peatland degradation: A case Nathong and Saming Village, Champhone district, Champasack Province, Lao PDR

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Abstract

The major impact on land use change and peatland degradation was directly from human activities and inappropriate management. Changing of land use and land cover (LULC) influence directly on peat land drained and degraded. Nathong and Saming Village, Champhone district, Champasack Province, Lao PDR is one of proposed peatland area and rapid LULC changes from 2016 due to a social-economic growth. Therefore, the assessment of land use change is required for sustainable peatland management. The main objectives of this study were to assess LULC and its change between 2011 to 2016 and 2016 to 2021. In this study, remote sensing data has been used for LULC classification using random forest classifier in Google Earth Engine (GEE). Then, the post-comparison change detection algorithm was applied for detected LULC changes. The result revealed that mixed deciduous area was continually decrees 523.44 ha and 607.05 ha from 2011 to 2016 and 2016 to 2021. Additionally, cassava and dry dipterocarp were increase from 138.24 ha in 2011 to 2016 to 386.1 ha in 2016 to 2021 and 93.15 ha in 2011 to 2016 to 156.42 ha in 2016 to 2021 respectively. Additionally, the derived overall accuracy and Kappa hat coefficients of the land use and land cover map in 2011,2016 and 2021 were higher than 85%. The average producer's accuracy and user's accuracy for all land use and land cover types were also more than 83%. The derived information of land use and land cover data of this study can be used as information to support decision-makers and land use planners for to awareness and sustainable peatland management.

Keyword: *land use and land cover change, peatland, degradation, remote sensing, Google Earth Engine*

1. Introduction

Peatland are found in at least 175 countries and cover around 14 million km^2 or 3% of the world's land area. The largest peat deposits are located on northern Europe, North America, and Southeast Asia. Peatland in Southeast Asia cover 23,611,890 ha, Indonesia peatland cover about 20,695,000 ha (12% of the land area). Indonesia has more tropical peat land and mangrove forests than any other nation on earth. (ASEAN Peatland Forest project, 2020). In Lao PDR peatland cover about 19,100 ha that found in the survey and there still have many places that would be peatland (MONRE, 2020). Peatlands within and surrounding Beung Kiat Ngong (BKN) Ramsar site in Champasack province are the most valuable and biggest peatland area identified in Lao PDR (IUCN, 2017). Most of studies on BKN focus on climate change adaptation, wetland biodiversity (flora and fauna), and livelihoods, however no studies to date have specifically documented the important of peatlands in Laos and their socio-economic value to local communities living adjacent to peatlands. Phengsisomboun, et al., (2022) studied on peatland ecological service shown the important of peatland ecology resources as a daily source of nutrition and household income for communities.

Peatlands are known throughout Southeast Asia as an important source of natural resources and non-timber forest product (NTFP) for community to harvest for household needs.

Peatland extraction, land conversion and changes to water regimes, lead to the loss of peatlands and/or the degradation of peatland function. Peatlands across the globe are recognized as vulnerable and their degradation increases the risk of climate change through the release of stored carbon, forest fire, and the loss of ecosystem services and habitat that biodiversity and local communities depend on. In some region, up to 80% of peatland have been damage (IUCN, 2018; IUCN, 2021).

Over the years, various machine learning techniques have been applied to satellite image processing, including support vector machines (SVM) (Huang et al., 2002; Shao & Lunetta 2012; Thanh Noi & Kappas 2018), random forests (RF) (Xiong et al. 2017; Oliphant et al. 2019; Li and Xu 2020), and artificial neural networks (ANNs) (Yuan, Van Der Wiele, and Khorram, 2009; Song, Duan, and Jiang, 2012). However, random forests have become increasingly popular for land use and land cover (LULC) classification due to their ability to handle high dimensional data, require few tuning parameters, and produce accurate results (Breiman, 2001; Tamiminia et al., 2020). Google Earth Engine (GEE) is a popular platform for LULC classification and mapping (Xiong et al., 2017; Tokar, Vovk, Kolyasa, Havryliuk, & Korol, 2018; Zurqani et al., 2018; Oliphant et al., 2019; Ghorbanian et al., 2020; Gumma et al., 2019; Xie et al., 2019), wetland delineation (Amani et al., 2019; Mahdianpari et al., 2020a), LULC extraction (Zurqani et al., 2018; Ghorbanian et al., 2020), and crop mapping (Xiong et al., 2017; Gumma et al., 2019; Oliphant et al., 2019; Xie et al., 2019), and it offers several classification algorithms, including random forests.

Land use and land cover (LULC) change have been among the most significant perceptible changes taking place around the World. The LULC change reveals between human activities and the transformation of the Earth’s surface. Particularly, increasing anthropogenic activities are a significant element of environmental changes, which are direct and indirect impacts on soil, water, and atmosphere (Meyer & Turner,1994; Roy & Roy, 2010; Puangkaew & Ongsomwang, 2020). An understanding of historical, current, and future LULC status and change information is critical for city planners, land managers, and resource managers in any rapidly changing environment (Meyer & Turner, 1994; Warner et al., 2009). Therefore, to understanding LULC change statuses over the time will be reflect significant information to awareness and sustainable peatland management.

The main objectives of this study were to assess LULC status and its change between periods 2011 to 2016 and 2016 to 2021 and to understand on how land use change status over time will reflect to sustainable peatland use and management in the future.

2. Materials and Methods

2.1 Study area

The study area was conducted in proposed as potential peat land area: Nathong and Saming Villages, Champhone district, Champasack Province, Lao PDR (Figure 1a). Both villages are tributaries and locate in northeast of BKN wetland Ramsar catchment and borderline connected to Dong Hua Sao National Protected Area (NPA) of Laos in the north part of villages. The BNK catchment area is 143 km^2, include the Ramsar site area is 23 km^2. Lay in between the Bolaven Plateau to the north & the low-lying hill of Xe Pian NPA to the south, with elevation ranges from 120-200 MSL (Gitec, 2019). LULC of twos villages have been rapidly changed since 2018 due to socio-economic trends in this region and population of each village has been instant increase from 2005 to 2019 about 19% and 46% respectively (Phengsisomboun et al., 2021). However, two studied villages are included in the cluster village of district development plan but exclude from development project of Lower Mekong Basin Wetland Management and Conservation Project-MRWP.

2.2 Data

Three main data types of GIS data, remote sensing data and ground referents were collected and prepared (Table 1). GIS data includes administration boundary, river and proposed peatland were collected from Nation Geographic Department (NGD). Remote sensing data consisted of Landsat-5 image spatial resolution 30m acquired with clouds mask in November 2011 (Figure 1b), Sentinel 2 imageries spatial resolution 10 m on 02 December 2016 and 21 December 2021 (Figure 1c and 1d). satellite imageries were selected based on less cloud's coverage and similar phenological conditions according to season in the area.

2.3 Research methodology

Satellite data, including Landsat-5 in 2011, Sentinel-2 in 2016, and Sentinel-2 in 2021, were pre-processing, processing, and post-processing using the GEE cloud-based platform (Figure 2). Pre-processing involved data acquisition, filtering (date, cloud cover, and cloud mask), and subset the images based on the study area. Satellite imagery was then processed using an RF algorithm based on seven LULC types: built-up, mixed deciduous, dry dipterocarp, paddy fields, cassava, water area, and miscellaneous land (Table 2). The LULC maps for 2016 and 2021 were resampled to match the resolution of the 2011 LULC map. Accuracy assessment of the LULC maps for 2011, 2016, and 2021 employed 196 stratified random sampling points based on a bimodal probability distribution (Figure 3). Reference data included a false-color composite (B4, B5, B3) of the 2011 Landsat-5 image, a very high-resolution image from the previous time series on Google Earth in 2016, and field survey data collected in 2021, respectively. LULC maps for 2011, 2016, and 2021 were further used to assess LULC status and change detection using post-comparison algorithms between 2011-2016 and 2016-2021. Area measurements were double-checked by ground surveys with local people, covering villages, fields, and agricultural areas.

3. Results

The LULC classification in 2011, 2016 and 2021 are depict in Figure 4, while the LULC area, percent and area change in study period are summarized in **Error! Reference source not f ound.**. As the result the most three dominants of LULC types are dry dipterocarp, mixed deciduous and paddy field which covers the area 2809.44 ha or 57.82%, 1709.82 or 35.19% and 192.06 or 3.95% respectively in 2011 (Figure 5 and **Error! Reference source not found.**). The m ost three LULC types in 2016 are dry dipterocarp, mixed deciduous and paddy field which covers the area 2902.59 ha or 59.73%, 1186.38 ha or 24.42%, and 449.82 ha or 9.26% respectively. Furthermore, the most three LULC types in 2016 are dry dipterocarp, mixed deciduous and cassava which covers the area 3059.01 ha or 62.95%, 579.33 ha or 11.92%, and 624.34 ha or 10.79% respectively.

The studied clearly shown that LULC change analysis showed a significant loss of mixed deciduous at 523.44 ha or 10.77% in initial period 2011-2016 and 607.05 ha or 12.49% in final period 2016-2021 continuously. Additionally, cassava, Dry dipterocarp and build up are increase at 138.24 ha, 93.15 ha and 5.94 in initial period 2011-2016 and continuously increase at 386.1 ha, 156.42 ha and 8.37 ha in final 2016-2021. During the same period, the other LULC types: paddy field, water body and miscellaneous land showed both increases and losses (**Error! Reference source not found.** and REF _Ref106873971 \h * MERGEFORMAT **Error! Reference source not found.**).

4. Discussion

The result of the study area revealed continuous changes in land use and cover (LULC) in both periods, 2011-2016 and 2016-2021, in the same direction. This consistent trend is attributed to increasing community activities within the area (Roy & Roy, 2010; Puangkaew & Ongsomwang, 2020). According to ground truth, mixed deciduous area is the overlapping land use by community and Dong Hua Sao national protected area to the upper part down to swam nearby villages, where local communities claim this area as their traditional farmland. Over the ten-year period (2011-2021), an estimated 607.05 hectares of this mixed deciduous area were lost. Dry dipterocarp is classified as old and young follows by community, with some fields located inside mixed deciduous area; some were old plantations: Teak, coffee, and rice field. Casava fields emerged as another significant area of land use change. From virtually none in 2011, the area under cassava cultivation increased by over 386 hectares by 2021. This dramatic rise is attributed to the doubling of cassava prices in the region during 2020-2021 (Phengsisomboun et al., 2022). This aligns with research by Junquera et al (2020) demonstrating the significant impact of crop prices on rapid agricultural expansion and increase deforestation because it provides an incentive for further clearing.

Saming village has a larger population and agricultural area than Nathong village. Most of agricultural areas located in mixed-deciduous area practiced by people from Saming village, and most of dry dipterocarp area is turning into casava field by people from both villages. Due to limitations in image interpretation, some areas were shown as dry dipterocarp while most of them had become cassava by 2021. The built-up area is increasing mostly in Saming village because of population growth. Some farmers filled their paddy area and built houses for their children, and some are thinking of planting casava instead of rice. This aligns with research by Alam et al (2019) demonstrating the built-up area has been expansion mostly encroaching the agriculture land and wetlands. Particularly expanding along roads and peripheral zones. Another area to be concerned is miscellaneous land known as community area authorized by cluster village office, because of road construction expansion was clear some part of NPA and affected to water body lost and dry out. So, this area is now reserved for the community for urban expansion in the future. However, water resources in these two villages remain available year-round compared to other villages near Ramsar site and community created conservation area with regulations to control and keep water resource for community own-used.

5. Conclusion

In this study, assessment of land use and land cover change in two period of 10 years, 2011 to 2016 and 2016 to 2021. The studied by interpret satellite image from Landsat-5 and Sentinel-2 derived from the same time with clear clouds. The result significantly showed mixed deciduous forest was continuously lost from 2011 to 2021. While dry dipterocarp forest shown positively increased. Casava a new and biggest source of household income to people in the region recently, the area is rapidly increased at the beginning 2011 to 2021. In fact, people had turned their old follows, some plantation area into casava field. Some were existing inside Dong Hua Sao NPA. Paddy fields were conversion to building house and some perspective to plant casava later than growing rice in the next season.

People shown less concern on Dong Hua Sao protected area and the boundary, as people claimed their field, some reported as their old plantation in the upper hill inside NPA and keep growing, expanding casava area. The area of water body is to be concerned in the future. As people reported water dry circumstance then community had their own conservation area and regulations to prevent some wetland/peatland area in the villages.

6. Conflict of Interest

We certify that there is no conflict of interest with any financial organization regarding the material discussed in the manuscript.

7. Acknowledgments

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Earth Engine. International Journal of Applied Earth Observation and Geoinformation. Vol. 69: 175-185. https://doi.org/10.1016/j.jag.2017.12.006

Table 1 Lists of data collection and preparation

Data	Data collection	Source
GIS data	Administrative boundary River Proposed peatland	NGD, Laos
Remote sensing data	Landsat 5 in 2011 Sentinel 2 in 2016 and 2022	USGS European Union/ESA/Copernicus GEE
Ground truth	gamin GPSMAP 65	

Note: NGD: Nation Geographic Department

Table 2: LULC classes and description

No	LULC Classes	Description
1	Built up	It includes residential places, offices and premises of organizations, public facilities, trade and service facilities, Cultural land, and other constructions
2	Mixed deciduous	It trees with thickness and crown cover more than 20%
3	Dry dipterocarp	It is natural forest areas with low tree density and a specific forest ecology
4	Paddy fields	It is an active paddy field
5	Cassava	It consists of cassava.
6	Water area	It consists of river and stream, wetland, swamps, ponds, lakes, saturated grass land, water spring land, natural or human made water storage or waterways, either permanent or temporary.
7	Miscellaneous land	It includes glass land, bare land, and outcrop

LULC classification and description (table 2) followed by guideline from division of forest inventory, department of Forestry, ministry of Agriculture and Forestry, Lao PDR. (DoF, 2017).

Table 3: LULC area, percent in 2011, 2016 and 2021 and area change between 2021 to 2016 and 2016 to 2021

		LULC data in 2011		LULC data in 2016		LULC data in 2021		Area change (ha)	Area change (ha)
No	LULC type	Area in ha	percentage	Area in ha	percentage	Area in ha	percentage	2011-2016	2016-2021
1	Built up	11.52	0.24%	17.46	0.36%	25.83	0.53%	5.94	8.37
2	Mixed deciduous	1709.82	35.19%	1186.38	24.42%	579.33	11.92%	-523.44	-607.05
3	Dry dipterocarp	2809.44	57.82%	2902.59	59.73%	3059.01	62.95%	93.15	156.42
4	Paddy fields	192.06	3.95%	449.82	9.26%	497.88	10.25%	257.76	48.06
5	casava	0.72	0.01%	138.24	2.84%	524.34	10.79%	137.52	386.1
6	Water bodies	78.84	1.62%	62.55	1.29%	54.72	1.13%	-16.29	-7.83
7	Miscellaneous land	56.79	1.17%	102.15	2.10%	118.08	2.43%	45.36	15.93
Grand Total		**4859.19**	**100%**	**4859.19**	**100%**	**4859.19**	**100%**		

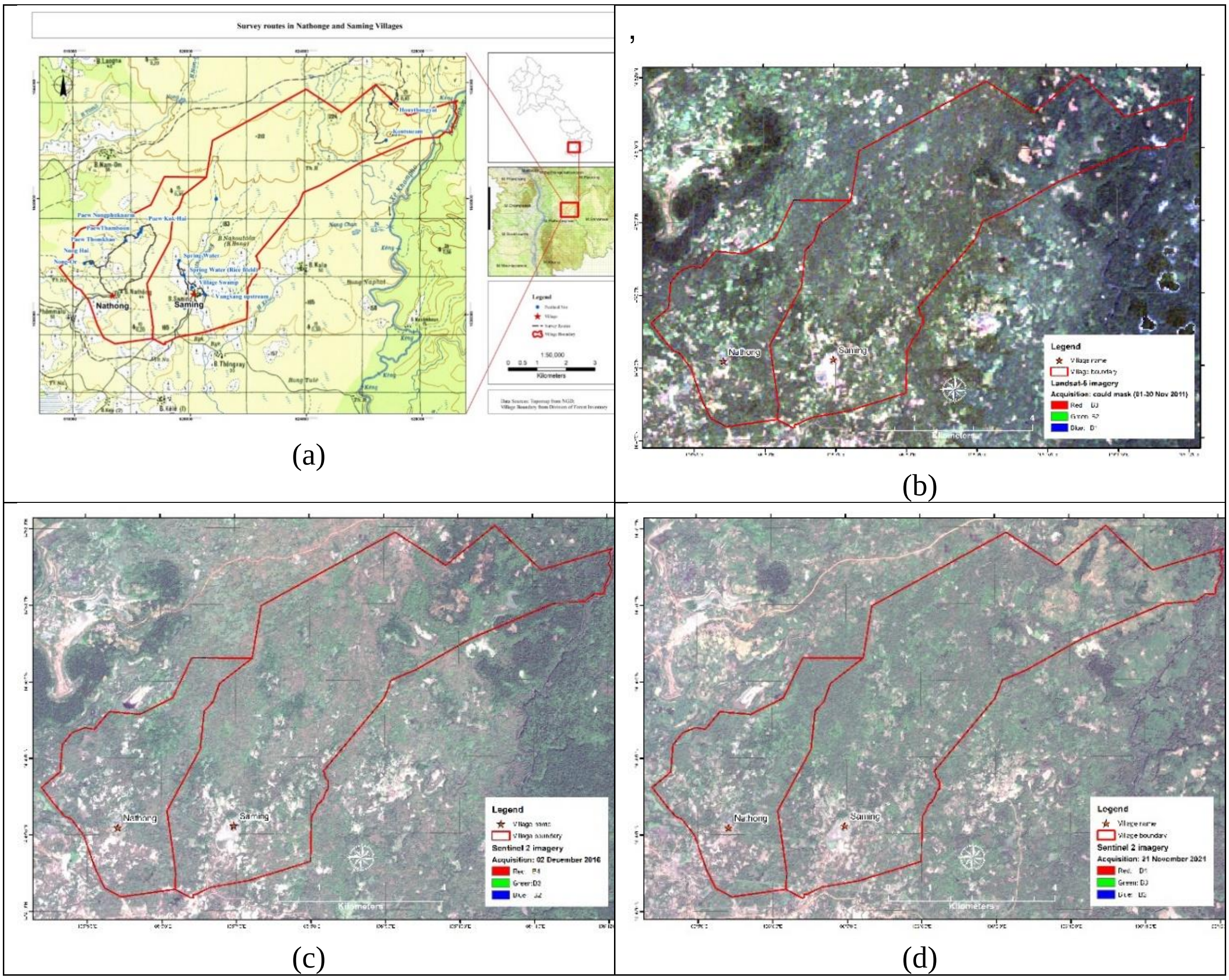


Figure 1 Location of study area and satellite imageries: (a) location map, (b) Landsat-5 imagery on could mask between date 01 to 30 November 2011, (c) Sentinel 2 imagery on 02 December 2016 and (d) Sentinel 2 imagery on 21 November 2021.

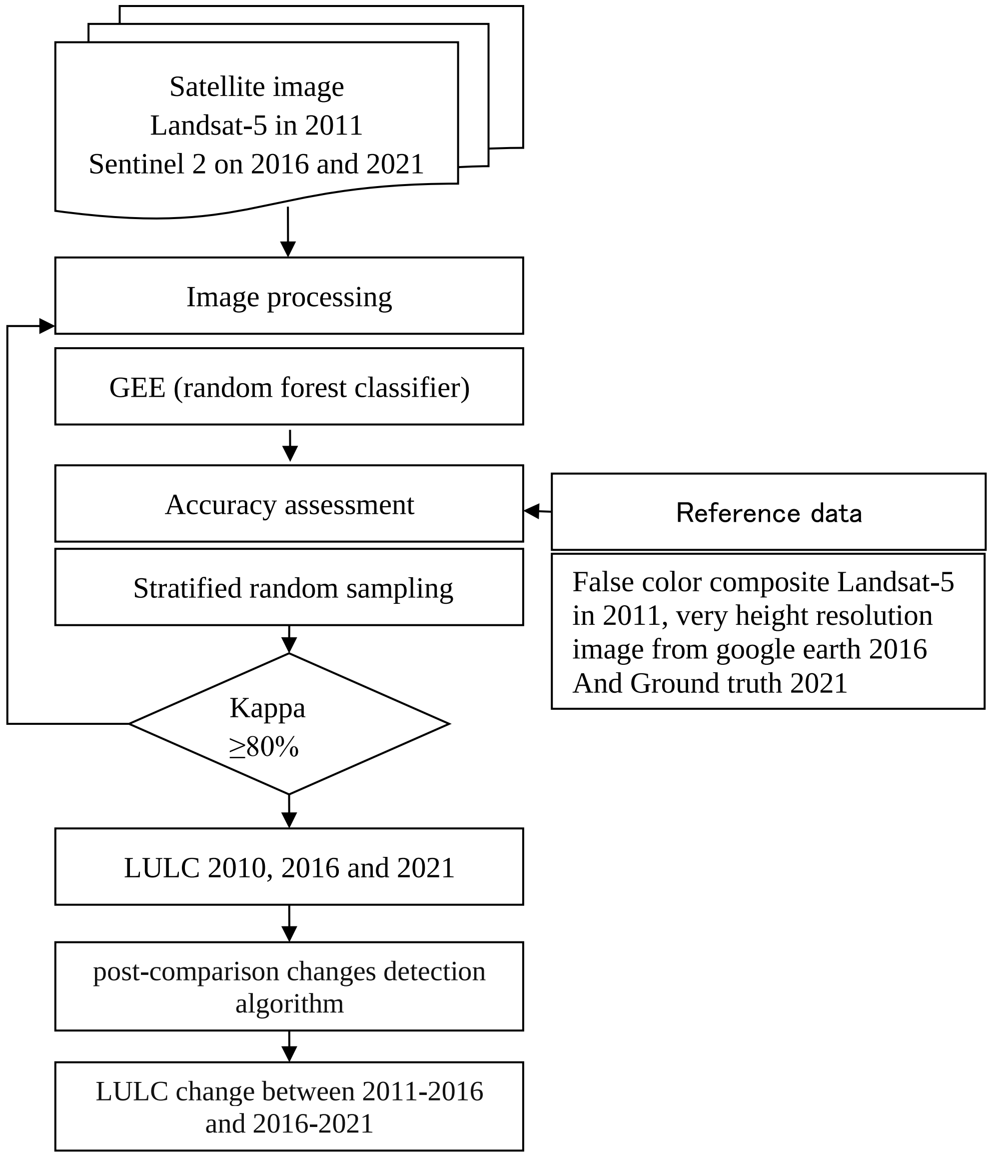


Figure 1: workflow of the research methodology

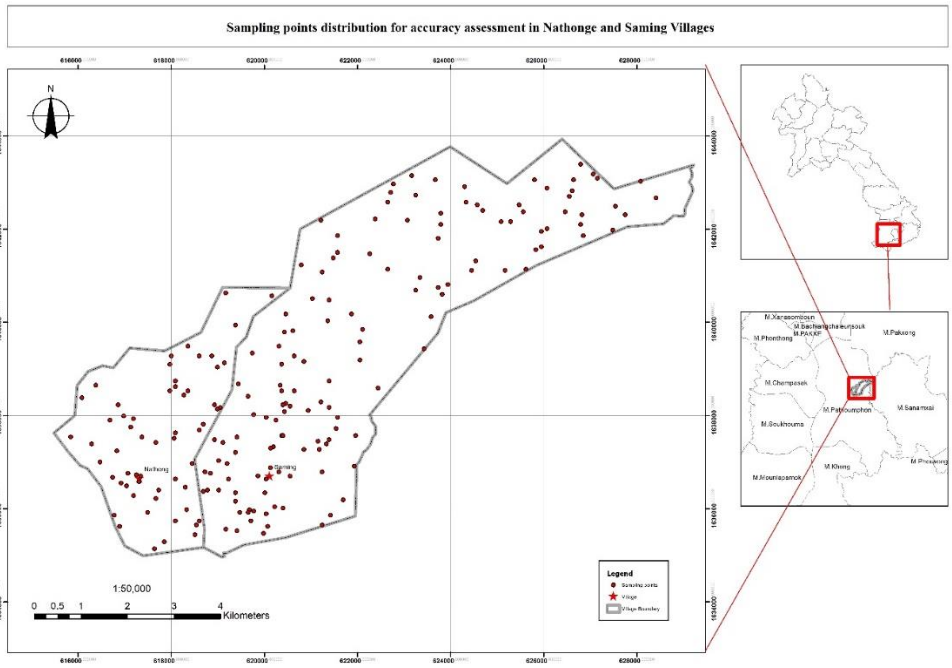


Figure 3 Distribution of sampling point for accuracy assessment

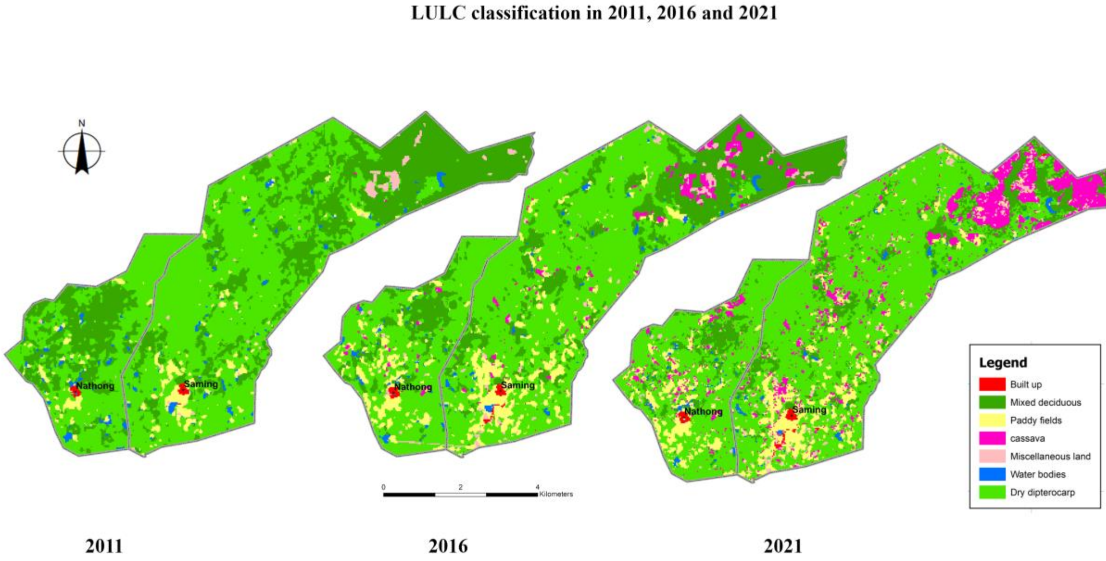
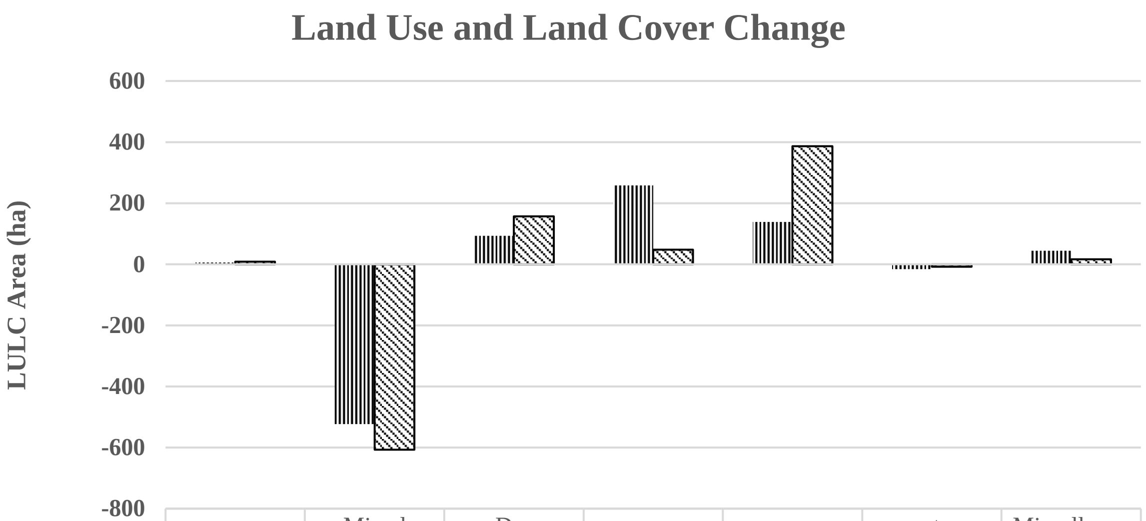


Figure 4 LULC classification in 2011(a), 2016(b) and 2021(c)



	Built up	Mixed deciduous	Dry dipterocarp	Paddy fields	cassava	water bodies	Miscellaneous land
Y2011-2016	5,94	-523,44	93,15	257,76	138,24	-16,29	44,64
Y2016-2021	8,37	-607,05	156,42	48,06	386,1	-7,83	15,93

LULC types

Figure 5: Pattern of LULC change in terms of gain and loss of each LULC type of two periods 2011-2016 and 2016-2021