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Analysis of Land Cover Change in Paunglaung Forest Reserve, Myanmar Using Satellite Imageries

Thura Htike Aung
Staff Officer
Forest Department

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Thura Htike Aung, Staff Officer
Forest Department

Abstract

Monitoring and analyzing changes in forest cover is of great significance to the sustainable development and management of forest ecosystems. Remote sensing and geographic information system technology were used in this thesis to study the land cover dynamics of the Paunglaung Forest Reserve in Myanmar in recent years. Landsat 8 OLI satellite images were chosen as the information source, and through maximum likelihood supervised classification, the land cover maps containing five land cover types in years of 2014, 2017, and 2020 were generated. On this basis, the ArcGIS landscape pattern analysis plug-in of patch analyst was used to analyze the landscape pattern dynamics of the study area from 2014 to 2020, and the cellular Automata-Markov chain (CA-Markov) model was used to predict the land cover condition of the study area in 2023. Research results show that: (1) The supervision classification accuracy of 2014, 2017 and 2020 was relatively high, with overall accuracy of 86%, 88%, and 84% respectively, and the kappa coefficients were 0.82, 0.85 and 0.80 respectively; (2) From 2014 to 2020, the area of closed forest in the study area decreased by 1.44%, and the area of open forest and cultivated land increased by 0.26% and 1.24% respectively. After construction of Paunglaung Dam in 2014, the area of bare land (residential land) in the study area increased. From 2014 to 2020, the area of closed forest decreased by 1.47%, and the area of open forest increased by 0.41%; (3) The landscape analysis from 2014 to 2020 indicated that the area of forest patches was decreased, while the area of non-forest patches was increased;(4) The forecast of land cover types in 2023 indicates that the forest area will remain stable and the bare land area will increase significantly. Through this study, it is found that the main causes of deforestation and forest degradation in the study area are agricultural expansion, timber over-exploitation and dam construction. Research shows that the future management of Paunglaung Forest Reserve should focus on raising local ecological protection awareness, launching family economic development plans, strengthening forest protection law enforcement, establishing community forestry, creating village-owned plantations, and building more eco-tourism sites.

Keywords: land cover change; landscape pattern; CA-Markov; Paunglaung Forest Reserve

မြန်မာနိုင်ငံရှိပေါင်းလောင်းသစ်တောကြိုးဝိုင်း၏ မြေအသုံးချမှုပြောင်းလဲအခြေအနေများအား ဆန်းစစ်လေ့လာခြင်း

သူရထိုက်အောင်၊ ဦးစီးအရာရှိ
သစ်တောဦးစီးဌာန

စာတမ်းအကျဉ်း

သစ်တောဖုံးလွှမ်းမှု ပြောင်းလဲမှုအခြေအနေများကို စောင့်ကြည့်လေ့လာခြင်းနှင့် ခွဲခြမ်းစိတ်ဖြာခြင်းသည် သစ်တောဂေဟစနစ်များ စဉ်ဆက်မပြတ် ဖွံ့ဖြိုးတိုးတက်ရေးနှင့် စီမံခန့်ခွဲခြင်းလုပ်ငန်းများအတွက် အလွန်အရေးကြီးပါသည်။ မကြာသေးမီ နှစ်အနည်းငယ် အတွင်း မြန်မာနိုင်ငံရှိ ပေါင်းလောင်းသစ်တောကြိုးဝိုင်း၏ မြေယာဖုံးလွှမ်းမှုအခြေအနေ များကိုလေ့လာရန်အတွက် အဝေးမှအာရုံခံခြင်းနှင့် ပထဝီသတင်းအချက်အလက် နည်းပညာ (RS and GIS) များကိုအသုံးပြုခဲ့ ကြပြီးဖြစ်ပါသည်။ ယခုစာတမ်းတွင် Landsat 8 OLI ဂြိုလ်တုဓာတ်ပုံများကို သတင်းအချက်အလက် အရင်းအမြစ်အဖြစ် ရွေးချယ်ခဲ့ပြီး ဖြစ်နိုင်ခြေ အများဆုံးကြီးကြပ်မှု အမျိုးအစားခွဲခြင်းစနစ်ကို အသုံးပြု၍ ၂၀၁၄ ခုနှစ်၊ ၂၀၁၇ ခုနှစ်နှင့် ၂၀၂၀ ခုနှစ် များအတွက် မြေယာဖုံးလွှမ်းမှု အမျိုးအစား ငါးမျိုးပါဝင်သော မြေအသုံးချမှု ပြောင်းလဲမှု မြေပုံများကို ဖော်ထုတ်နိုင်ခဲ့ပါသည်။ ပေါင်းလောင်းကြိုးဝိုင်း၏ ၂၀၁၄ ခုနှစ်မှ ၂၀၂၀ ခုနှစ် အတွင်းမြေယာအမျိုးအစားပြောင်းလဲမှုများကိုဖော်ထုတ်ရန် Patch Analyst Software ကိုအသုံးပြုခဲ့ပြီး ၂၀၂၃ ခုနှစ်အတွက် မြေအသုံးချမှုပြောင်းလဲမှု အခြေအနေကို ခန့်မှန်းရန် cellular Automata–Markov Chain (CA–Markov) မော်ဒယ်ကို အသုံးပြု တွက်ချက်ခဲ့ပါသည်။ သုတေသနရလဒ်များအရ ၂၀၁၄ ခုနှစ်မှ ၂၀၂၀ ခုနှစ်အတွင်း ပေါင်းလောင်း ကြိုးဝိုင်း၏ တောပိတ်ဧရိယာမှ ၁.၄၄ ရာခိုင်နှုန်းလျော့ကျခဲ့ပြီးသစ်တောမြေ ၀.၂၆ ရာခိုင်နှုန်း နှင့် စိုက်ပျိုးမြေဧရိယာ ၁.၂၄ ရာခိုင်နှုန်းတိုးလာခဲ့ပါသည်။ ၂၀၁၄ ခုနှစ် ပေါင်းလောင်းဆည် တည်ဆောက်ခဲ့ပြီးနောက် တောပိတ်ဧရိယာလျော့ကျသွားပြီး သစ်တောမဟုတ်သည့် ဧရိယာ လူနေဧရိယာများ တိုးလာခဲ့ကြောင်း၊ ၂၀၂၃ ခုနှစ်အတွက် မြေဖုံးလွှမ်းမှုခန့်မှန်းချက်အရ သစ်တောဧရိယာ (တောပိတ်၊ တောပွင့်) များမှာ သိသိသာသာပြောင်းလဲမှုရှိမည် မဟုတ်ကြောင်း ခန့်မှန်းတွက်ချက်တွေ့ရှိရပါသည်။ လေ့လာချက်များအရ ပေါင်းလောင်းကြိုးဝိုင်း၏သစ်တော ဧရိယာများအား ရေရှည်တည်တံ့နိုင်ရေးအတွက် ဒေသခံပြည်သူများအား အသိပညာ မျှဝေ ခြင်း၊ လူမှုစီးပွားဖွံ့ဖြိုးတိုးတက်မှုအစီအစဉ်များဖော်ထုတ်ခြင်း၊ ဒေသခံပြည်သူအစုအဖွဲ့ပိုင် သစ်တောစိုက်ခင်းများတည်ထောင်ခြင်း၊ သစ်တောဥပဒေ၊ နည်းဥပဒေများအားကောင်း လာစေပြီးစီမံအုပ်ချုပ်နိုင် စေခြင်း၊ ဂေဟစနစ်အခြေပြု ခရီးသွားလုပ်ငန်းများကို အာရုံစိုက် လုပ်ဆောင်သင့်ပါကြောင်း သုတေသနစာတမ်းများက ဖော်ပြထားပါသည်။

Analysis of Land Cover Change in Paunglaung Forest Reserve, Myanmar Using Satellite Imageries

1. Introduction

1.1 Background and Problem

Forest plays not only an important role in mitigate climate change but also provide a wide range of ecosystem services, food and livelihood opportunities etc.[1]. Sharma et al. (2019) also estimated the global forest lost rate is 0.6% per year in the world. The world natural forests have suffered major changes since 2010 with the decrease of 6.5 million hectares per year[2]. Myanmar is located at the intersection of the Himalayan, Indochinese and Malayan Peninsular eco-regions[3]. Myanmar has rich diversity of habitat types and ecological diversity. Forest types include alpine in the northern mountainous region, dry and deciduous forests in the central dry ecosystems, and rainforest and mangroves in the southern floodplains [3, 4]. Myanmar has a widest forest cover in the world and has been well known for its abundant natural resources, especially forests[5]. Myanmar is one of the countries which are rich in forest resources in Southeast Asia. According to the Food and Agricultural Organization (FAO) of the United Nations, about 45.04% of the land area of Myanmar is still covered with natural forests[6]. Despite Myanmar's long history of scientifically based forest management practices, the country is currently facing severe deforestation and forest degradation after more than 50 years of political and economic hardship[7, 8].

The total land area of the Republic of Union of Myanmar is 676,577 km^2,stretching for 936 km from east to west and 2,051 km from north to south, and bordered with China, Laos, Thailand, India and Bangladesh. The estimated population is 53.37 million, in which 68% were Burmese[5, 9]. The rich forest in Myanmar not only makes an important contribution to global carbon sequestration but also to world biodiversity conservation[5]. The Food and Agricultural Organization (FAO) of United Nations reported that mean annual forest loss of 3430 km^2 and an annual deforestation rate of 1.03% during 2000-2010[5].Studies on forest cover change pattern of Myanmar using satellite imagery have described that the country had lost about 12000 km^2 of forest cover nationwide over a ten year period (1990-2000) with annual deforestation rate of 1.17%[10]. Though, the FRA 2020 reported a mean annual deforestation area and rate in Myanmar of 2890 km^2 and 0.96%.During (2010-2020),Myanmar has been ranked the seventh highest forest loss country in the world[11] .

Almost 60% of the population mainly rely on forest resources for basic needs[1]. Myanmar is one of the largest exporter of valuable wood products to the world, while the rural communities continue to depend on the forest to complement for their livelihood[12]. During the years of 2000 to 2005, the roads construction was a significant factor for forest changes[8]. Commercial and state-owned plantations, shifting cultivation practices, expansion of agricultural land, timber extraction, fuelwood collection, mining, construction of roads and dams, hydropower development are the major land use change elements for deforestation[13].

In the developing country, expansion of agricultural land has rapidly grown over the past decades[14, 15]. Rapid agricultural development became a major driver for deforestation in Myanmar, Congo and Columbia[16]. That's why monitoring changes in forest cover is important for the making and implementation of forest conservation policies[14]. Land cover mapping using the techniques of remote sensing and GIS has been developed over the past decades[4, 8, 14, 17-19] and these techniques are most useful tools to assess and predict the forest cover change.

Paunglaung Forest Reserve is located in Pinlaung township of Shan State which is the largest state in Myanmar with rich diversity and forest resources. It was established in 2012 by Forest Department (FD), Ministry of Natural Resources and Environmental Conservation. Local people of this area mainly rely on forest for their basic needs. Agriculture is the major livelihood and many people grow ginger, tea leaves, rubber and so on. According to the record by Kalaw Township Forest Department, most of the forest areas are encroached by people for agricultural land and housing expansion. There is very few research on forest cover changes in this study area and the previous researches mainly focus on watershed area and dependence of local communities on forest by questionaries survey. So, assessing and predicting forest cover changes are urgently needed in this area. Accordingly, we examined the changes of forest cover in Paunglaung Forest Reserve. Our research results will contribute to making and implementation of policies for local forest conservation.

1.2 Objectives

The study aimed to analyze land cover changes in Paunglaung Forest Reserve using remote sensing and GIS techniques.

1.3 Specific Objectives

Specifically, the aims of this study are (i) to quantify land cover and spatial pattern changes from 2014 to 2020;(ii) to predict land cover in 2023 and (iii) to reveal the causes of land cover changes to provide support for the making of conservation policies of national forest reserves.

2. Literature Review

2.1 Status of world's forest and Myanmar forest

It is well known that forests are very important for global forest carbon cycle, climate change, biodiversity conservation and human livelihood[20, 21]. According to the Global Forest Resources Assessment(2015)[2] released by Food and Agricultural Organization of United Nations (FAO)located in the center of Rome, the world's total forest area declined by 3% from 1990 to 2015. The FAO's study supposedly estimated a current global rate of forest cover loss at 0.6% per year[22]. The annual rate of deforestation was estimated at 10 million hectares in the recent five years 2015-2020[23]. Drivers for forest decreasing include agricultural expansion, urbanization, large scale timber extraction, climate change, demographic and economic factors and policy and institutional factors[24]. Together with invasive species and forest fragmentation, forest degradation poses a severe threat to biodiversity richness, ecosystem services, and habitat quality[21]. Because of the rising demands for food and other resources in the process of population growth and economic development, forest cover has been declined for most developing countries in the world[25]. Population growth is one of the environmental threats to world's forests and causes for forest cover loss and global deforestation[26-28].

With the population increasing of Myanmar by 1.5% annually[1], the consumption of fuelwood and charcoal has accounted for 76.41% of total energy consumption in Myanmar[29]. Higher population growth will directly bring higher pressure on land and forest resources for food and livelihood opportunities[29]. Myanmar, one of the least developing country, has been suffering from serious deforestation and it ranks the seventh forest loss country in the world[23]. The major drivers for forest cover change were legal and illegal logging, agricultural and urban expansion, fuelwood consumption and others[30]. It is necessary to examine country situations and find suitable underlying drivers of changes in forest resources[28]. Guided by the government-led reforestation policy, forest transition started in the mid of 1950s in South Korea[31]. In Myanmar, the rate of deforestation is reduced in later 2010 with the changes from the military-ruled government to elected government[4].

2.2 Previous studies about analysis of forest cover changes and deforestation in Myanmar

According to the study on forest cover changes in Myanmar (1990-2000) by Leimgruber et al. (2005), they made a countrywide forest map and estimated deforestation using Landsat imagery from 1990s and 2000s. During 10-year period, the country had forest cover of over 67% (442,00 km^2) of total land area in 1990s and the forest cover was decreased to 65% (430,000 km^2) in 2000s and the total forest loss was 12,000 km^2 with the annual deforestation rate of 0.2%.However,they claimed that there was 3000 km^2 of forest was regenerated. They also reported the causes of deforestation by identification of 10 deforestation hotspots such as tropical dry forests and mangroves. They found that the annual forest clearing rate was 0.4% to 2.2 %,which was above the countrywide data. At the same time, they reported that the drivers of deforestation in those regions were agricultural expansion, fuelwood consumption and charcoal production, commercial logging and plantation development[10].

Yang et al. (2009) examined that that 30 % of forest cover (110,621 km^2) was lost during the period of 1988-2017 with the annual deforestation rate of 0.87 % and they also found that forest loss is the highest in low- attitude regions where there is rapid growing economy, high population density, concentrated arable land. They investigated that the drivers of deforestation and found that the expansion of agricultural land is the main driver for about 74% (91,033 km^2) of lost forest area converted to agricultural land, followed by urban expansion. This is because the more the growth of population, the more the need for agricultural land. 70% of population in Myanmar is depending on agriculture for their livelihoods[14].

According to the study by Sharma et al. (2019), 7.3 % (1769.38 km^2) of forest area was seriously declined during the 8-year period (2008-2016). Pinlaung township was ranked the highest forest loss in the country since its forest of 893.345 km^2 was changed into non-forest area and the water category has increased because of the reservoir construction where the forest area of 63.5 km^2 was clearly cut. To evaluate the drivers of deforestation, they used eight factors as variables such as elevation, slope, proximity to previously deforested area, proximity to roads, proximity to waterways, proximity to newly constructed reservoirs, proximity to settlements and local-level population density. They reported that forest areas were rapidly converted into agricultural area, urban areas and bare land. Though infrastructure developments such as roads, reservoirs, dams, fuelwood consumption, forest fires were the main reasons for rapid deforestation in the study area, the indirect threats such as population density, poverty and policy lacking were also indirectly threatening the forested areas[1].

There is one study about deforestation in Paunglaung watershed area by Mon et al. The author found out that the 7.7% of forest was degraded during the period of 11 years (1989-2000) and the annual deforestation rate is 0.7 % (32.61 km^2)[19]. The author adopted a logistic regression model to analyze the factors affecting deforestation in the Pinlaung watershed area. These factors included land class types, distance to roads, distance to towns, distance to villages, distance to water resources, soil types, area under logging, elevation and slope. She found that elevation, soil types, area under logging, distance to roads, distance to towns and distance to water resources are enforcing factors of deforestation. The results showed that the probability of deforestation is directly proportional to topography factors of elevation, distance from the towns and water resources. There was low possibility of deforestation in the area if attitude is higher and the area far from the towns. The author also revealed that the deforestation was most frequently occurred in area with suitable soil types for agriculture. It was coincident with the recent study by Sherma et al., that proximity to infrastructure (reservoirs and roads), proximity to previously deforested area, topography and growing population are strongly and directly closed with deforestation in the region[19]. When applying another logistic regressing analysis to study three reserved forests in Bago Mountain, the author also found that elevation and distance to nearest town strongly affect the probability of deforestation and forest degradation[7]. Htun et al. applied the multinominal logistic regression model to analyze deforestation in Popa Mountain Park. Their research results revealed that distance from villages was closely correlated to the occurrence of deforestation and forest degradation of closed forest areas during two periods (1989-2000) and (2000-2005)[17]. Most of the literature revealed that the main causes of deforestation and forest degradation are agricultural expansion, legally and illegally over-exploitation of timber and fuelwood consumption, and road and dam construction[1, 13, 19].

Based on the analysis of Landsat satellite imaginary and spatial distribution of Myanmar’s intact forests and degraded forest in 2014, the author Tejas et al. (2017) found that 63% (42,365,729 hectares) of land was covered by forests but the annual net loss of forest is 0.3 % between the period of 2002-2014. They divided two categories of forest based on the canopy cover such as intact forest (>80% canopy cover) and degraded forest (10-80% canopy cover). They estimated that there were approximately 38% of the intact forest but the loss of intact forest was estimated to be over 2 million hectares with an annual rate of 0.94%. They also examined that forest were declining due to multiple factors, such as over exploitation of timber, fuelwood consumption, shifting cultivation, and non-forest land uses like mining, clear-cutting for agriculture, infrastructure development and expansion of plantation of rubber, palm oil and sugarcane, hydropower and reservoir construction. According to the study, they claimed that Shan State was one of the regions where intact forests are located and it was ranked the highest state in overall intact forest loss due to forest fragmentation and agricultural expansion. They also reported that Shan State has also the largest total area of plantation expansion of 162,534 hectares during the past 12 years period[32].

According to the spatial analysis results by Myint (2015), the forest cover in Myanmar was decreased from 52.38 % in 2005 to 44.86 % in 2010 and 44.33 % in 2015 with the average annual deforestation rate of 1.62 %. The loss rate was above forest resource assessment data provided by FAO. Myint also discovered that forest cover in Shan State changed from 52.38% in 2005 to 41.45% in 2010 and a somewhat increase to 48.14% in 2015. The author found that the major causes are agricultural expansion, shifting cultivation with short fellow period and poppy plantations, over timber harvesting and unsustainable fuelwood consumption, infrastructure development, mining and forest fire. Indirect threats are population growth (natural and migration), economic growth (international and national), weak in law enforcement, poverty and subsistence, conflicting policies, language barriers, land tenure uncertainties and inadequate natural resource planning and monitoring[33].

2.3 Use of RS/GIS in analysis of forest cover change

Forest cover change processes include deforestation, forest degradation, reforestation, afforestation and forest improvement[34]. Satellite remote sensing and the use of geographical information system (GIS) have developed as powerful tools of natural resources inventory and play crucial roles in monitoring and analyzing spatial and dynamic changes of and area[35]. Using satellite remote sensing can provide objective and consistent information suitable for mapping forest cover changes at a fine scale[36]. Remote sensing and GIS technology in recent years have become essential tools of monitoring the changing pattern of forest cover[37]. Remote sensing was also recognized as an art tool for monitoring forest ecological systems, which is capable of increasing knowledge of deforestation patterns and distribution of tropical forests[38]. Majority of work in remote sensing and GIS was mainly focused on environmental studies in the last few decades[39]. It has been effectively and widely used in single thematic analysis, land use and land cover mapping, forest monitoring, watershed management and forest fire management[40-43]. In several studies, satellite remote sensing at regional scales have been adopted to monitoring the dynamics in forest cover using spatial and temporal remote sensed data at worldwide[44]. Analysis of the changes in forest cover at different spatial and temporal scales could provide useful information for planning and sustainable management of forests[45].

Geospatial technology has provided the opportunity to develop a model for understanding the future change of land cover[46]. Common-used models for estimating land cover changes are analytical equations-based models, statistical models, expert system models, cellular models, Markov models, hybrid models, multi-agent models. But now the Markov chain and Cellular Automata (CA-Markov) model, one of the mixed models, is most widely used model in land use change monitoring[47]. The Reddy et. al made a prediction of forest area change in Myanmar between 2016 and 2027 by using classified map of 1950 to 2016[12]. No systematic study for future prediction of land cover change of Paunglaung forest reserve had been done from past to present using consistent methods.

3. Materials and Methods

3.1 Study Area

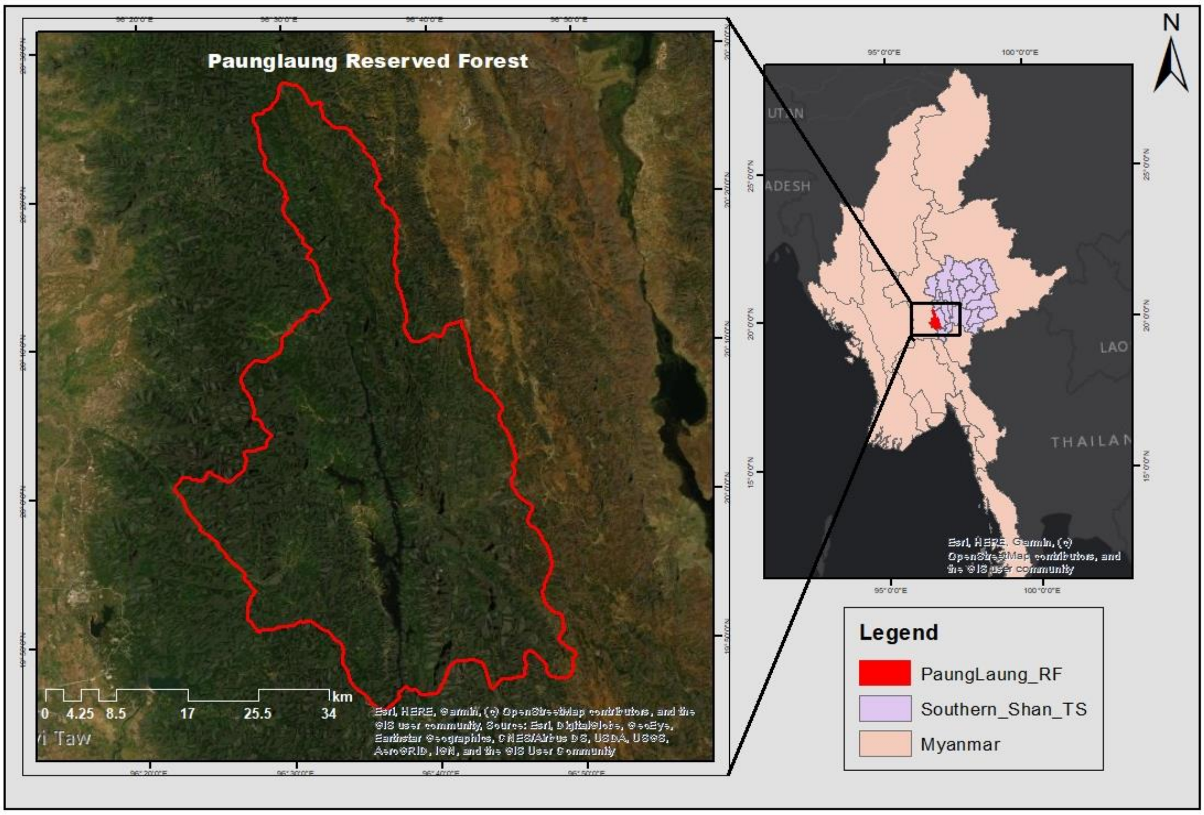

Figure 1. Location map of study area

The study area, Paunglaung Forest Reserve , located in three administrative boundary areas between Nay Pyi Taw Council Region, Mandalay Region and Shan State, Myanmar, with a total land area of 1700 km^2, lies between latitude 19°45′ to 20°28′ N and longitude

96°22′ to 96°49′ E [19, 48, 49]. The maximum and minimum total annual rainfalls are 2167 mm and 817 mm respectively, the precipitation of the study area is higher in eastern part of Shan State[19]. According to the local meteorological station, the maximum temperature is 32.2°C and the minimum temperature is -3.2°C. Most parts of the forest reserve is covered by natural forests which can be broadly classified as mixed deciduous forests and evergreen forests[50]. Paunglaung river is the main stream which is running from north to south and turning to the west in the middle of the study area. Paunglaung dam which is located on Paunglaung river was built in 2012. It is the first and largest hydraulic project in Myanmar to generate electricity amounting to about 900 million kilowatt/hour annually and to provide irrigation for 28,330 hectares of various crops[19]. Local people in this region grow paddy and orchard plantations such as turmeric and ginger. Besides, they rely on forests for their subsistence and they mainly harvest non-timber forest products such as bamboo shoots, konjac, broom grass and bamboo. This area is an important source for both local and commercial timber supply. Accordingly, Paunglaung watershed area has diverse ecological values not only to the local and national economy but also to the biological diversity conservation[48, 50]. Location map of study area is shown in Figure 1.

3.2 Satellite Images and Processing

Table 1. Satellite image data

Year	Satellite type/ Sensor	Path/Row	Observation Date	Pixel Resolution (m)	Cloud Cover
2014	LANDSAT_8/ OLI_TIRS	132/046	24.12.2014	30 × 30	1.26
		133/046	31.12.2014		2.71
2017		132/046	16.12.2017		1.26
		133/046	23.12.2017		0.00
2020		132/046	22.11.2020		0.47
		133/046	31.12.2020		0.04

Landsat 8 images were used in this study. This satellite was launched by United States Geological Survey (USGS) and National Aeronautics and Space Administration in 2013. It contains two sensors of operational land imager and thermal inferred sensor[51]. Most remote sensing approach involves the applying of satellite images of two or multiple dates for quantifying land use land cover changes in any area, so it is necessary to collect at least two time periods images for comparison[52]. Based on the study’s aim of analyzing land cover changes, the images were downloaded from USGS website, acquired in 2014, 2017 and 2020 with less than 5% of cloud cover (detail description in Table 1). Image selection was based on data availability. Only the images in the dry season are taken into consideration, so as to get images with less cloud[53]. In this study, the satellite data used for land cover change process were derived from Landsat 8 OLI (level 1) for three-year times period of 2014, 2017 and 2020. The spatial resolution of all data is the same (30m × 30m) and data were acquired on November and December. All the data were projected to the same geographical reference system UTM zone 46, WGS 84 datum. The study area falls under the path 132, 133 and row 046 in Worldwide Reference System of Landsat. Image processing and classification were conducted in soft environment of ENVI 5.3 (Exelis Visual Information Solutions, Boulder, CO, USA), where band stacking, colour balancing, visual interpretation of images, and creation of regions of interest (ROI) for classification was done[53]. The images were already geo-referenced, only radiance correction and mosaicking of two raster imageries were applied.

3.3 Field Data Collecting

Field work was carried out during July 2021 for collecting ground truth for defining the characteristics of forest cover class[54] and for further refinement of classification. Data about forest conditions on ground were collected in the upper, middle and lower parts of study area as much as possible. Due to the pandemic and country's security situation, there are limitations for some extent. During field visit, photos were taken to visually expand the understanding of specific land cover types (Figure 2).

Figure 2. Photos of land cover situation: (a) closed forest ;(b) open forest ;(c) cultivated land ; (d) bare land (settlement); (e) water

3.4 Classification and accuracy assessment

Land use cover changes, together with forest cover changes, can be obtained from the multi-band raster imageries through the process of image interpretation and classification[55]. After processing the images, supervised classification method was performed for the images in years 2014, 2017 and 2020, with the maximum livelihood classifier to classify the individual images independently. Maximum livelihood classification is the most common type of supervised classification and has been widely used because of its ease in application, simple operation and good performance[56, 57]. This method has measured not only the mean or average values in assigning classification but also the variability of brightness values in each class[58]. A good understanding and knowledge of the region was useful to conduct image classification in visual feature recognition, aided by high resolution imagery available in Google Earth[53]. Based on the FAO land cover classification system [59] and the actual situation of the study area, five land cover classes were delineated: closed forest, open forest, cultivated land, bare land and water to meet the main objective of this study (detail description in Table 2). The forest in the study area has been further classified as closed forest (dark greener pixels) and open forest (less dense and light green pixels) based on visual recognition and ground field data[60].

The term accuracy was typically used to express the measure of correctness of classification map which is assessed through the creation of error matrix[52, 61]. The accuracy assessment is important for analyzing and evaluating remote sensed land use/ land cover classification[62]. Many methods, including cross-tabulation, confusion matrix, and generation of random sample, are applied to assess the accuracy of classification[63, 64], and have been used in the classification studies. In this study, the confusion matrix (error matrix) was constructed using 250 equalized stratified random points with the help of ArcMap 10.5 to represent different land cover class. The statistical value of the overall accuracy, kappa coefficient, user's and producer's accuracy were computed for classification maps in 2014, 2017 and 2020[62].

Table 2. Description of land cove classes and description

Land Cover Class	Description
Closed Forest	Spanning more than 0.5 hectares; with trees higher than 5 meters and a canopy cover of more than 40 percent, or trees able to reach these thresholds in situ.
Open Forest	Spanning more than 0.5 hectares; with trees higher than 5 meters and a canopy cover between 10 and 40 percent, or trees able to reach these thresholds in situ.
Cultivated Land	Pasture, orchards, crop land, and nurseries
Bare Land	No vegetation and none of trees, settlement areas, and roads
Water	Water body of river, stream area, permanent open water, lakes, ponds, canals, seasonal wetland, low lying areas, mushy land, and swamps

3.5 Land Cover Change Analysis

3.5.1 Land cover change based on transition matrix

Image post processing, is an important step used to evaluate the remote sensed classification, and is implemented by computing the changes between different time periods[65]. After obtaining land cover classification results in the study area, the change detection analysis were calculated to make the transition matrix[51]. The confusion matrices were also exported to a table (in excel format) for further interpretation. The changes of forest in each time periods between 2014-2017 and 2017-2020 were analyzed in terms of rate (area) and percentage.

3.5.2 Land cover change based on dynamic degree

In order to analyze statistical changes in land cover, the author [66] established a dynamic degree index widely used for evaluating land use change rate. It is generally calculated according to Equation (1).

$$K = \frac{Ub - Ua}{Ua} \times \frac{1}{T} \times 100 \quad (1)$$

where K is land use dynamic degree index, measuring the change rate of the target land use type; U_a and U_b are the area of the target land use type at the beginning and end of the study period respectively and T is the study period, which is usually measured with the unit of year. The index of K can briefly express the overall characteristics of the change of a certain land use type in the study period. However, it is accepted that K has missed some information on the spatial process of land use change.

3.6 Dynamic change analysis of landscape spatial pattern from 2014 to 2020

Landscape pattern metrics are used in combination with geographic information system (GIS). GIS and related technologies are used for a long time in studies related to the ecology, and it has made a major contribution to the study of landscape metrics. Thus, landscape pattern metric is a great help, as an essential approach in quantifying landscape spatial patterns in the analysis of changes in land use pattern and associated ecological effects[66]. Landscape pattern metric tools have been used in landscape ecology as supporting landscape management decisions and landscape planning[67].

In order to quantify changes in spatial patterns in the study area, landscape indices were calculated using Patch Analyst in ArcGIS software version 10.5[68], and five classes of land cover were converted to two land cover classes: Forest (closed and open) and Non-Forest (cultivated land, bare land and water). In this approach, five metrics were chosen for the analysis of landscape patterns; number of patches, mean patch size, mean shape index and edge density to detect and measure patch size, shape and edge. Used of these five landscape metrics were chosen to describe landscape composition, the shape of patches and diversity of the landscape. Table 3.provides the detailed descriptions of these metric indies.

Table 3. Landscape spatial metrics and descriptions

Metric	Description/ calculation scheme	Unit/ Value range
Number of Patches (NP)	Total number of forest patches in the class/landscape level.	NP>0
Mean Patch Size (MPS)	Average patch size of forest patches in the class/ landscape level	MPS>0 (ha)
Mean shape index (MSI)	Total sum of each patch perimeter divided by the square root of patch area (hectares) for each class (class level) or all patches (landscape level)	no unit
Edge density	Total length of edge of a certain LULC class per unit area (m ha^{-1})	m/ha
MPAR	Total sum of each patches perimeter/area ratio divided by number of patches	no unit

3.7 Prediction of land cover in 2023 using CA-Markov

The Markov chain model was used to calculated the amounts of change of the selected locations in the future[69, 70]. The Markov chain describes the probability of change from one state to another. The transition probability matrix is expressed in test file that records the livelihood of moving land cover category to other category, while the transition area matrix represented in text format records the number of pixels required to transition from one land cover class to another over the specific number of time[71]. The CA-Markov model combines cellular automata and Markov chain to predict the characteristics and trends of land use land cover change over time[72-74]. Moreover, this model is commonly used to illustrate the dynamics of forest cover, land use/ land cover, settlement expansion and watershed management[75], and used to predict the extent of land use change and stability of future land development in concern area[76].

In this study, future land cover was predicted using CA-Markov model under the support of IDRISI Selva software version 17.0. The transition function from 2017-2020 was calculated in Markov chain analysis. Based on these transition matrix, CA Markov model was used to predict the land cover classes in 2023. The regular 5 × 5 contiguity filter was used as the neighborhood definition.

4 Results

4.1 Land cover classification and accuracy assessment

Summary statistics results of land cover classes of Paunglaung Forest Reserve obtained from the supervised classification are listed in Table 3. As shown in Figure 3, the area of closed forest increased 2040.33 hectares during 2014-2017 and decreased 4532.4 hectares during period of 2017-2020. It can be seen that closed forest was degraded into open forest and cultivated land in 2017-2020. Forest losses occurred mainly through forest degradation (closed forest to open forest) rather than direct deforestation such as clear cutting[4]. The forests with degraded and open canopy cover are likely to be replaced by commercial plantation or subsistence agriculture[77]. The annual declining rate of closed forest was calculated as 2.63%. As a result, annual change rate of open forest and cultivated land were increased 3.73% and 0.66% respectively.

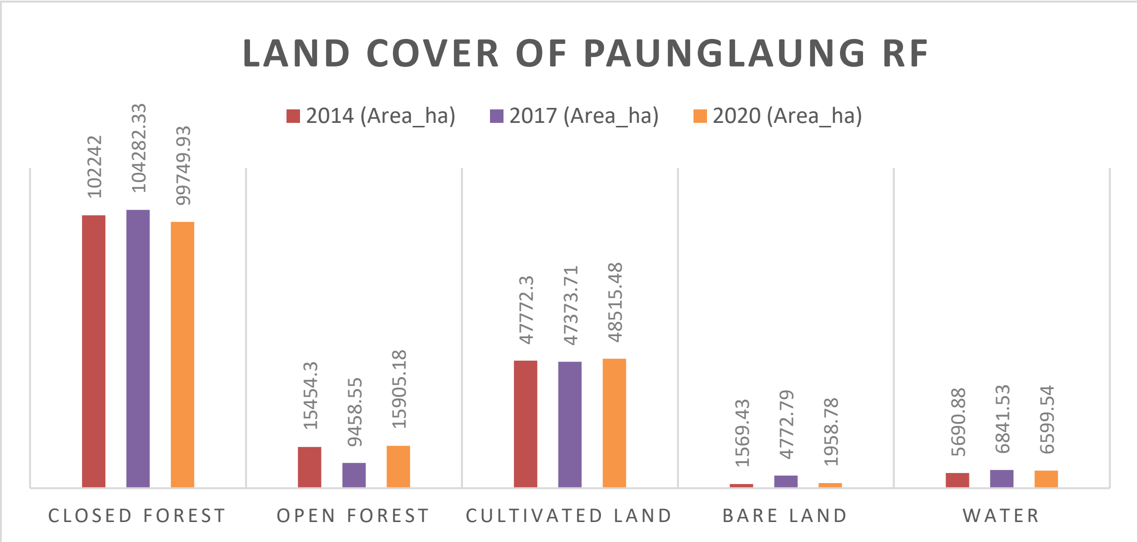

Figure 3. Land cover of Paunglaung Forest Reserved during 2014-2020

According to the supervised classification results of maximum livelihood, the total forested areas in study area were 117696.3 hectares, 113740.88 hectares, and 115655.11 hectares in years of 2014, 2017, and 2020 respectively (Figure 3 and 4).

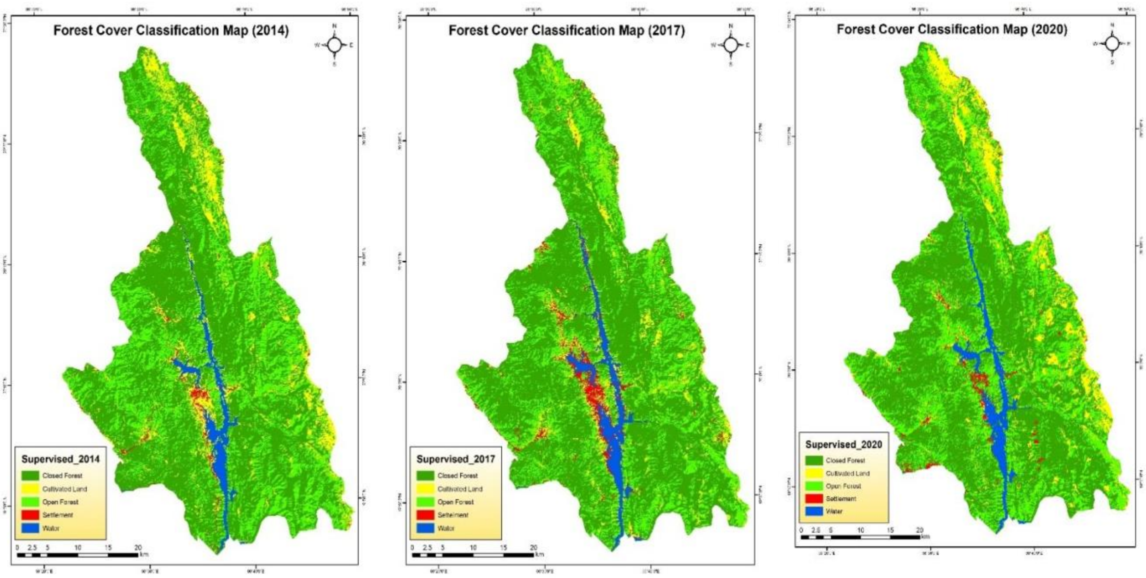

Figure 4. Land cover classification map in year 2014, 2017, and 2020

The overall classification accuracy in study area in 2014, 2017 and 2020 was 86%, 88%, and 84% and kappa coefficient was 0.82, 0.85 and 0.80 respectively, which are shown in Table 4, 5, 6. According to the research[61, 78], kappa statistics values can be divided into three groups as follows: (1) higher than 0.80 representing a strong agreement, (2) values in range from 0.40 to 0.80 expressing a moderated agreement, and (3) values under 0.40 representing a weak agreement. So, the classification of three periods shows a strong agreement between map classification and ground reference data.

Table 4. Confusion matrix using maximum livelihood supervised classification in 2014

Class Name	CF	OF	CL	BL	W	Total	U_Accuracy	Kappa
CF	38	9	3	0	0	50	0.76	0
OF	8	38	4	0	0	50	0.76	0
CL	0	2	43	4	1	50	0.86	0
BL	0	0	5	45	0	50	0.9	0
W	0	0	0	0	50	50	1	0
Total	46	49	55	49	51	250	0	0
P_Accuracy	0.83	0.78	0.78	0.92	0.98	0	0.86	0
Kappa	0	0	0	0	0	0	0	0.82

Table 5. Confusion matrix using maximum livelihood supervised classification in 2017

Class Name	CF	OF	CL	BL	W	Total	U_Accuracy	Kappa
CF	41	6	3	0	0	50	0.82	0
OF	1	39	10	0	0	50	0.78	0
CL	0	2	45	3	0	50	0.9	0
BL	0	0	5	45	0	50	0.9	0
W	0	0	1	0	49	50	0.98	0
Total	42	47	64	48	49	250	0	0
P_Accuracy	0.98	0.83	0.7	0.94	1	0	0.88	0
Kappa	0	0	0	0	0	0	0	0.85

Table 6. Confusion matrix using maximum livelihood supervised classification in 2020

Class Name	CF	OF	CL	BL	W	Total	U_Accuracy	Kappa
CF	35	10	4	1	0	50	0.7	0
OF	0	40	10	0	0	50	0.8	0
CL	0	0	50	0	0	50	1	0
BL	1	3	9	36	1	50	0.72	0
W	0	1	0	0	49	50	0.98	0
Total	36	54	73	37	50	250	0	0
P_Accuracy	0.97	0.74	0.68	0.97	0.98	0	0.84	0
Kappa	0	0	0	0	0	0	0	0.8

4.2 Land cover change analysis

4.2.1Land cover change based on transition matrix

It can be seen from Table 7, during the period 2014-2017, over 85% of land in study area was still covered by forest. Based on the results during this period, the percent of no change area of closed forest was 85.97%, closed to open forest was 10.38% and closed forest to other land class was 3.65%. 30202.4 hectares of land was covered by open forest and change area of open forest to closed forest was 14541.6 hectares. The area percentage of forest to other land was 6.34%. Open forest was decreased by about 400 hectares in 2017. Seen from Table 7, change from cultivated land to open forest is 41.43%. Due to the construction of Paunglaung Dam, which is one of the development projects that had negative impacts on local people, flooding and the displacement of 8000 people in 23 villages occurred in Paunglaung river valley. The government moved most of 23 villages to a large settlement near the middle part of reservoir[79]. The classification results show that the bare land area was increased by over 3000 hectares in 2017, and construction of dam made water area increased too.

Table 7. Land cover change transition matrix from 2014 to 2017

Land Cover Class	CF (2017)		OF (2017)		CL (2017)		BL (2017)		W (2017)		Total Area (2014)
	Area(ha)	(%)	Area(ha)	(%)	Area(ha)	(%)	Area(ha)	(%)	Area(ha)	(%)	
CF (2014)	87892.74	85.97	10615.5	10.38	1782.59	1.74	1627.73	1.59	323.44	0.32	102242
OF (2014)	14541.6	30.44	30202.4	63.22	2623.37	5.49	339.87	0.71	65.06	0.14	47772.3
CL (2014)	1769.05	11.45	6402.21	41.43	4718.64	30.54	1790.74	11.59	773.66	5.01	15454.3
BL (2014)	75.54	4.81	148.98	9.49	324.77	20.69	980.85	62.5	39.29	2.5	1569.43
W (2014)	3.4	0.06	4.62	0.08	9.18	0.16	33.6	0.59	5640.08	99.11	5690.88
Total Area (2017)	104282.33		47373.71		9458.55		4772.79		6841.53		**172728.91**

No Change in each class

One of the objectives of this study is to detect how much forest area has changed during the study periods. The greatest changes occurred among closed forest, open forest and cultivated land classes. During 2017-2020 period, approximately 13219.7 hectares of closed forest changed to open forest , 6969.69 hectares of open forest and 4010.87 hectares of closed forest converted to cultivated land (Table 8). Annual change rate of closed forest decreased by 0.87% in the second period of this study (2017-2020), while open forest and increased by 1.24% and also cultivated land increased by 0.22% (Table 9).

Table 8. Land cover change transition matrix from 2017 to 2020

Land Cover Class	CF (2020)		OF (2020)		CL (2020)		BL (2020)		W (2020)		Total Area (2017)
	Area(ha)	(%)	Area(ha)	(%)	Area(ha)	(%)	Area(ha)	(%)	Area(ha)	(%)	
CF (2017)	86647.53	83.09	13219.7	12.68	4010.87	3.85	325.71	0.31	78.52	0.08	104282.33

OF (2017)	9936.33	20.97	30165.05	63.67	6969.69	14.71	276.3	0.58	26.34	0.06	47373.71
CL (2017)	1143.11	12.09	3860.69	40.82	4120.28	43.56	278.88	2.95	55.59	0.59	9458.55
BL (2017)	1755.75	36.79	1064.11	22.30	708.27	14.84	1044.1	21.88	200.56	4.2	4772.79
W (2017)	267.21	3.91	205.93	3.01	96.07	1.4	33.79	0.49	6238.53	91.19	6841.53
Total Area (2020)	99749.93		48515.48		15905.18		1958.78		6599.54		**172728.91**

No Change in each class

Table 9. Landcover change statistics in Paunglaung Forest Reserve from 2014 to 2020

Land Cover	2014 (Area-ha)	2017 (Area-ha)	2020 (Area-ha)	Change (%) 2014-2017	Change (%) 2017-2020	Annual Change Rate (%) 2014-2017	Annual Change Rate (%) 2017-2020
Closed forest	102242	104282.33	99749.93	1.18	-2.62	0.39	-0.87
Open forest	15454.3	9458.55	15905.18	-3.47	3.73	-1.16	1.24
Cultivated land	47772.3	47373.71	48515.48	-0.23	0.66	-0.07	0.22
Bare land	1569.43	4772.79	1958.78	1.85	-1.63	0.62	-0.54
Water	5690.88	6841.53	6599.54	0.67	-0.14	0.22	-0.05
Total	172728.91	172728.91	172728.91				

Based on the classification result, over 4000 hectares, 52.91%, of land cover transformed to forest area during these three period because of the shifting cultivation system of local people, government and private-owned plantation, and agriculture garden. Figure 7 to 10 illustrate the changes of one class to other land classes during two study periods.

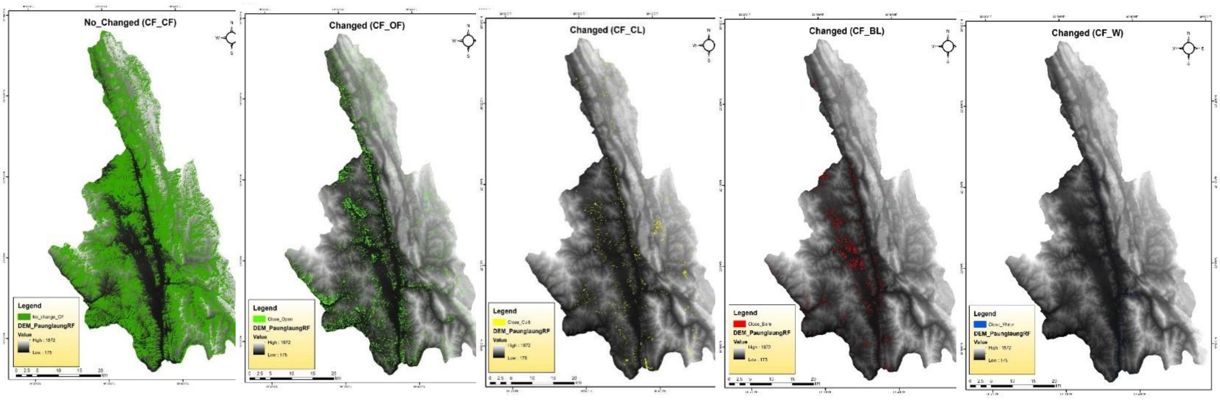

Figure 7. Unchanged and changed areas of closed forest (2014-2017)

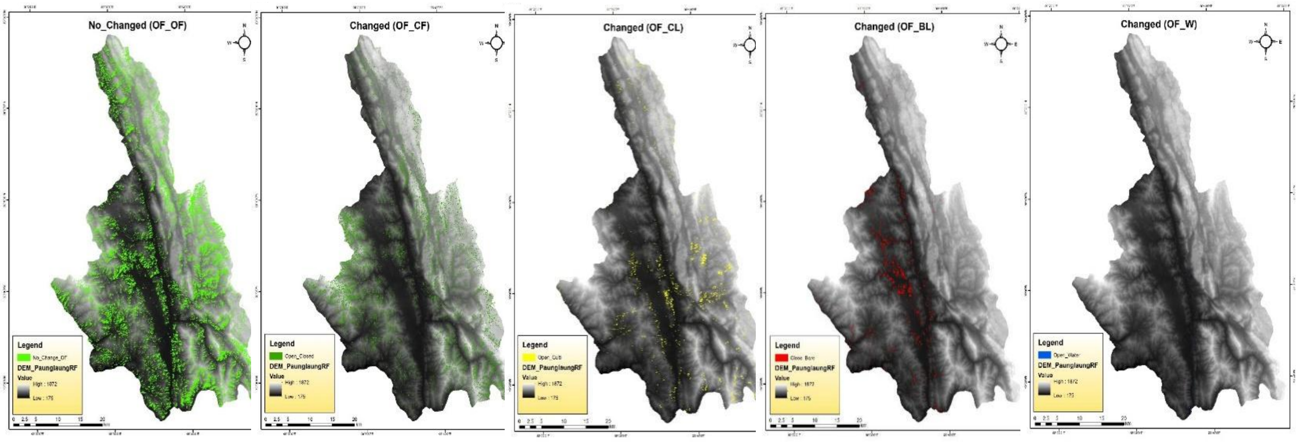

Figure 8. Unchanged and changed areas of open forest (2014-2017)

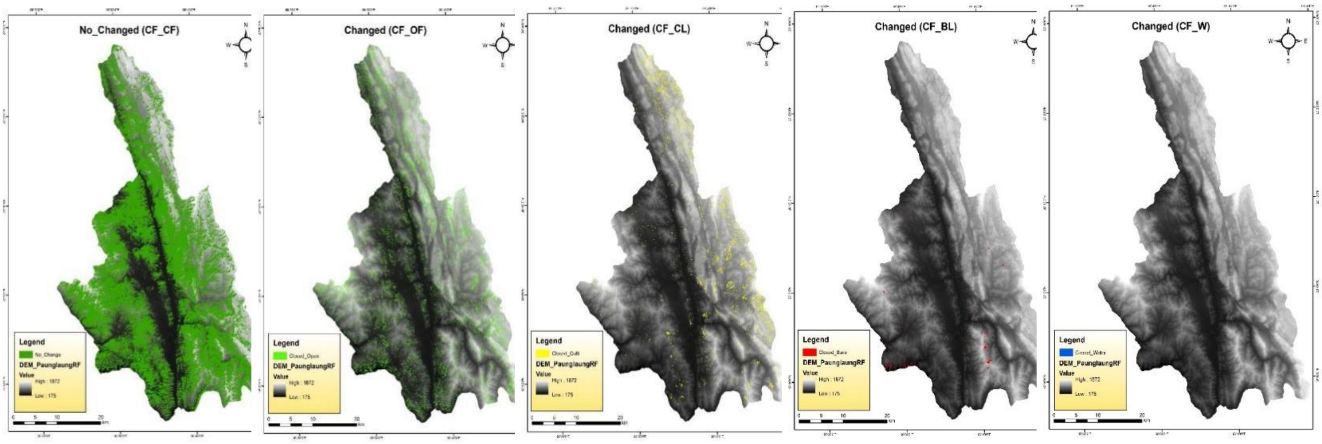

Figure 9. Unchanged and changed areas of closed forest (2017-2020)

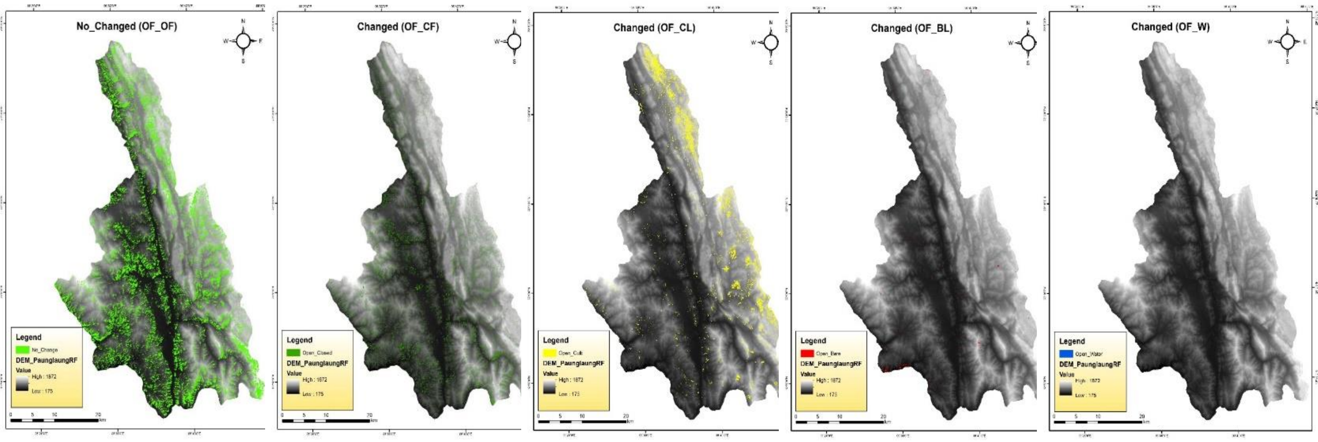

Figure 10. Unchanged and changed areas of open forest (2017-2020)

4.2.2 Land cover change based on dynamic degree

As shown in Table 10, the index of *K* reflects the summation of conversion loss and gain of target land use type, and the value of *K* measure annual net increasing rates of each land cover class. Bare land scored the highest increasing rate with a value of 67.35 during the first study period (2014-2017), while closed forest and open forest accounted the lowest with a value of -0.28 and 0.63 respectively. But cultivated land reached the highest with a value of 22.49 during the second period (2017-2020), while closed forest and bare land had the lowest *K* value of -1.43 and -19.46 respectively.

Table 10. Dynamic degree of each land cover classes in 2014-2017 and 2017-2020

Land Cover Class	CF	OF	CL	BL	W
2014-2017	0.63	-0.28	-12.8	67.35	6.67
2017-2020	-1.43	0.8	22.49	-19.46	-1.17

In summary, dynamic degree of each land cover type in Paunglaung Forest Reserve was little high with quite differences during the 2014-2020 period (Figure 11).

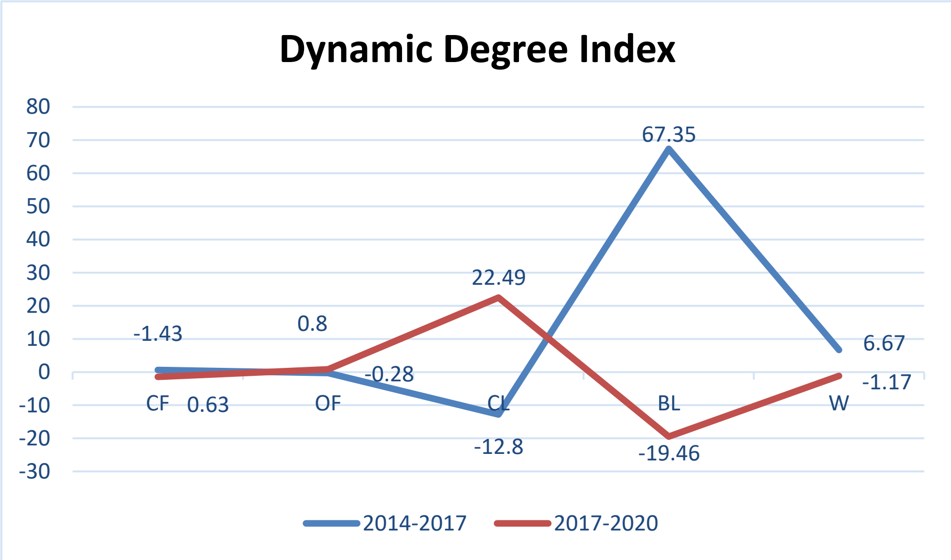

Figure 11. Land cover dynamic index in different periods from 2014 to 2020

4.3 Dynamic change analysis of landscape spatial pattern from 2014 to 2020

The spatial metrics were calculated and their dynamics are presented in Table 11(class level) respectively. The table shows the result of the class metrics for both forest and non-forest areas with reference to the four spatial metrics of Number of Patches (NP), Mean patch size (MPS), Mean Shape index (MSI) and Edge Density (ED).

Table 11. Results of class level spatial index

Landscape pattern index	2014		2017		2020	
	Forest	**Non-Forest**	**Forest**	**Non-Forest**	**Forest**	**Non-Forest**
NP	5845	2228	5684	2943	3462	2218
MPS	78.36	313.44	80.49	352.84	71.39	401.75
MSI	3.09	5.10	3.09	5.05	3.10	5.20
ED	91.08	19.02	89.37	19.80	88.46	18.18

Open forest and closed forest are combined into forest area and cultivated land, bare land and water are classified into non-forest area. The number of forest patches decreased, the mean patch size of forest increased but the mean shape index and edge density also decreased in year 2014 and 2017. And number of forest patches also decreased 3462 in 2020. In forest area, the number of patches and the edge density were the largest in 2014, but mean patch size was the smallest (71.39) in 2020. The mean shape index was the largest (3.10) in 2020 with 0.1 difference in 2017. As of edge density, it was the largest (91.08) in 2014.

For non-forest area, number of patches and edge density were the greatest in 2017, but mean patch size was the least in 2014. The mean shape index was the dominant in 2020.

Table 12. Results of landscape level spatial index

Year	NP	MPS	MSI	MPAR	ED
2014	8073	21.345	1.526	322.880	110.097
2017	8627	19.974	1.513	322.877	109.167
2020	7917	21.723	1.515	317.721	106.640

As shown in Table 12, the number of patches and mean patch size were the greatest in 2017. It can be seen that the greater the number of patches, the greater the degree of forest fragmentation if the area of landscape was constant. But the number of patches decreased in 2020. The mean shape index, mean parameter area and edge density were the largest in 2014 with lesser NP than 2017. The results showed that the forest became fragmented during the two study periods in Paunglaung Forest Reserve.

4.4 Prediction of forest cover in 2023 using CA-Markov

The results of land cover prediction using CA-Markov analysis are shown in Table 13 and Figure 12. According to the prediction result (Table 13), 57.76% of land is covered by closed forest, and open forest, cultivated land, bare land and water are 28.07%, 9.22%, 3.82% and 1.13% respectively. The area of open forest increased from 2014 to 2020, while closed forest decreased 1.47% from 2014 to 2020 time period. But compared with 2020 classification result, the areas of closed forest, open forest and cultivated land will not change, but bare land will increase by 2.69% and water class will decrease by 2.69% respectively. The author[1] estimated the forest cover change of Taunggyi District, Shan State. His research result showed that the forest area in Pinlaung township will loss 35% in 2030. In summary, prediction for next three year does not change much for most land cover classes in Paunglaung Forest Reserve. The findings suggest that a reasonable land use plan should be developed in harmonization way with sustainable conservation of forest resources.

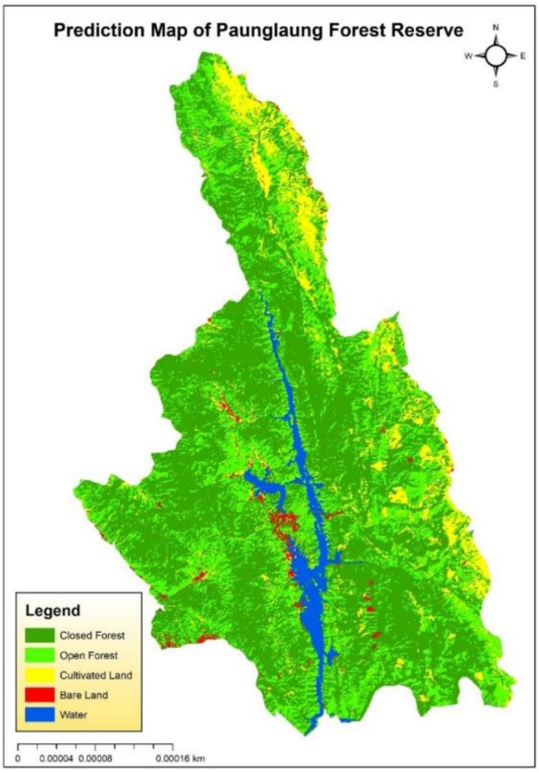

Figure 12. Prediction map of Paunglaung forest reserve in 2023

Table 13. Percentage of each land cover classes in year 2014, 2017, 2020 and 2023

Class	Year (%)			
	2014	2017	2020	2023(prediction)
CF	59.23	60.37	57.76	57.76
OF	27.66	27.42	28.07	28.07
CL	8.91	5.49	9.22	9.22
BL	0.90	2.76	1.13	3.82
W	3.30	3.96	3.82	1.13
Total	**100.00**	**100.00**	**100.00**	**100.00**

5. Discussion

5.1 Analysis of Forest Cover Change of Paunglaung Forest Reserve

Forest cover in Paunglaung Forest Reserve was significantly increased in 2017, but it was degraded to open forest in 2020. Conversion of land cover from one class to another class was also shown in the research result. The research of Sharma [1] showed that the highest change from forest to non-forest happened in Pinlaung township between 2008 to 2016, where 54.27 km^2 (5427 hectares) of forest area was converted to water because of the constructed reservoirs. Total land area of Shan State was covered by 50.99%, 38.65%, and 56% forests in 2010, 2015, and 2020 respectively (Planning and Statistics Division, Forest Department). In this study, the area of forest class transformed to cultivated land was 4405.96 hectares during 2014-2017 and 10980.56 hectares during 2017-2020 periods, respectively. Other study also found similar causes of forest decline in the eastern part of the study area where forest converted to agricultural land; i.e., farmland growing green tea and orange which are the main economic products for household income in the research region[19]. The results displayed in this thesis show that the expansion of agricultural activities contributed to the modification of forest cover, indicating the possibility of decrease in the forest cover in near future[80].

The results showed significant land use changes in quantitative structure. Cultivated land and bare land had the highest land use dynamic degree during two study periods. According to the results, loss and gain of forest cover in the study area is related with human settlement and rural economic development.

Landscape level metrics are useful indices in providing information about the whole region without detailing class relations[81], while class level metrics are more suitable in defining ecological processes[82]. The number of patches and the change in number of smaller patches as measured by patch density are the most important indicators of landscape fragmentation. Increase in the edge density was considered as primary outcome of habitat fragmentation, and involved a decrease of habitat in large, homogeneous patches. Forest landscapes with small patches or irregular shapes would have higher edge density values than landscapes with large patches or simple shapes[83]. Forest fragmentation, coupled with land cover changes, may lead to forest degradation that could adversely affect biodiversity, quality of natural habitat and ecosystem services, and people's livelihoods[84]. By comparing landscape metrics, there was distinct decrease in the mean patch size of forest with the increase of non-forest during the second study period. It can be concluded that most of the forest areas in 2017 were converted to cultivated land and bare/settlement land in 2020.

According to the prediction results in 2023 with interval time of three years, the area of bare land increased drastically. The increase may primarily be caused by increasing population, expanding crop land and residential area that leading to forest degradation in the future.

5.2 Causes of Forest Cover Change

Agricultural expansion is one of the main drivers for global deforestation[15, 85]. Land conversion for agriculture is likely to be highest in tropical developing countries where natural forests have been replaced by 80% of new cropland[15]. There are large forested areas suitable for agriculture in the tropics where climates are suitable for high value crops and where population growth rates are also high. As in this thesis, conversion of forest areas to agricultural land (new non-forest) is significant and widespread across both outside and within the forest reserves of Myanmar[77]. The majority of land granted for agricultural concessions are located in heavily forested and politically contested regions [86]. Following decades of over-harvesting and environmental concerns, government of Myanmar began to ban on the export of raw logs in 2014 that led to decrease in the number of logging[13]. At the same time, the agricultural master plan and land policies began to aim to increase the number of agricultural activities[87].

Lim et al. (2017) identified agricultural expansion as a direct causes and major driver for forest loss[13]. Likewise, other studies pointed out that commercial agriculture (oil palm and rubber plantation) contributed to deforestation of Myanmar than subsistence agriculture[77, 88]. Based on the research of Myint (2015), local communities in southern Shan State highly rely on agriculture economically. Crop fields are prevalent in lowland basins and people used to sustain shifting cultivation system on the hillsides. But now, the traditional cultivation had already changed to short-fellow shifting cultivation which was not sustainable because of the population growth pressure[33].

Although Myanmar has long historically practiced science-based forest management with the Myanma Selection System (MSS) which was evolved from the Brandis system since 1856, most of the studies have shown that unsustainable timber extraction has contributed to deforestation and forest degradation[4, 89]. The Annual Allowable Cut (AAC) and 30 years cutting cycle of production forests are fundamental rules of Myanma Selection System[87]. Selective logging practice has been mostly used in tropical forests worldwide[90], but there have been increasing concerns about the sustainability of wood extraction[91]. Myanmar Timber Enterprise, which is responsible for timber extraction, selectively logged valuable tree such as “Teak” (*Tectona grandis*) and other hardwoods in the production forests under the MSS, leading to degradation of forests[4, 87]. In terms of Shan State, according to the regional office data, in Taunggyi district, Teak had been extracted in 2014/2015 without any AAC, hardwood had been also extracted with the number over the quota of AAC in 2011/2012.

Furthermore, Myanmar forests have been facing additional pressure from illegal logging, removal of fuel wood and harvesting of NWFPs (non-wood forest products). Illegal logging is a common problem. Usually, it is carried out by forest dwellers and small local merchants who take advantage of the backward traffic conditions in forest areas and weak law enforcement. The fundamental causes of illegal logging are, increasing demand for forest products in local and neighboring countries, particularly timber and fuel wood and high timber prices due to supply-demand imbalance and corruption[33]. In addition, illegal logging has also contributed to deforestation and forest degradation in Myanmar[92]. Illegal logging has occurred for both timber extraction and fuelwoods[93]. About 2 billion people in the developing countries are still mainly depending on fuelwood and charcoal for cooking and heating in both rural and urban areas[88]. Fuelwood consumption should be the third priority driver for deforestation and forest degradation. According to the fuelwood consumption study paper in Taunggyi District, it was found that the main causes of deforestation and forestation is fuelwood collection (60%) and others including agricultural expansion, wild fire, mining, increased population, illegal logging, and shifting cultivation, made a contribution of 40%[29].

Dam construction is also included as a key driver of world's deforestation and forest degradation. Global population growth, economic development and industrialization over the past four decades have increased the demand on energy, leading to the expansion of hydropower projects and dam constructions across the world[94]. Chen et al. (2015), estimated that 48 hydropower projects which are located in dense forested areas with higher biodiversity values, were operating and under construction in Myanmar[94]. Shimizu et al. (2017) found that water expansion was the second largest disturbance of deforestation in Bago mountain regions[18]. Large forested areas in Bago mountain regions were impacted by water expansion due to the dam construction. Actually, the construction of dam has negatively impacted not only on deforestation and forest degradation but also local livelihood of near construction area. Based on the classification result of this study, after construction of Paunglaung dam, agricultural land was decreased in 2014 but was increased 0.66% during 2017-2020 period. However, impacts of dam construction on the environment has not been under deep research in Myanmar[4].

6. Conclusions

In the thesis, forest cover decreased during 6 years period (2014-2020) and the annual lost rate of forest cover is 0.24% in Paunglaung Forest Reserve. Then forest cover was significantly degraded and lost during the second period of this study (2017-2020). Continued degradation of forest will conclusively result in the decrease of forest cover. Sustainability of Paunglaung RF is important for indigenous communities and is necessary for social, ecological, and economic benefits.

Currently, Forest Department of Myanmar introduced a specific plan of 10-year Myanmar Reforestation and Rehabilitation Programme (MRRP) from 2017-2018 to 2026-2027 with the establishment of new forest plantation on degraded forests and the restoration of heavily depleted forests through reforestation, enrichment planting, and natural regeneration through silvicultural operations countrywide[34]. This programme was implemented in collaboration with related stakeholders, including NGOs, civil society organizations, the private sector, local community groups and indigenous people. Likewise, the establishment of community forestry is a multi-disciplinary way to protect forest resources through local people participation and awareness conducted by forest department.

With the development of remote sensing and GIS technologies, there are new possibilities of rebuilding long term history of land cover. To address forest degradation and deforestation, it is needed to reduce the dependency on natural resources.

Based on the results of land cover change, the study recommends the following strategic options; developing policy intervention to conserve Paunglaung Forest Reserve from deforestation and forest degradation, enhancing establishment of community forestry and private forest plantation, creating job opportunities for local communities and introducing Agro-Forestry practices. The purpose of this study is to provide up to date and recent land cover change in Paunglaung Forest Reserve. Although there are limitations of geographic data and impacts of domestic security situations in Myanmar, the classification maps and detection statistics will provide a reference for making of sustainable forest management programme and protection policies.

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