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NANJING FORESTRY UNIVERSITY

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Paper for Professional Master Degree

论文题目/Title：**Mapping forest cover change from multi-temporal remote sensing data in Central Suau Forest Management Area Milne Bay Province, Papua New Guinea (1978 -2014)**

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研究方向/Research Area：**Forestry**

指导教师/Supervisor：**Professor Mingshi Li (PhD)**

年/Year **2016** 月/Month **May**

DEDICATION

This thesis is first and foremost dedicated to God Almighty for his divine wisdom, protection, love, courage, trust and plan on my education career. To both my late adopted mum Elizabeth Lalo and biological mum Gervina Vogone Inzing and adopted father Paul Batot Lalo, wife Alma Keis Sabai and kids Gervina, Herick, Inzing and Jacob. To my biological father Billy Inzing, family members, mentors and friends.

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Lastly I thank two unanimous reviewers for their comments on this thesis.

ABSTRACT

Mapping forest cover change is essential for assessing the effectiveness of the existing forest management approaches, budgeting forest carbon sequestration and promoting climate change studies. The major objective of the current analysis was to map forest cover change during the period 1978 to 2014 from multi-temporal satellite observations, in Central Suau Forest Management Area (FMA), Milne Bay Province, Papua New Guinea (PNG), and to penetrate the socio-economic drivers responsible for the observed forest cover changes. After an intensive field visit and consultation with local natural resource managers, six major land use/land cover classes (*inland water body, mangrove forest, primary forest, other naturally regenerated forest, other land, cloud/shadows*) were classified from the 1997 Landsat 5 TM imagery, the 2010 RapidEye imagery and the 2014 Landsat 8 OLI imagery using the Maximum Likelihood classifier, simultaneously the 1978 local land use/land cover map was vectorized using ArcMap as the baseline for analyzing forest cover change.

Results suggested that the overall accuracies of land use/land cover classifications for 1997, 2010, and 2014 were 86%, 93%, and 84%, with Kappa coefficients of 0.81, 0.89 and 0.75 respectively. The study's average annual rates of deforestation and forest degradation were 1.1 % yr^{-1} and 1.5 % yr^{-1} respectively. In addition, the average annual rates of local forest cover change were 4.5 % yr^{-1} (*mixed swamp forest*), 1.1 % yr^{-1}(*mangrove forest),* 0.4 % yr^{-1} (*low altitude forest on plains and fans)* and 0.2 % yr^{-1} (*low altitude forest on uplands).* Subsistence cultivation, built-up areas and small scale-logging were the main drivers of deforestation and forest degradation and also identified as major factors contributing to forest cover change. Deforestation activities were thematically represented by other land (OL) and forest degradation by other naturally regenerated forest (ONRF) classes.

Analyzing multi-temporal medium and high resolutions remotely sensed observations is an effective and reliable means to map forest cover changes, which helps to reconstruct forest disturbance and recovery histories with spatially explicit implications and insights. There is an opportunity to extend these methods to other areas of PNG as well as other neighboring tropical countries to fully understand differences of land use and local forest cover changes at varying socio-economical and geographical scales.

Keywords*: Forest cover change, Maximum Likelihood classification, Deforestation, Forest degradation, Papua New Guinea*

1 INTRODUCTION

1.1 Background

In PNG 97% of its forest land is held under customary ownership and the precise nature of this ownership varies from one culture to another (Bird et.al. 2007; FRA 2010; FRA 2015). Notably, about 80 % of the population live in rural areas and they heavily depend on forest land for subsistence agriculture or cultivation (Sitango 2006) and other human-induced activities, which cause continuous forest cover change at different geographical scale and time. Shearman et.al. (2008) stated in 1972 PNG had 38 million hectares of intact forests covering 82% of the country's total land area of 46.2 million hectares. In 2002 there were 25.3 million hectares of intact rainforest remaining across the country and 2.9 million hectares of secondary forest had been degraded through logging. The conversion of forest land to gardens for subsistence agriculture accounted for 3.6 million hectares and was the main driver of deforestation in PNG between 1972 and 2002. Schlund et.al. (2014) argued that it is important to track land-use conversions like deforestation, for sustainable forest management and land use planning, for carbon balancing and to support the implementation of international initiatives like reducing emissions from deforestation and forest degradation plus enhancing carbon stock (REDD+).

In 2010 the present study site (Central Suau FMA Milne Bay Province) was assigned as Papua New Guinea Forest Authority's (PNGFA's) pilot site to trial various initiatives of REDD+ with similar objective done in some South-East Asian and tropical countries.

1.2 Problem Statement

Only few studies relating to mapping forest cover change or land use change using remote sensing (RS) and geographical information system (GIS) techniques have been conducted in Papua New Guinea (PNG) over the last three decades. However, methods applied (Shearman 2010;Tapulu et. al. 2014) studies focused on only two time study periods over small to large spatial extents in determining rates of forest cover changes. Thus studies using multi-temporal remote sensed data at project, regional and national levels are also few in PNG (Ningal et. al. 2008; Shearman et.al. 2009; Gunarso et. al. 2013) even though it is considered very significant because it give precise results (Kennedy et. al. 2010) as compared to only two time study periods. Also, our nation's capacity on standard methodological knowledge about forest cover change assessment in PNG is still insufficient thus makes research and policy-making regarding international climate change initiatives such as REDD+ rather difficult. For these aforementioned reasons, the present study design used multi-temporal remote sensed data to investigate forest cover change at the project level and compare its results against previous studies.

1.3 Objectives

The three main objectives of this study were:

1) Map major land use/land cover classes from multi-temporal remote sensed data,
2) Investigate rate of forest cover change through identifying deforestation and forest degradation activities over different periods using land use/land cover change detection techniques and;
3) Provide precise results to policy and decision makers which is very significant because recently published annual rates of deforestation (7.7 % yr^{-1}) and forest degradation (7.7 % yr^{-1}) by SPC and GIZ (2014a) on same study site (Central Suau FMA Milne Bay Province PNG) is understood to be very high when compared with similar studies that were done in PNG and its neighboring countries (Hammermaster and Saunders 1995; McAlpine and Quigley 1998; Shearman et.al. 2008; Filer et.al. 2009; Ningal et al. 2008; Shearman et.al. 2009; Shearman 2010; Shearman et. al. 2010; Gunarso et. al. 2013).

Importantly, the methods and results from present study will significantly achieve and improve expected outcomes of "*principle 5: Improving understanding of forestry and climate change*" of *Climate Change Framework for Action 2009 – 2015* (PNGFA 2009) which is a framework for action that outlines the broad priorities for the PNG government thus provides strategic platform not only for use by decision makers at all levels but also for the development and strengthening of partnerships for implementation of national, sub-national and community initiatives (FRA 2015).

1.4 Thesis outline

This paper consists of seven sections. Section 1 presents the background to the study, problem statement and objectives. Section 2 presents literature review of remote sensing and Geographical Information System (GIS) data, land use/land cover classification, change detection and drivers of forest cover change. Section 3 gives detail of the site and its environmental characteristics. Section 4 describes the data and methods used. Section 5 presents the study results. Sections 6 discusses the results, limitations and compare with other studies and also points out new findings. Section 7 concludes present study's general findings against published papers and draw attention of its importance and future research. Important references cited at the end of this paper provide useful information and link to this study.

2 LITERATURE REVIEW

2.1 Remote sensing and GIS data

Present study integrated remote sensing (RS) and geographical information system (GIS) applications and technology in order to extract required information on land use /land cover change that occurred in Central Suau Forest Management Area (FMA) Milne Bay Province, PNG. Lillesand and Kiefer (2000) explained that RS technology involves the technique of obtaining information about an object or feature through the analysis of data acquired by a device that is not in contact with the object or feature under investigation. Winther (2015) pointed out that GIS is a scientific inter-discipline tool aiming to discover patterns in, and produce visual displays of, spatial data. GIS products include topographic and thematic maps of the Earth's surface, climate maps, and spatially referenced demographic graphs and charts. Lambin (1997) confirmed that GIS and RS have been efficiently and widely used much in single thematic analysis such as land use and land cover change mapping. Pillay (2010) also stated that there are many satellite sensors that can be used for land use and land cover mapping and change detection. These include; IKONOS, Quick bird, Advanced Very High Resolution Radiometer (AVHRR), Advanced Space Borne Thermal Emission and Reflection Radiometer (ASTER), Satellite Pour l' Observation de la Terre (SPOT), Landsat Thematic Mapper (Landsat TM), and Moderate Resolution Imaging Spectrometer (MODIS). Each satellite sensor has different spatial, temporal and spectral characteristics.

2.2 Classification and accuracy assessment

The two main approaches that is use for land use/land cover classifications are: object-based and pixel-based classifications (Budreski et.al. 2007; Martinfar et.al. 2007; Hayder and Husam 2013; Hanh et. al. 2015). Object-based classification combines both spectral and spatial information of different objects in an image. The image is segmented according to different objects, textures and shapes that are based on a fuzzy theory with more than one class containing different threshold values (Flanders et. al. 2003; Martin et.al. 2004). Pixel-based classification utilize multispectral data to perform the classification and the spectral pattern present within the data for each pixel is use as the numerical basis for categorization of different feature types with different combination (Lillesand et. al. 2004) based on conventional statistical techniques such as Maximum Likelihood supervised classification (Martinfar et.al. 2007).

Present study used pixel-based Maximum Likelihood supervised classification for years 1997, 2010 and 2014. However, 1978 land use/land cover base map was digitized using on-screen method similar to studies done by Ningal et.al. (2008) and Shearman et.al. (2009). Manual on-screen digitizing method is presumably same to object-base methods because features are interpreted and identified and digitized according to standard land use classes by experts. The main difference is most studies tend to use object-based automated classification using RS and GIS software to produce fast results, for example using the e-cognition software **(**Flanders et. al. 2003; Martin et.al. 2004; Tian et.al. 2014).

Error matrices and Cohen's kappa (k) are commonly used for accuracy assessment. Kappa can be used as a measure of agreement between model predictions and reality (Congalton 1991) or to determine if the values contained in an error matrix represent a result significantly better than random (Jensen 1996). The result of performing a Kappa analysis is a KHAT statistic (an estimate of Kappa), which is another measure of agreement or accuracy. In error matrix overall accuracy it only incorporates the major diagonal and excludes the omission and commission errors thus KHAT (Cohen's Kappa) accuracy indirectly incorporates the off-diagonal elements as a product of the row and column margins (Congalton 1991). Many other studies discuss classifications with overall accuracies below the general target of 85% and have a large range in the accuracy with which the individual classes have been classified (Foody 2002).

2.3 Similar studies

Many studies within the Asia Pacific region including the world used multi-temporal remote sensing data to identify major land use/land cover classes in order to develop land use/land cover maps to meet specific study's objectives. For example, Hanh et. al. (2015) used Landsat MSS (Multi Spectral Scanner), Landsat TM (Thematic Mapper) and SPOT **(**Satellite Pour l' Observation de la Terre)satellite images to study dynamics of land cover/land use changes in the Mekong Delta of Vietnam from 1973 to 2011. They identified seven major land cover/land use classes which include; cultivated lands, aquaculture ponds, mangrove forest, melaleuca forest, built up areas, bare lands, and natural water bodies. The satellite images were georeferenced, classified using per-pixel method, validated, and compared by post classification techniques to detect change in decades. Overall, from 1973 to 2011, bare lands, cultivated lands, mangrove forest, and melaleuca forest decreased by 104 km^2 (10,400 ha.), 77 km^2 (7,700 ha.), 61 km^2 (6,100 ha.), and 5 km^2 (500 ha.), respectively, as a consequence aquaculture lands and built up areas increased by 123 km^2 (12,300 ha.), and 120 km^2 (12,000 ha.), respectively.

Ningal et. al. (2008) used topographic maps of 1975, Landsat TM images of 1990 and 2000 to investigate changes in population in relation to land use change in the Morobe Province of PNG. They identified six land use classes as follow: agriculture, forest, grassland, plantation, urban, and water. They did on-screen vectorizing of topographic maps and satellite images by overlaying with existing GIS mapping files to derive land use class boundary attribute data for each study years. Their study revealed agricultural land use increased considerably between 1975 and 2000 where most of the expansion occurred at the expense of primary forest, which decreased over the same period. There were expansions in most land use types but agriculture increased more than others. The annual gain in agricultural land use between 1975 and 1990 was 3%, compared to 0.9% between 1990 and 2000. Annual loss in forest was 0.8% between 1975 and 1990, but 0.4% between 1990 and 2000. Between 1975 and 2000, agriculture gained 15% from forest, which is the highest compared to gains in other land use types. They concluded that in the absence of improved farming systems the current trend of increased agriculture with rapid population growth is likely to continue.

Shearman et.al. (2009) created the 1972 land cover map for PNG through visual classification and manual delineation of polygon class boundaries of vegetation types from topographic maps. Their 2002 land cover map for PNG was created by applying a Tasseled Cap and Brovey transformation to Landsat ETM+ imagery, and red/green/blue/infrared color enhancement to their SPOT 4 and 5 imagery and finally used the object recognition software 'eCognition' to automatically segment the satellite imagery into spatially continuous and spectrally homogeneous regions consistent with land-cover features. The basic land cover used were: tropical rainforest (referred to here as 'forest'), swamp forest, dry-evergreen forest, mangroves, scrub, herbaceous swamp, non-vegetation, water and grassland. But within the change analysis, they grouped the land cover classes into two categories: forest (rainforest) and non-forest (non-rainforest). Their study revealed between 1972 and 2002, a net 15 % of primary rain forest was cleared and 8.8 % degraded to secondary forest through logging. Overall, 48.2 % of this forest change was due to logging, 45.6 % was related to subsistence agriculture, 4.4 % due to forest fires, 1.2 % due to plantations, and 0.6 % due to mining. They estimate that over the period 1990–2002, overall rates of change generally increased and varied between 0.8 and 1.8 % yr^{-1}, while rates in commercially accessible forest have been far higher, having varied between 1.1 and 3.4 % yr^{-1}.

Gunarso et.al. (2013) used cloud free Landsat TM and Landsat ETM+ (Enhanced Thematic Mapper Plus) to document land cover and land use change in three palm oil producing countries, namely Indonesia, Malaysia, and Papua New Guinea between 1990 and 2010. They combined both pixel based methodologies and on-screen manual interpretation and identified thirteen land cover classes following the Ministry of Forestry of Indonesia (MOFRI) and Ministry of Agriculture of Indonesia (MOARI) land use/land cover classes to monitor oil palm extension in PNG for the years 1990, 2000 and 2010. The land cover classes include; undisturbed upland forest, disturbed upland forest, upland shrub and grassland, undisturbed swamp forest, disturbed swamp forest, swamp shrub and grassland, agroforest and plantation, oil palm plantation, intensive agriculture, bare soil, settlements/mines and clouds, mangroves and water. They found growth in oil palm plantation areas have fluctuated between 3 to 6% annually (2,440 to 4,261 ha.) over the three temporal periods. The largest source of land cover type for the oil palm expansion was found in disturbed upland forest.

SPC and GIZ (2014a) study on the same study site (Central Suau FMA), used Landsat ETM+, Landsat 8 OLI (Operational Land Imager), and PNG Forest Authority Forest Base map 2012 developed from RapidEye (Scherer and Krischke 2001) high optical satellite images. The study identified seven major land cover classes including: primary forest, secondary forest, mangrove, agriculture, agriculture plantation, grassland/herbland, and lakes/large rivers. They did on-screen vectorizing using enhanced images to derive land cover class boundary and attribute data for 2001, 2011 and 2014 land cover maps respectively. The study revealed rates of deforestation and forest degradation were approximately 2,226 hectares or 171 hectares per year (7.7 % yr^{-1}) and 1,999 hectares or 154 hectares per year (7.7 % yr^{-1}) respectively, from 2001 to 2014.

2.4 Land use/land cover change

According to a recent study conducted on same site by SPC and GIZ (2014a), they revealed the main drivers of land use/land cover change activities were subsistence cultivation, small-scale logging, built-up areas, and unpaved road construction. In rural PNG similar trends of land use/land cover activities are occurring, for instance Shearman et. al. (2009) confirmed that rapid and substantial forest change has occurred in PNG, with the major drivers being logging in the lowland forests and subsistence agriculture throughout the country with comparatively minor contributions from forest fires, plantation establishment, and mining. Ningal et. al., (2008) highlighted that the absence of improved farming systems encouraged the current trend of increased agriculture activities due to rapid population growth.

Studies conducted by Ningal et. al. (2008), Shearman et.al. (2009) and SPC and GIZ (2014a) generally reported on annual rates of land use/land cover change due to each specific study's objectives and omit reporting on local forest cover change. Local forest cover change study in PNG is vital for REDD+ planning and awareness in mitigating climate change effects at the local and national level. This missing information is paramount and has urged current study to further investigate how to compute annual rates of local forest cover change from results of mapping land use/land cover classes using topographic maps for year 1978, Landsat 5 TM imagery for year 1997, Rapid Eye imagery for year 2010 and Landsat 8 OLI imagery for year 2014.

3 STUDY SITE

3.1 Location

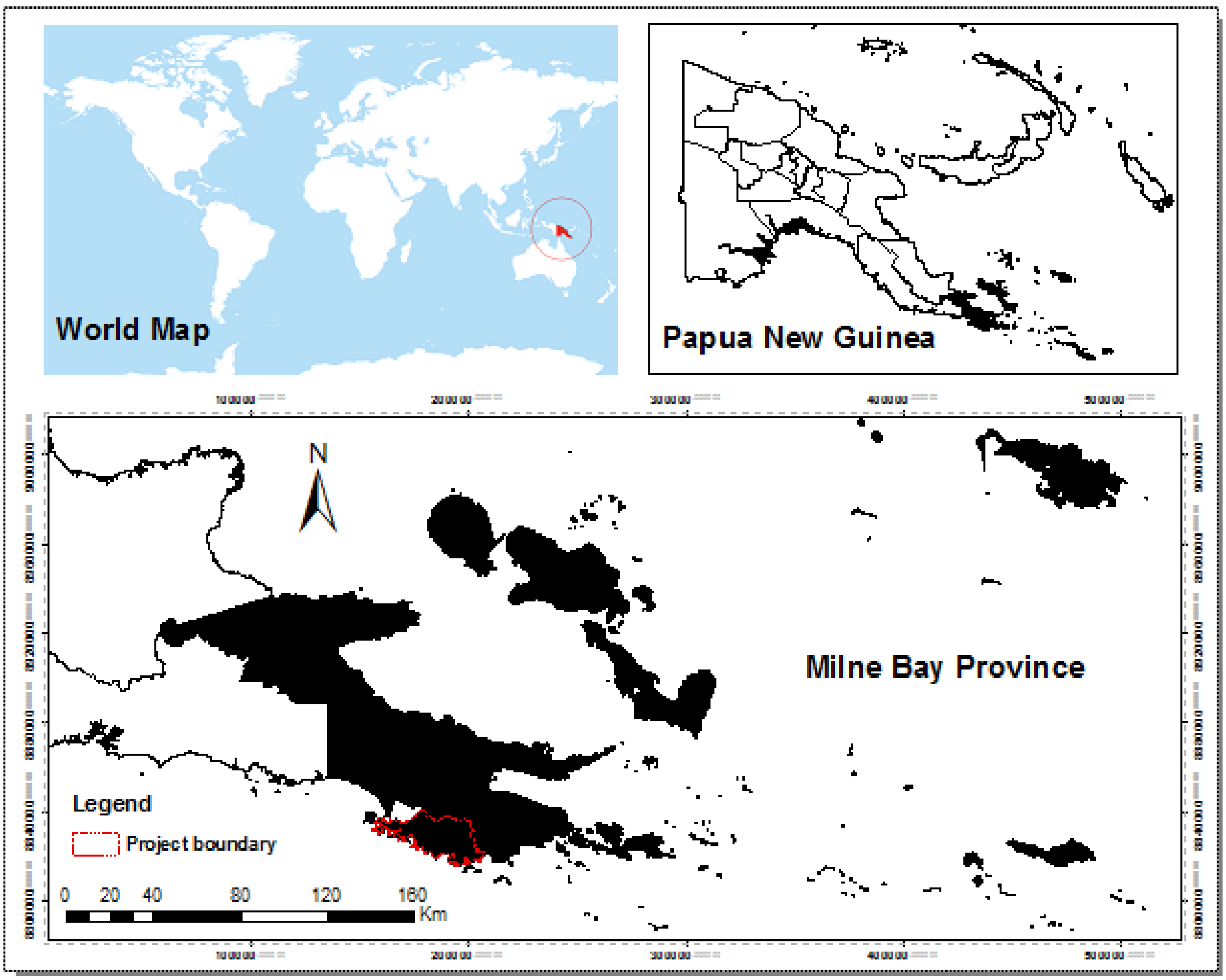

Figure 1. *Location map of the study site in Milne Bay Province, Papua New Guinea.*

Central Suau Forest Management Area (FMA) is located in the independent state of Papua New Guinea (Figure 1), towards the south eastern tip of the main New Guinea Island. It is located approximately 10° 35.278'S and 150° 10.042'E below the equator. The site's elevation ranges between 0 to 1300 meters above sea level. It has a gross area of 60,000 hectares (ha) and the topography varies from flat to hilly terrains and mountainous regions towards north, north eastern and central part of the study site. Site comprised of 24 villages or communities with sparse population around 100 to 700 people per village. These indigenous people own the land and forest resources and their livelihood is more dependable on these land and forest resources including marine resources. Accessibility to the site is through roads, ships or boats and walking tracks along the coast and jungles.

3.2 Climate and soil types

The site's climatic condition is tropical which is hot and wet all year round and has an annual mean temperature range of approximately 23 to 31 ^{o}C (Samanta and Aiau 2015). Rainfall varies a lot within the site from 2400 millimeters (mm) to 3700 mm per year (PNGRIS 2009). The wettest region is located at the south-eastern and least is towards the north-west and western part of the study site (Figure 2). According to PNGRIS (2009) soil type classification follows the United States Department of Agriculture (USDA) soil taxonomy classes. Out of the 12 world major Soil Orders the site has 6 Soil Orders and 13 Great Groups as listed: (1) Alfisol (*Tropudalfs & Plinthaqualfs*), (2) Entisols (*Fluvaquents, Hydraquents, Sulfaquents, Tropofluvents & Troporthents*), (3) Histosol (*Tropohemists*), (4) Inceptisol (*Dystropepts & Eutropept*), (5) Oxisol (*Eutrorthox & Haplorthox*) and (6) Ultisol (*Tropudults*). Dystropepts is the dominant Great Group soil type whilst the least is Haplorthox (Figure 3).

3.3 Species composition

The site contains diverse tree species that are found in the tropical lowland rainforest of Papua New Guinea including the Island of New Guinea. Ten most dominant tree species include *Myristica fatua (Myristicaceae), Aporusa bogorensis (Euphorbiaceae), Pterocarpus indicus (Fabaceae), Myristica buchneriana (Myristicaceae), Pometia pinnata (Sapindaceae), Elaeocarpus amplifolius (Elaeocarpaceae), Cryptoccarya depresa (Lauraceae), Pimeleodendron amboinicum (Euphorbiaceae), Ficus itoana (Moraceae) and Cleistanthus insignis (Euporbiaceae).* One of the endemic tree species of the New Guinea Island is *Myristica buchneriana (Myristicaceae)* showing third most dominancy on the site, however it has been listed in the International Union for

Conservation of Nature (IUCN) Red List as Vulnerable species since 1998. Its dominancy raises expectation of more undiscovered endemic flora maybe present. The palm species *Hydriastele costata (Arecaceae)* and shrubby *Osmoxylon novoguineensis (Araliaceae)* are dominant on the lower shrub layer of the forest stand. Mangrove Forest is dominant with plant families like Rhizophoraceae, Myrtaceae, Lythraceae (Sonneratiaceae), Meliaceae, Icacinaceae, Avicenniaceae, Sterculiaceae, and Euphorbiaceae. Also noted during the field work was the existence of exotic and invasive South-American shrub species *Piper aduncum (Piperaceae)* dominancy on disturbed forest areas, walking tracks, along river edges, new and old gardens thus its existence pose a major threat to the native floral population.

4 DATA AND METHODS

4.1 Data

Data used in this work included: (1) large scale local topographic maps (e.g. 1:100 000) composed in 1978, (2) least cloud free Landsat 5 TM image acquired on 12 November 1997, (3) Rapid Eye images of 2010 and (4) cloud free Landsat 8 Operational Land Imager (OLI) image acquired on 28 November 2014 (Table 1). Ancillary GIS data used include contour lines, project boundary polygon, rainfall (Figure 2) and soil types (Figure 3). The software used in this classification work were ENVI Classic and Arc Map 10.

Table 1. *Multi-temporal remote sensing data.*

Data type	Pixel res.(m)	Acq. Date	Source
Topographic maps (detailed)	8.5	1978	PNG Forest Authority
Landsat 5 Thematic Mapper (TM)	30	1997-11-12	USGS website[1]
Rapid Eye	5	2010	PNG Forest Authority
Landsat 8 Operational. Land Imager (OLI)	30	2014-11-28	USGS website

[1] United States Geological Survey (USGS) (http://earthexplorer.usgs.gov)

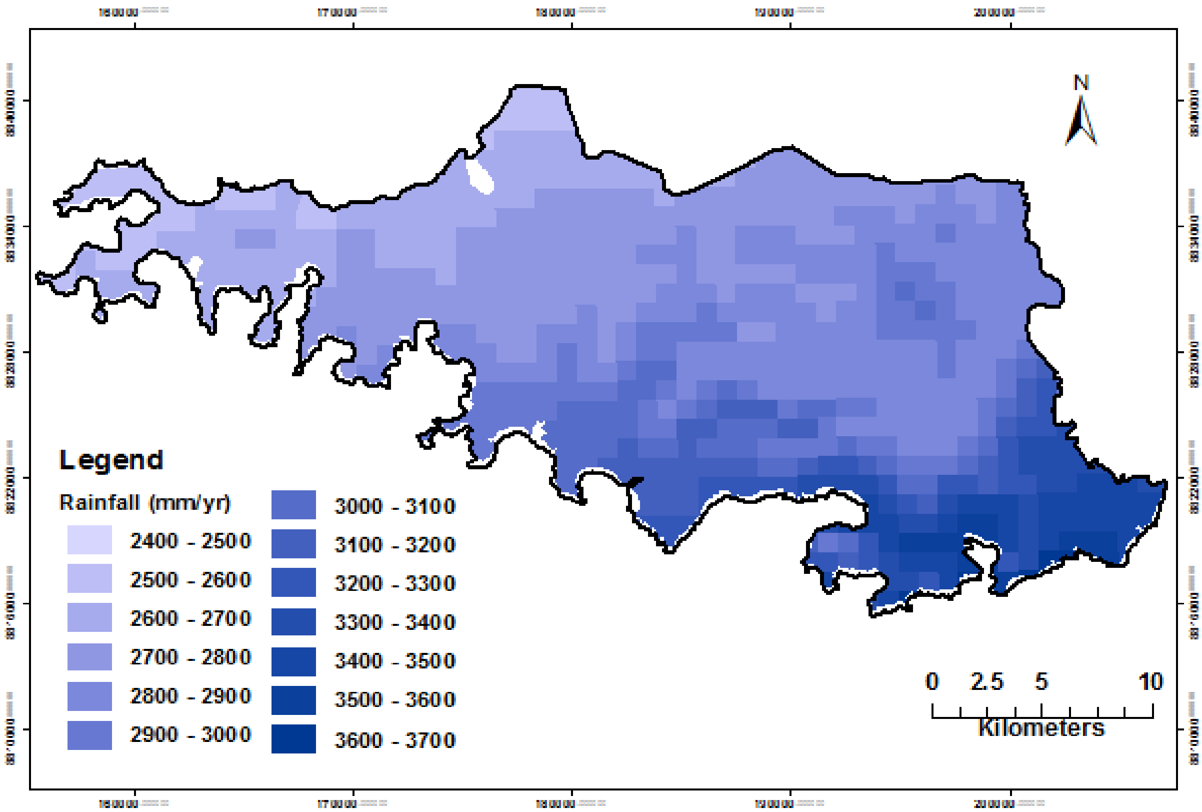

Figure 2. *Spatial map of annual rainfall distribution on the study site.*

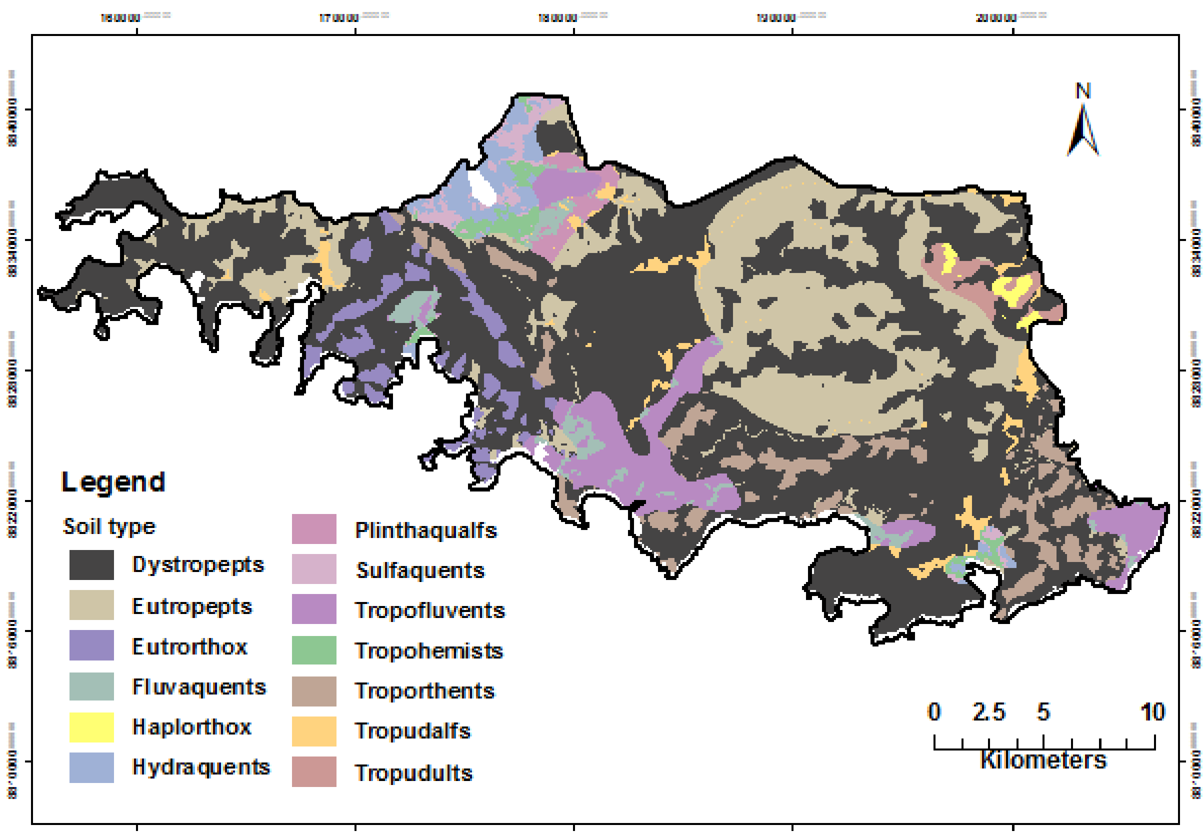

Figure 3. *Spatial map of soil type distribution of the study site.*

4.1.1 Topographic map

One topographic map sheet covers an area of 55 x 55 kilometers (km) and four (4) sheets cover the whole project area. The maps were originally developed using 1973 and 1974 aerial photos by Royal Australian Survey Corps. The map scale is 1:100,000 and the geometric accuracy is ± 25m horizontal positions and ±17m vertically with contour intervals at 40 metres (m) except in dense forest the accuracy of elevation may not be achieved (Australian Survey Corps 1978). Four sheets: TOPO8876AVA, TOPO8877ORANGERIE, TOPO8976MODEWA and TOPO8977ALOTAU were mosaicked, georeferenced and used in present study (Figure 4).

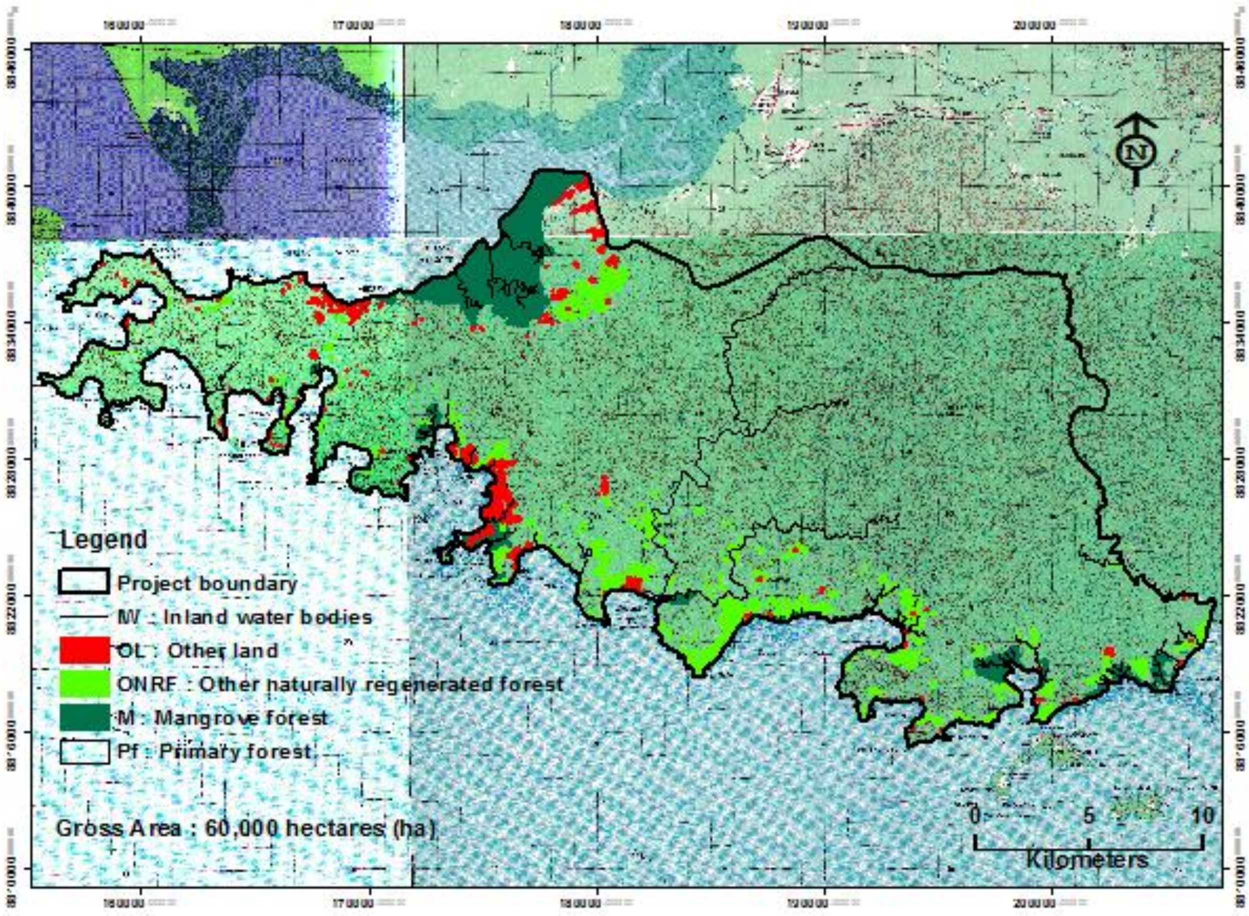

Figure 4. *Mosaicked and georeferenced topographic image for 1978 of the study site.*

4.1.2 Landsat 5 TM imagery

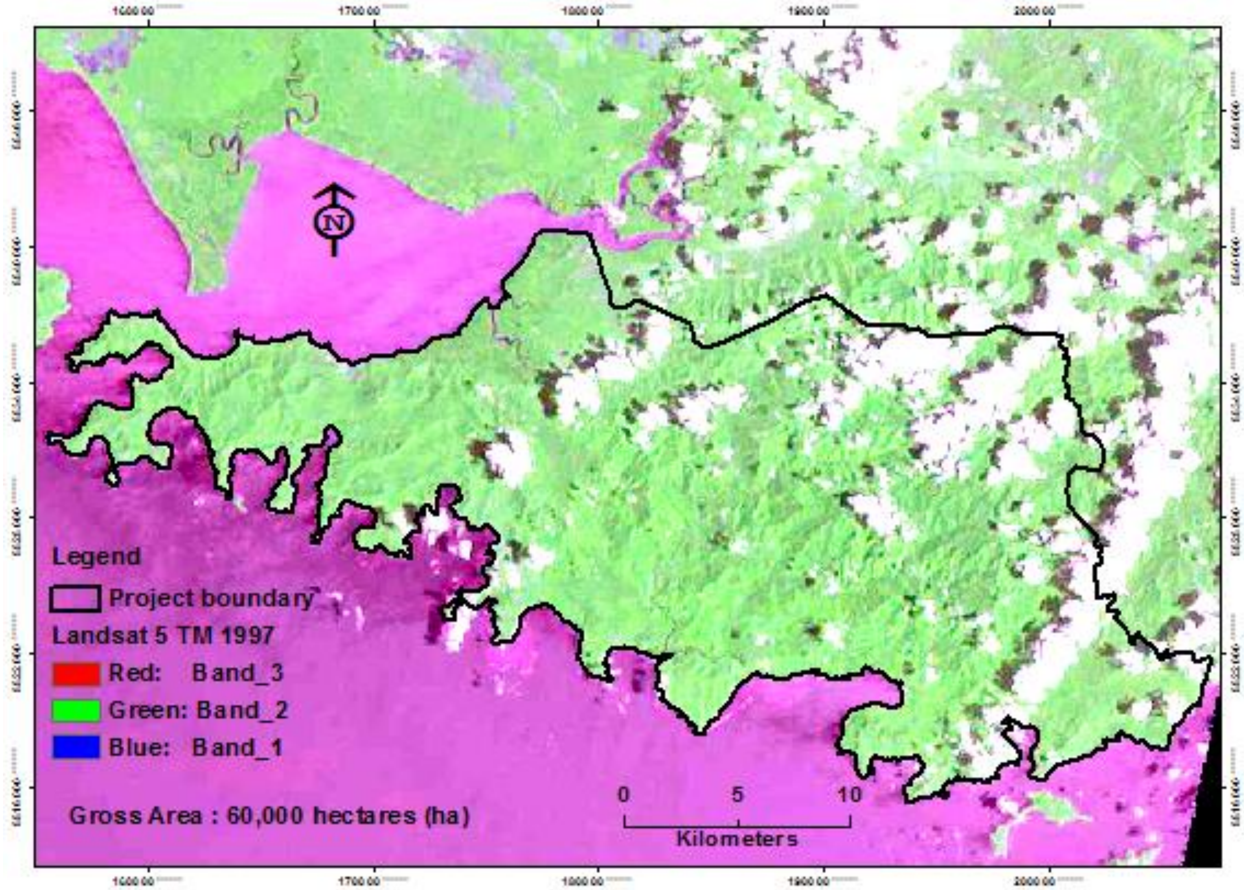

Figure 5. *Subset and georeferenced image of Landsat 5 TM for 1997 of the study site.*

Landsat 5 TM images consist of seven spectral bands with a spatial resolution of 30 meters for Bands 1 to 5 and 7. The spatial resolution for Band 6 (thermal infrared) is 120 meters, but is resample to 30-meter pixels. Approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi). The TM Band 6 was acquired at 120-meter resolution, but products processed before February 25, 2010 are resample to 60-meter pixels and products processed after February 25, 2010 are resample to 30-meter pixels (Table 2). The path and row identification number of full coverage of Landsat 5 TM image are 94 and 67 respectively. Figure 5 shows the subset and georeferenced image of Landsat 5 TM for the study site.

Table 2. Band designations for the Landsat 5 TM satellite image.[2]

	Landsat 4-5	Wavelength (micrometers)	Resolution (meters)
Thematic Mapper (TM)	Band 1	0.45-0.52	30
	Band 2	0.52-0.60	30
	Band 3	0.63-0.69	30
	Band 4	0.76-0.90	30
	Band 5	1.55-1.75	30
	Band 6	10.40-12.50	120 (30)
	Band 7	2.08-2.35	30

4.1.3 Rapid Eye imagery

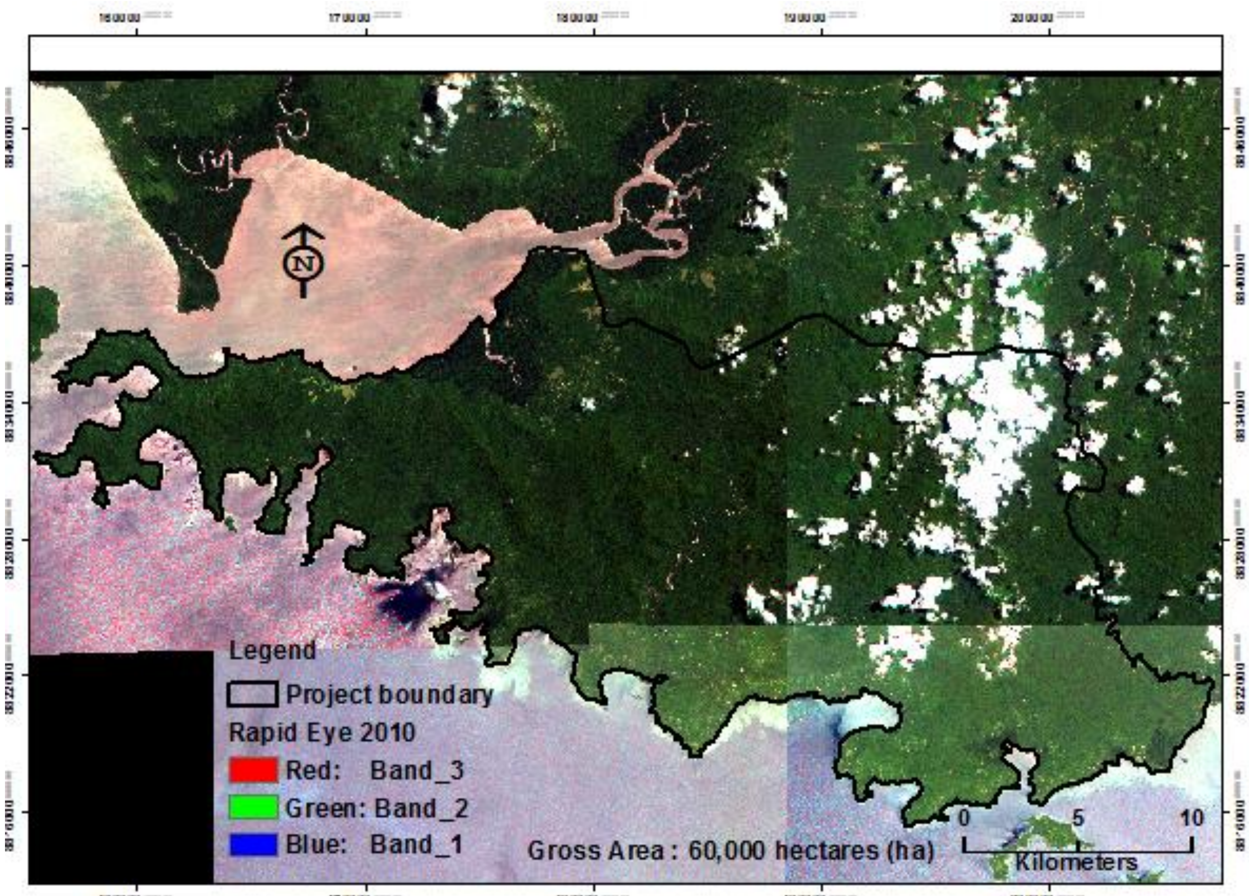

Figure 6. *Mosaicked and georeferenced Rapid Eye image for 2010 of the study site.*

[2] http://www.usgs.gov/faq/categories/10164/3839

Six high spatial resolution Rapid Eye scenes were acquired in 2010/2011 and purchased under the PNG Forest Authority and Japan International Cooperation Agency (PNGFA & JICA) project on "Capacity Development on Forest Resource Monitoring for Addressing Climate Change (Phase one: 2011-2014)" for the whole country (PNG). Only the following 6 identified scenes (5534128, 5534228, 5534101, 5534102, 5534201 and 553202) covering the study site were provided for this study.

According to Scherer and Krischke (2001) the Rapid Eye's imaging capabilities can be applied to a host of industries, including agriculture, forestry, oil and gas exploration, power and engineering and construction, governments, cartography and mining. The Red-Edge band is sensitive to changes in chlorophyll content (Table 3). Figure 6 show the mosaicked and georeferenced Rapid Eye image with a unified pixel resolution of 30 metres.

Table 3. *Band designations for RapidEye satellite image* [3]

Number of Satellites	5	
Spacecraft Lifetime	7 years	
Orbit Altitude	630 km in Sun-synchronous orbit	
Equator Crossing Time	11:00 am local time (approximately)	
Sensor Type	Multi-spectral push broom imager	
Spectral Bands	Capable of capturing any of the following spectral bands:	
	Type	Wavelength (nm)
	Blue	440 - 510
	Green	520 - 590
	Red	630 - 685
	Red Edge	690 - 730
	NIR	760 - 850
Ground sampling distance (nadir)	6.5 m	
Pixel size (orthorectified)	5 m	
Swath Width	77 km	
On board data storage	1500 km of image data per orbit	
Revisit time	Daily (off-nadir) / 5.5 days (at nadir)	
Image capture capacity	4 million sq km/day	
Dynamic Range	12 bit	

[3] http://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/rapideye/

4.1.4 Landsat 8 OLI imagery

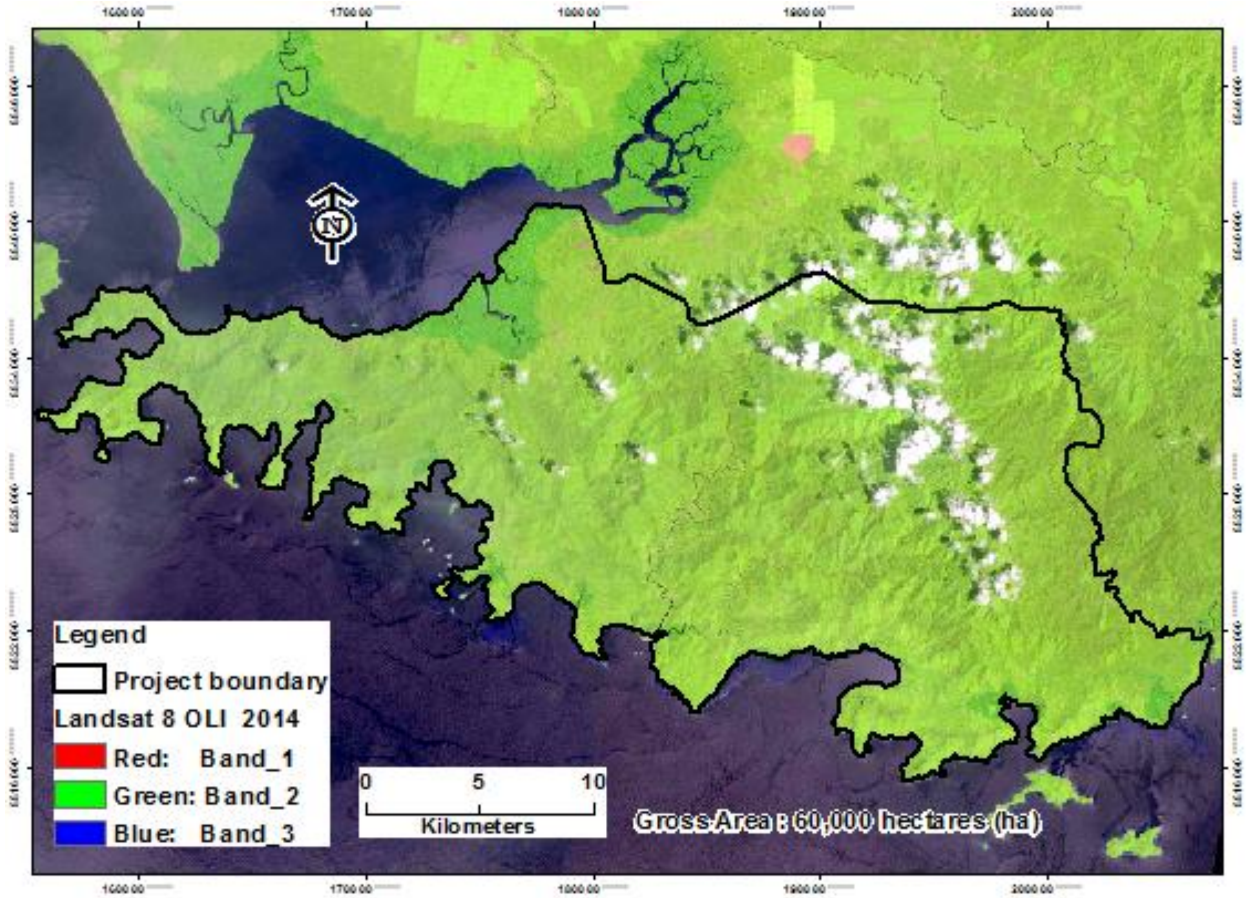

Figure 7. *Subset and georeferenced image of Landsat 8 OLI and TIRS for year 2014 of the study site (false color band combination).*

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. The new Band 1 (ultra-blue) is useful for coastal and aerosol studies. The new Band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. The thermal Bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi) (Table 4). The path and row identification number of full coverage of Landsat 8 OLI and TIRS image are 94 and 67 respectively. Figure 7 shows the subset and georeferenced image of Landsat 8 OLI and TIRS for the study site.

Table 4. *Band designations for the Landsat 8 OLI and TIRS satellite image.*[4]

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) *Launched February 11, 2013*	*Bands*	*Wavelength (micrometers)*	*Resolution (meters)*
	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 - Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - SWIR 1	1.57 - 1.65	30
	Band 7 - SWIR 2	2.11 - 2.29	30
	Band 8 - Panchromatic	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100

** TIRS bands are acquired at 100 meter resolution, but resampled to 30 meter in delivered data product.*

4.2 Methods

4.2.1 Image pre-processing

The satellite images (Landsat, RapidEye) and mosaicked topographic map were geometrically corrected to the Universal Transverse Mercator grid (UTM), zone 56 Southern Hemisphere, WGS84 ellipsoid and datum, using nearest neighbor resampling method. Topographic map was used as the base map for the geometric correction of each imagery at the project scale and the registration or georeferencing was done using 8 to 16 accurately identified ground control points. All images were resampled to a 30 meter pixel resolution for consistency in the classification work. During the georeferenced processes an average root mean square (RMS) error of less than 0.4 pixels was achieved.

4.2.2 Development of land use/land cover classification schemes

After a five week duration of field visits that was conducted in November to December 2012 within the study site in conjunction with an intensive consultation with the local natural resource management agency, six major land use/land cover classes were identified to be mapped in the study site (Table 5). Figure 8 illustrates field photos of land use/land cover classes including the five local forest types.

Mangrove forest (1) theoretically should be grouped as *primary forest (Pf)* class but is separated due to its different spectral reflectance property and is conspicuously visible in latest satellite images for classification work. *Primary forest* comprised of local forest types that include (2) *Low*

[4] http://www.usgs.gov/faq/categories/10164/3839

altitude forest on plains and fans (P) that consisted of large, medium and small crowned forest.

Table 5. *Major land use/land cover class definitions.*

Land use/land cover class	**Definition**[5]
Forest	*Forest area of 1 hectare (ha) that contains an average tree height of ≥ 3metres and have ≥ 10 % of canopy cover (*PNG Forest Authority's unofficial definition of forest*)
1. Primary forest(Pf)	*Naturally regenerated forest of native species, where there are no clearly visible indications of human activities and the ecological processes are not significantly disturbed. ** Also includes forest degradation conversion to primary forest lands over two time periods
2. Mangrove Forest (M)	**Consist of trees, scrubs, and shrubs that grow in saline coastal sediment habitats also along river mouths and lagoons
3. Other naturally regenerated forest (ONRF)	*Naturally regenerated forest where there are clearly visible indications of human activities. **Also include forest degradation and other land conversion to forest degradation lands over two time periods
4. Other land(OL)	*Land not classified as "Agricultural land" and "Forest area and other wooded land," including land used for aquaculture, land occupied by buildings, parks and ornamental gardens, built-up areas, roads or lanes, open spaces needed for storing equipment and products, barren land, wasteland, land under permanent ice, and any other land not reported under previous classes. ** Also include newly cleared forests for cultivation, grasslands and small scale-logging areas
5. Inland water body (IW)	*Area occupied by lakes, reservoirs, rivers, brooks, streams, ponds, inland canals, dams, and other land-locked (usually freshwater) waters
6. Cloud & shadow(CS)	

Also open forest with 30 to 40 meters tall emergent. Found in elevation less than 200 meters and considered to be the plant species abundance site. (3) *Low altitude forest on uplands (H)* consisted of large, medium and small crowned forest. Specifically contains medium crowned forest with an even and closed canopy with 25 to 30 meters in height. It is restricted to elevation equal to or greater than 200 meters to less than 1000 meters, and contains steep slopes and rugged terrains. (4) *Mixed Swamp Forest (FSw)*, comprised of mixed open irregular forest types found next to flat

[5] * FAO 2008, FRA 2010 and FRA 2015 **Present study definition

inundated areas and associated closely with *Mangrove forest* in this study site. Dominant species include sago palm (*Metroxylon sagus*) and nypa palm (*Nypa fruiticans*). (5) *Lower montane forest (L)* consisted of small to very small crowned forest. It is restricted to elevation greater than or equal to 1000 meters, and contains extreme slopes and rugged terrains (Hammermaster and Saunders 1995; McAlpine and Quigley 1998; PNGFA and JICA 2014; SPC and GIZ 2014a and 2014 b).

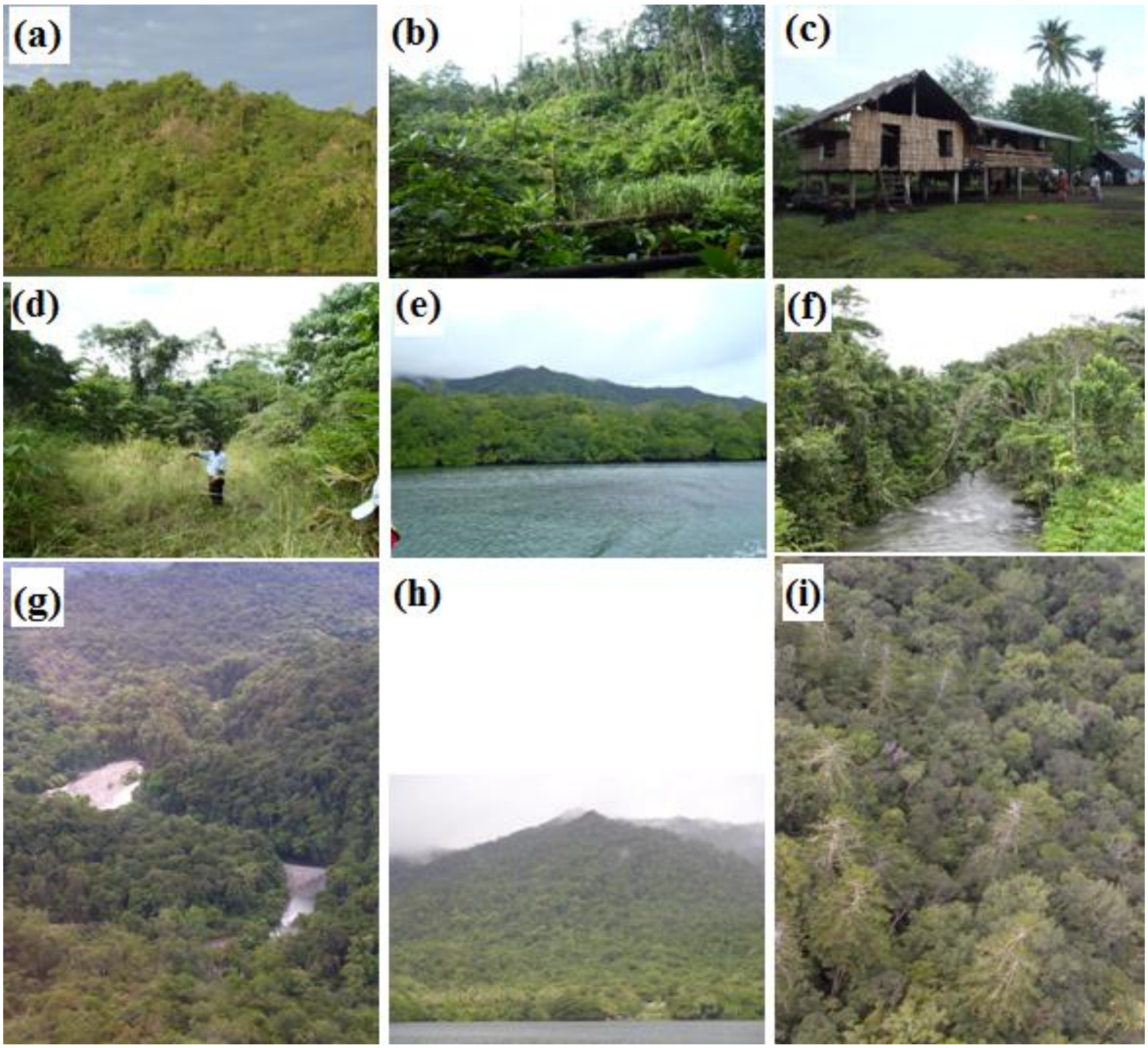

Figure 8*. Land use/land cover class with local forest type pictures from the field (****a****) Other land -newly cleared forest for cultivation; (****b****) Other land -old cultivated gardens; (****c****) Other land - built up or village semi-permanent houses; (****d****) Other naturally regenerated forests; (****e****) Mangrove forest ;(****f****) Mixed swamp forest;* ***(g)*** *Low altitude forest on plains & fans;* ***(h)*** *Low altitude forest on uplands; and* ***(i)*** *Lower montane forest.*
(Source: PNGFA/JICA project photos,2011-2014).

4.2.3 Identification of training and validation data sets

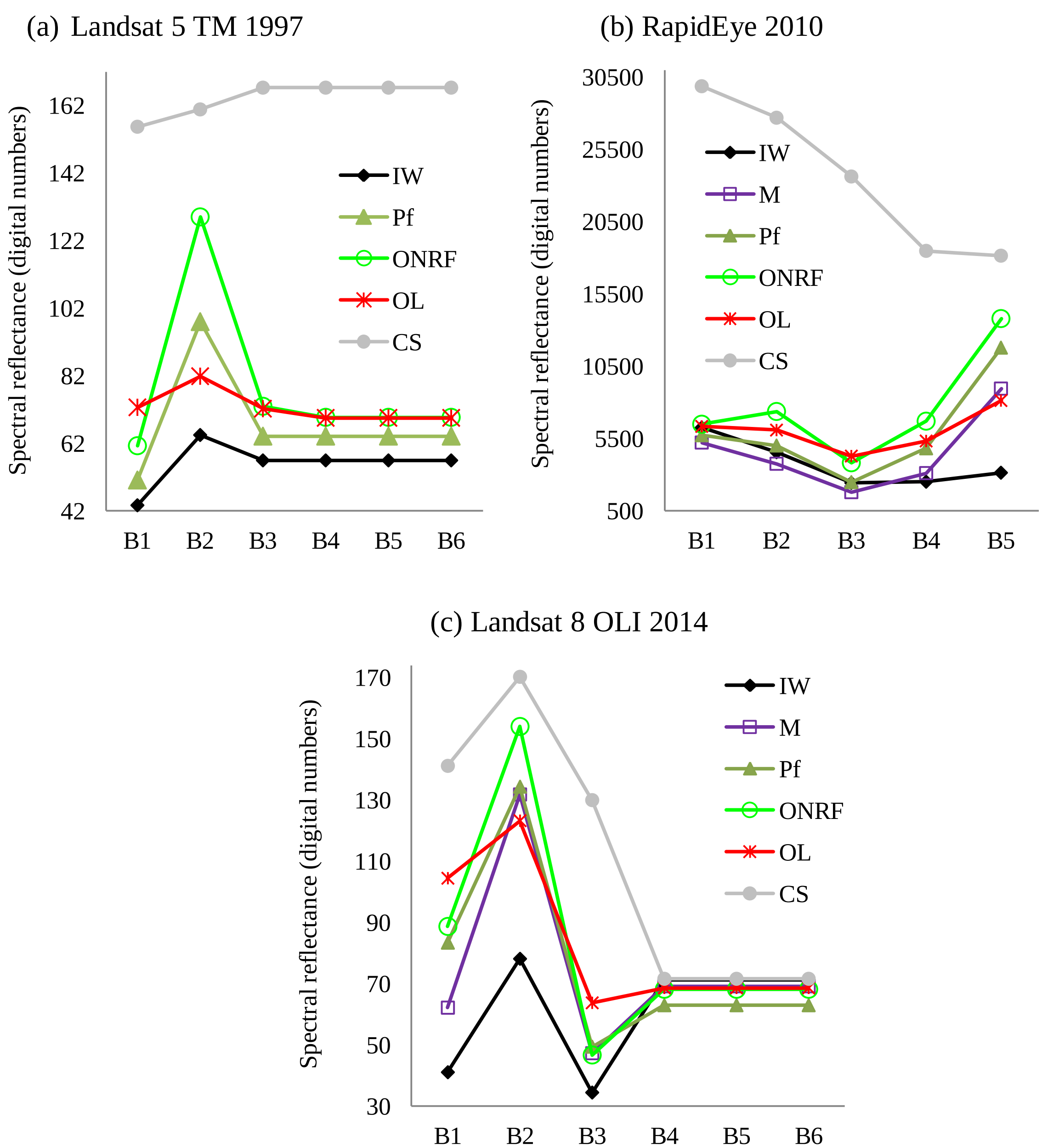

Figure 9*. Satellite image spectral reflectance properties corresponding to each land use/land cover class for (a) Landsat 5 TM 1997, (b) RapidEye 2010 and (c) Landsat 8 OLI 2014, respectively. The x-axis represents different wavelength bands.*

Thorough on-screen check of each satellite image against spectral reflectance properties for each selected land use/land cover class was conducted to identify threshold values as indicated in Figure 3 using ENVI Classic software. Spectral reflectance values for each class varies between each satellite image, consequently the approach taken were similar to studies done by (Kikon and Singh 2014; Hanh et.al. 2015; Shah and Sharma 2015). Two set of data were identified, (1) training samples were used for classification and the second set of data (2) ground truth samples were used for validation (Table 6). Training and validation data sets were selected and confirmed against threshold values using field GPS (global positioning system) points and mostly fair knowledge of the site's land use activities and local forest composition.

Table 6*. Six major land use/land cover classes with training and ground truth samples. Numeric digits represent pixels or raster cells.*

		1997		2010		2014	
Class		Training samples	Ground truth samples	Training samples	Ground truth samples	Training samples	Ground truth samples
1	IW	607	670	545	505	900	806
2	M	-	-	1028	800	809	774
3	Pf	930	2484	5011	13086	3280	15282
4	ONRF	292	367	203	1177	494	377
5	OL	651	875	239	628	515	532
6	CS	8258	1607	1361	3112	1477	1318

4.2.4 Implementation of Maximum Likelihood classification and land use/land cover map development

The standard implementation of supervised maximum likelihood classification requires training samples representing the feature types (Lillesand and Kiefer 2004; Kikon and Singh 2014; Hanh et.al. 2015; Shah and Sharma 2015). The number of pixels for training each class ranged from 203 (for other naturally regenerated forest class) to 494 pixels, as illustrated in Table 6. Classified raster classes were converted to polygon shape files using ENVI Classic for area calculation and further editing in Arc Map. Mangrove forest (M) class for year 1997 originally was not classified due to similar spectral reflectance properties shared with primary forest, inland water body and shadow features, but resolved through digitizing using contour lines.

The 1978 land use/land cover base map was vectorized using ArcMap through thorough on screen digitizing the mosaicked topographic image as background maps, similar to Ningal et.al. (2008) and Shearman et.al. (2009). The 1997, 2010 and 2014 land use/land cover classes were classified using maximum likelihood supervised classification (Kikon and Singh 2014; Hanh et.al. 2015; Shah and Sharma 2015) following six major land use/land cover classes, including *other land* (subsistence cultivation, build-up areas, small-scale logging etc.), *other naturally regenerated forest, mangrove forest, primary forest, inland water body* and *cloud/shadow* (Table 5 & 6). Local forest type boundaries for 1978, 1997, 2010 and 2014 were vectorized through on screen digitizing using contour lines following each class definition and expert judgment in Arc Map software. All boundaries were geo-referenced to present study's standard map projection and used to clip forest cover changes (deforestation or forest degradation) occurring in mangrove and local forest classes for each study year. The method used to develop the four land use/land cover maps is simple, efficient and cost-effective (Jensen 2009), however it requires a lot of time.

4.2.5 Change detection analysis

Post classification analysis is the most simple and obvious change detection method based on the comparison of independently classified images (Singh 1989; Alphan et.al. 2009; Hanh et.al. 2015) was used to detect changes. Time 1 and Time 2 land use classified map differences were compared based on results of cross tabulation matrices to detect land use/forest cover changes which was vital in achieving the study's objectives.

5 RESULTS

5.1 Land use/land cover classification and accuracy assessment

Table 7. *Result of confusion matrix accuracy assessment of (a) Landsat 5 TM, (b) Rapid Eye and (c) Landsat 8 OLI satellite images for years 1997, 2010 and 2014 respectively. Training samples from Table 6 are represented by the upper row codes and ground truth samples represented by first column codes.*

(a)	C	S	IW	OL	Pf	ONRF	∑	UA(%)
C	204879	0	0	21925	0	0	*226804*	*90.3*
S	0	96306	0	0	0	0	*96306*	*100.0*
IW	0	237	959287	23272	0	0	*982796*	*97.6*
OL	0	0	5801	52057	0	126	*57984*	*89.8*
Pf	0	13183	4817	30745	679301	49035	*777081*	*87.4*
ONRF	0	0	0	104062	106612	248355	*459029*	*54.1*
∑	*204879*	*109726*	*969905*	*232061*	*785913*	*297516*	*2600000*	
PA(%)	*100*	*87.8*	*98.9*	*22.4*	*86.4*	*83.5*		*2240185*
Overall Accuracy = (2240185/2600000)*100 = 86.161 % Kappa Coefficient = 0.8125								

Table 7 cont…

(b)	IW	M	Pf	ONRF	OL	CS	∑	UA (%)
IW	1457131	0	0	0	21808	12	*1478951*	*98.52*
M	236	103906	27359	0	20233	0	*151734*	*68.48*
Pf	13	40248	974001	18418	12138	0	*1044818*	*93.22*
ONRF	44	0	5002	25114	5505	0	*35665*	*70.42*
OL	3261	0	5845	2278	52231	0	*63615*	*82.1*
CS	24295	0	3495	54	43810	341865	*413519*	*82.67*
∑	*1484980*	*144154*	*1015702*	*45864*	*155725*	*341877*	*3188302*	
PA(%)	*98.12*	*72.08*	*95.89*	*54.76*	*33.54*	*100*		*2954248*

Overall Accuracy = (2954248/3188302)*100 = 92.659 %   Kappa Coefficient = 0.8892

(c)	M	Pf	IW	ONRF	CS	OL	∑	UA(%)
M	71708	22546	0	2915	0	0	*97169*	*73.8*
Pf	5530	100141 0	61	846	0	0	*1007847*	*99.36*
IW	19	192013	947360	251	0	0	*1139643*	*83.13*
ONRF	8893	138788	0	127892	0	0	*275573*	*46.41*
CS	0	10107	0	0	22914	0	*33021*	*69.39*
OL	0	32903	0	26	0	13818	*46747*	*29.56*
∑	*86150*	*139776 7*	*947421*	*131930*	*22914*	*13818*	*2600000*	
PA(%)	*83.24*	*71.64*	*99.99*	*96.94*	*100*	*100*		*2185102*

Overall Accuracy = (2185102/2600000)*100 = 84.04 %   Kappa Coefficient = 0.7447

Note: UA=User's accuracy, PA=Producer's accuracy

Overall accuracy for all three different temporal satellite images were 86 %, 93 % and 84 % with Kappa coefficients of 0.81, 0.89 and 0.75 for years 1997, 2010 and 2014 respectively (Table7). However, the 1997, 2010 and 2014 other land (OL) class showed low accuracy results. One possible reason was due to features representing OL in both the training and ground truth samples (Table 6) contained same spectral reflectance properties as other classes (Figure 9).

5.2 Land use /land cover maps

Table 8 sums up area data for each land use/land cover class including local forest classes per study year. Deforested areas (other land) for each study year were 2 %, 4 %, 4 % and 3 % for 1978, 1997, 2010 and 2014 respectively. Degraded forest areas (other naturally regenerated forest) for each study year were 3 %, 11 %, 5% and 5% for 1978, 1997, 2010 and 2014 respectively *(see discussion).*

Figures 10a, 10b, 10c and 10d spatially show land use/land cover classes for 1978, 1997, 2010 and 2014 respectively. Figures 11a, 11b, 11c and 11d spatially show land use/local forest classes for 1978, 1997, 2010 and 2014 respectively.

Table 8. *Major land use/land cover classes net areas (a-e). Local forest types comprised of Mangrove and Primary forest classes (1-5).*

LU Classes/ local forest types	***Area in hectares (ha.)& percentage (%)***							
	1978		***1997***		***2010***		***2014***	
	ha.	***%***	***ha.***	***%***	***ha.***	***%***	***ha.***	***%***
a Inland water bodies	*378*	*1*	*207*	*0.3*	*272*	*0.5*	*261*	*0.4*
b.Other land	*928*	*2*	*2264*	*4*	*2176*	*4*	*1893*	*3*
c. Other naturally regenerated forest	*2074*	*3*	*6789*	*11*	*2966*	*5*	*2722*	*5*
d.Mangrove forest (1)	*2730*	*5*	*2596*	*4*	*3182*	*5*	*2743*	*5*
e.Primary forest:								
Low altitude forest on plains & fans(2)	*26041*	*43*	*21475*	*36*	*24001*	*40*	*25494*	*42*
Low altitude forest on uplands(3)	*26130*	*44*	*25444*	*42*	*25993*	*43*	*25863*	*43*
Mixed swamp forest(4)	*1110*	*2*	*616*	*1*	*801*	*1.3*	*415*	*1*
Lower montane forest(5)	*609*	*1*	*609*	*1*	*609*	*1*	*609*	*1*
Total	***60000***	***100***	***60000***	***100***	***60000***	***100***	***60000***	***100***

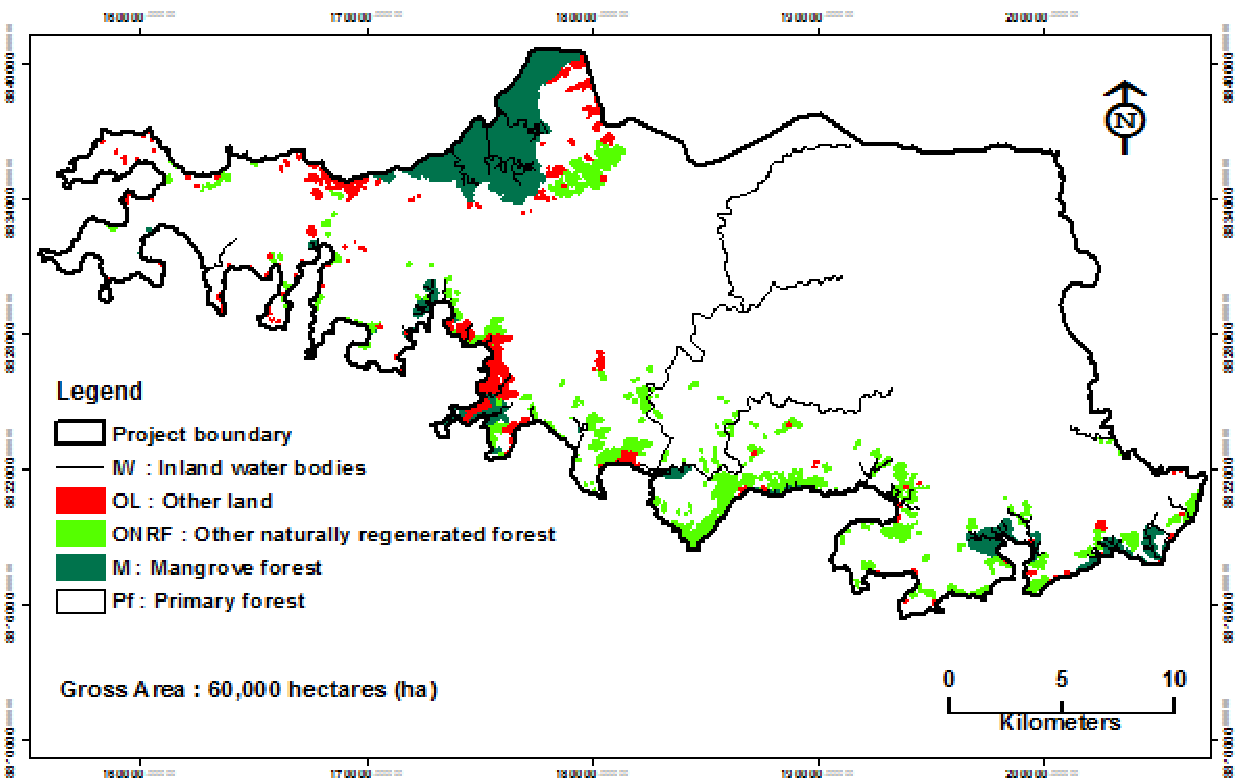

Figure 10a. *Classified land use/land cover base map for 1978 of the study site.*

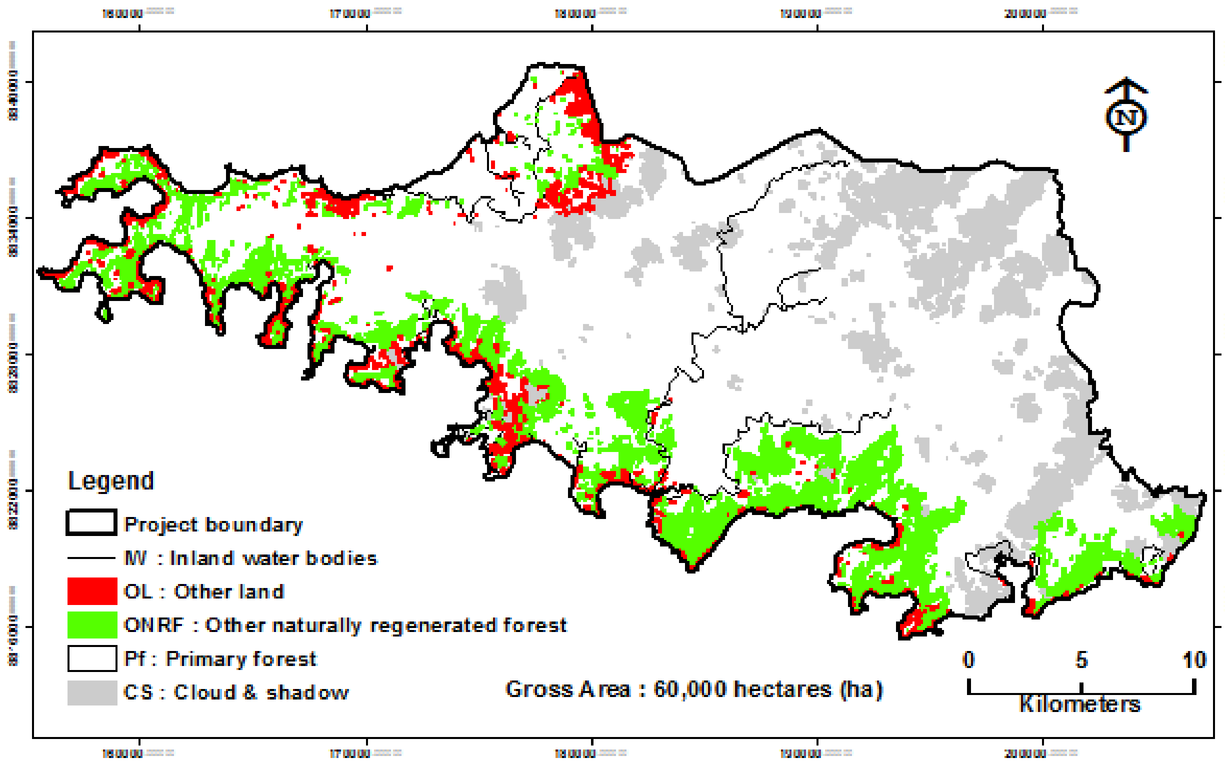

Figure 10b. *Classified land use/land cover map of 1997 of the study site.*

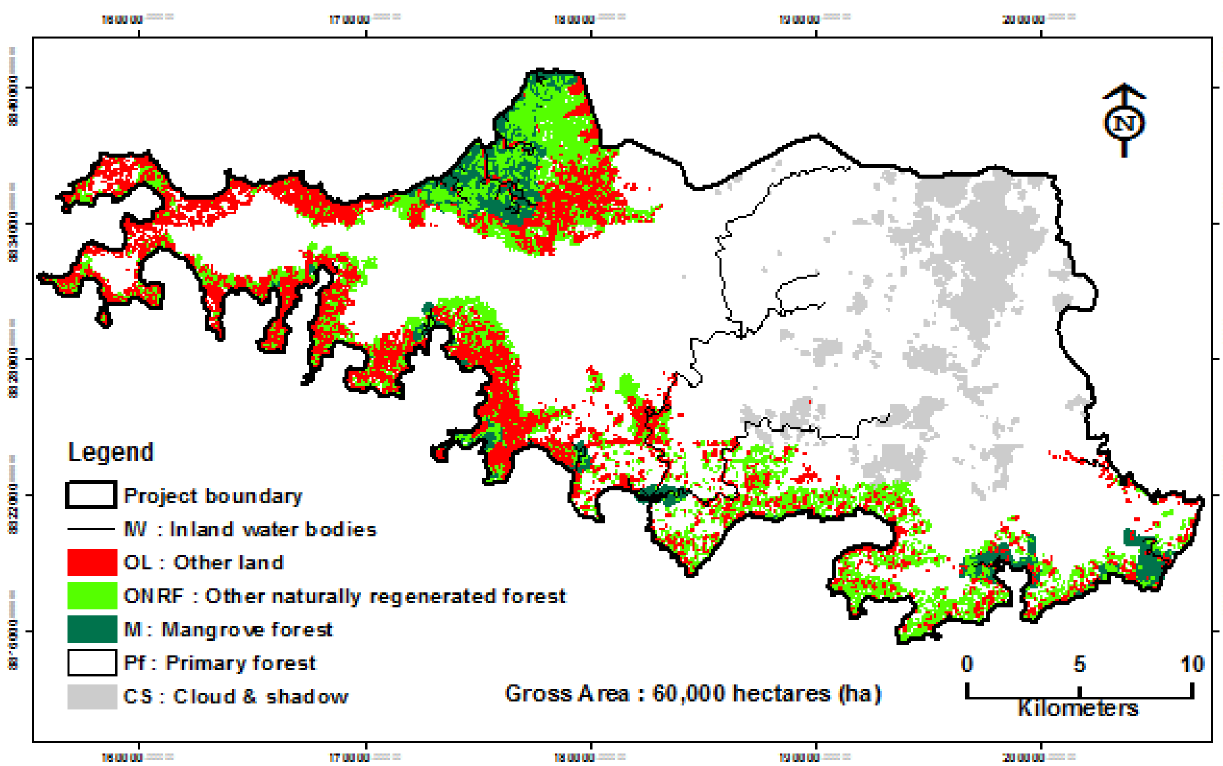

Figure 10c. *Classified land use/land cover map of 2010 of the study site.*

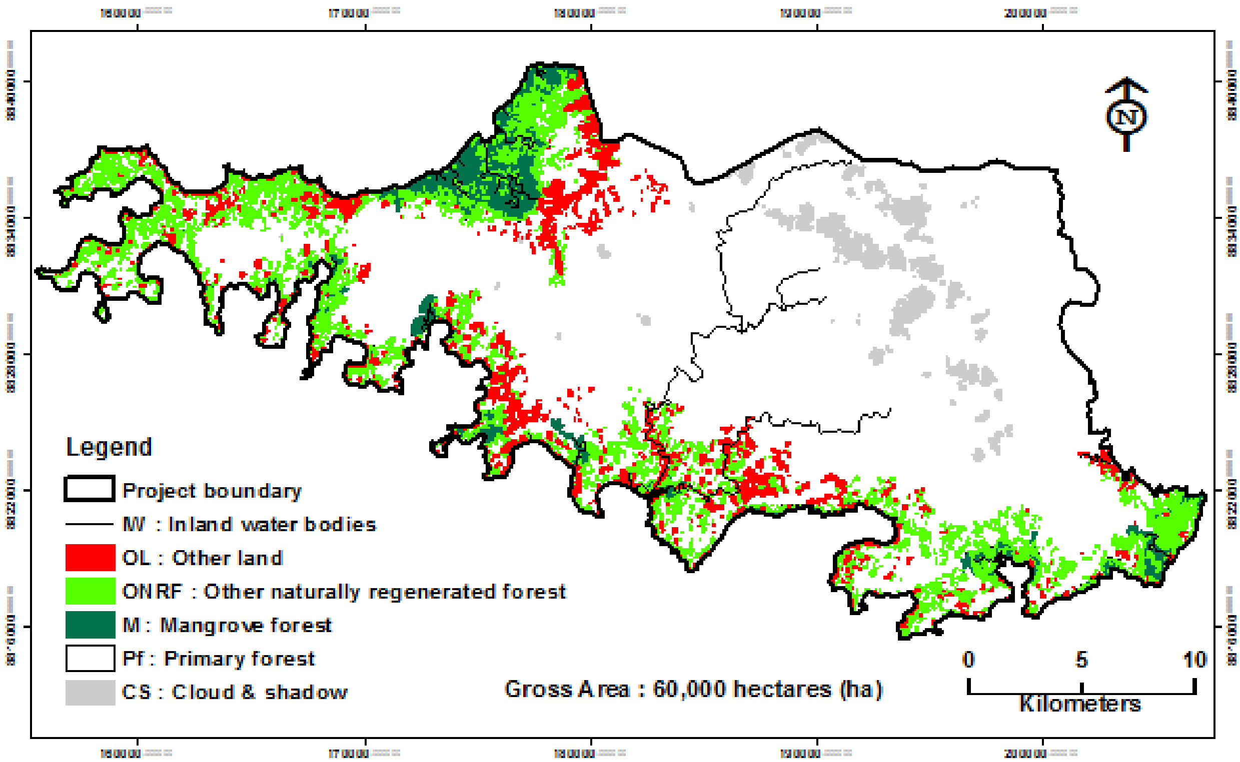

Figure 10d. *Classified land use/land cover map for 2014 of the study site.*

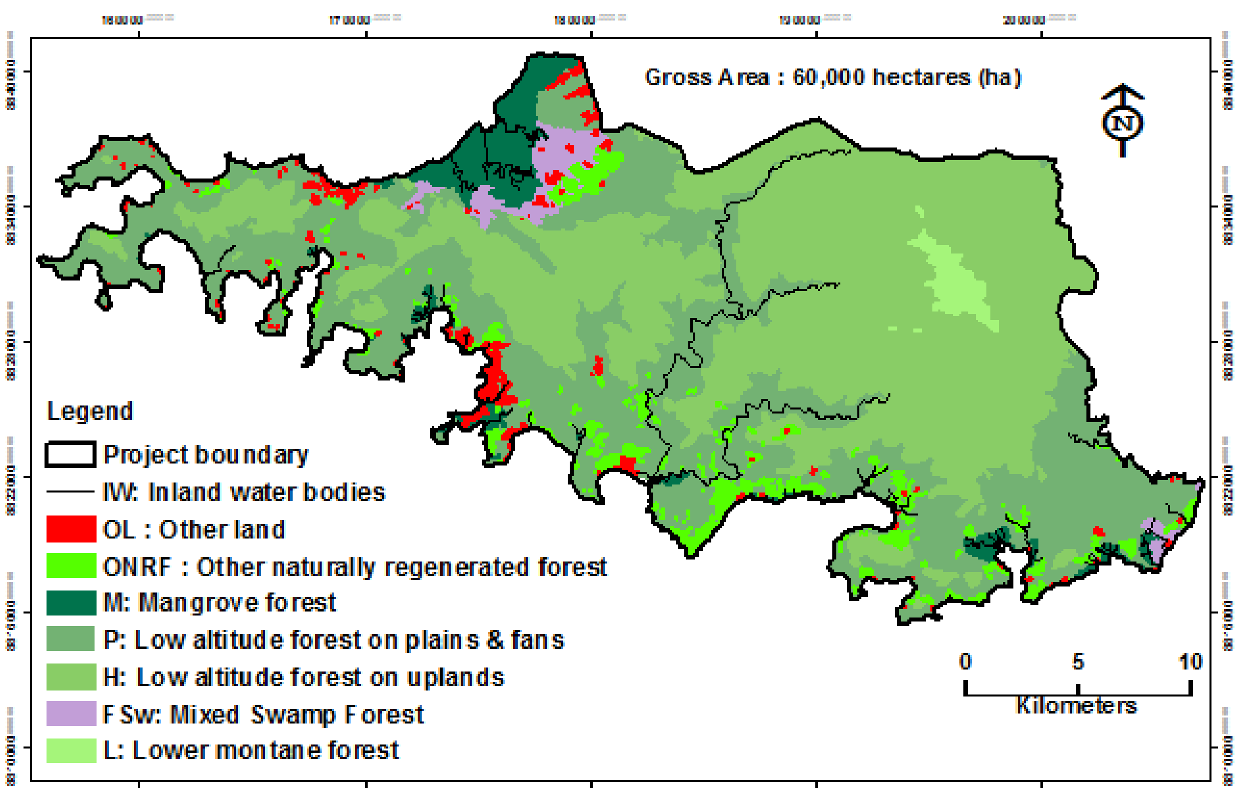

Figure 11a. *Land use/ local forest classes for 1978 used as the site's base map.*

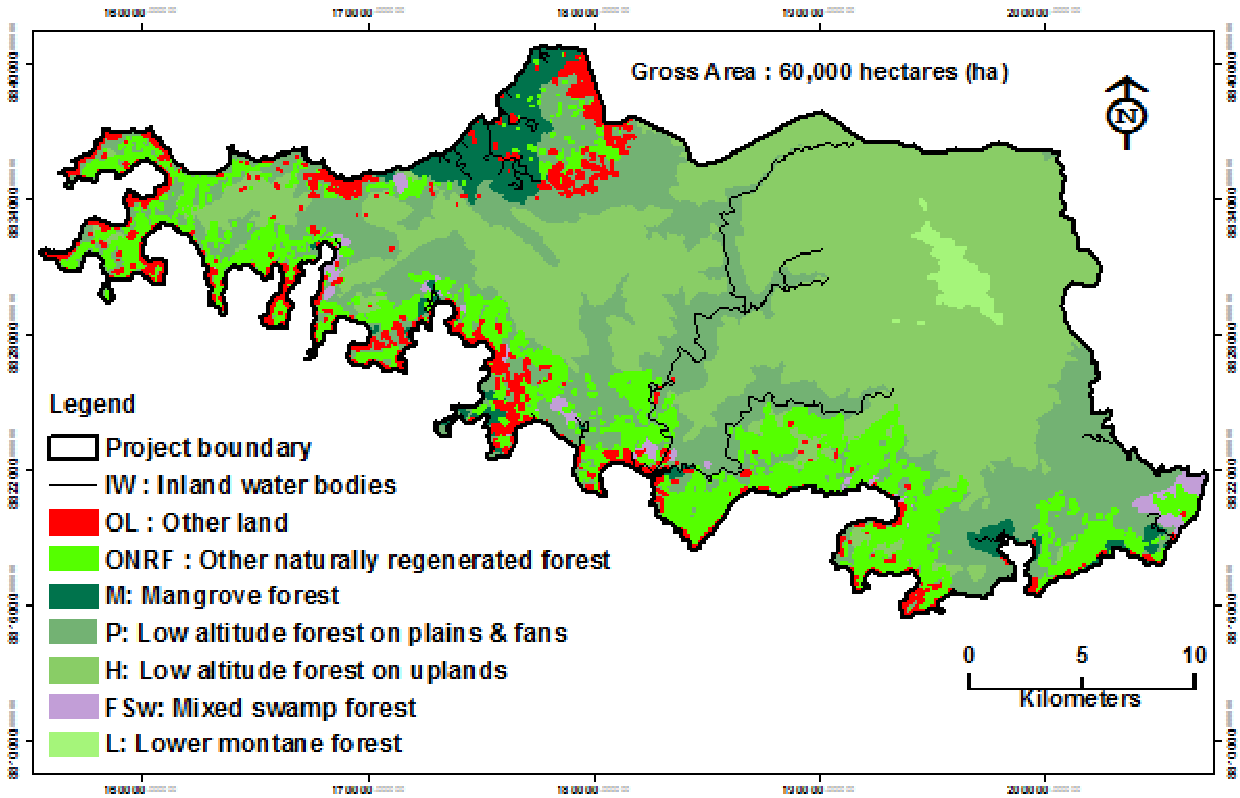

Figure 11b. *Land use/ local forest classes for 1997 of the study site.*

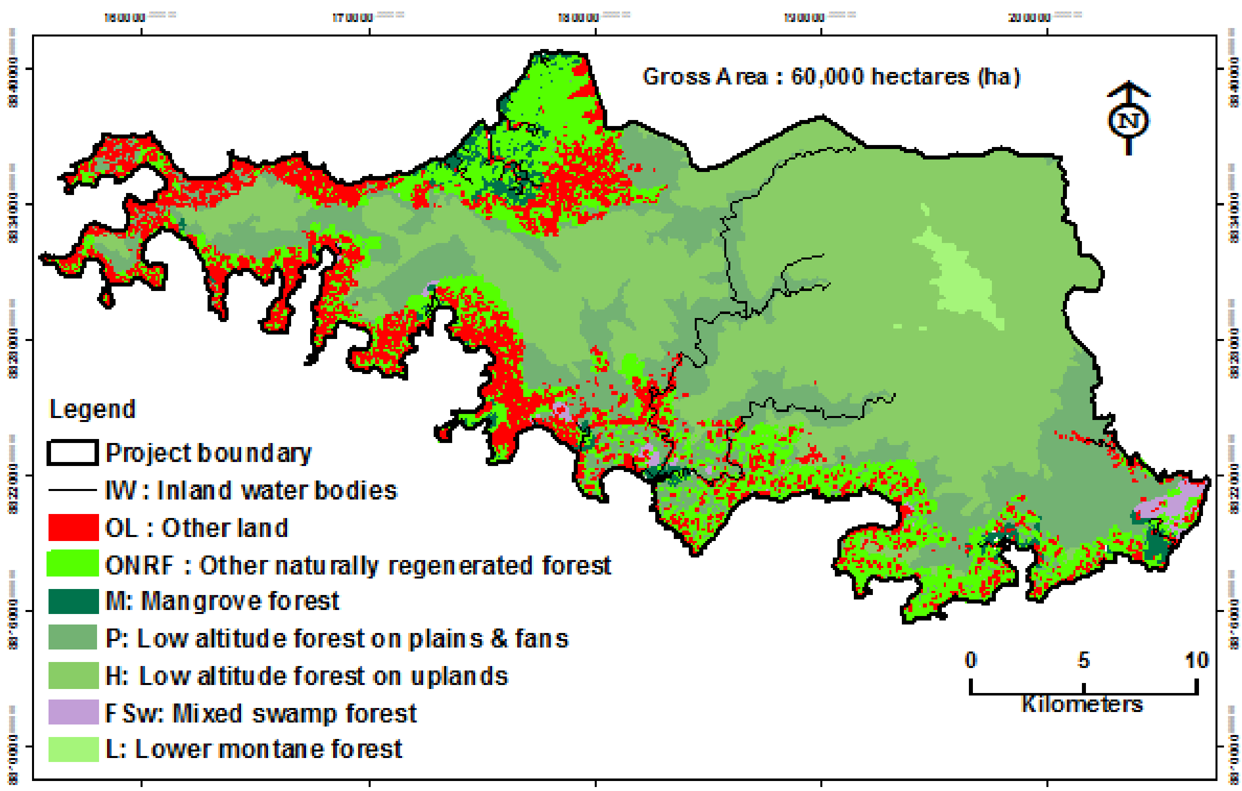

Figure 11c. *Land use/ local forest classes for 2010 of the study site.*

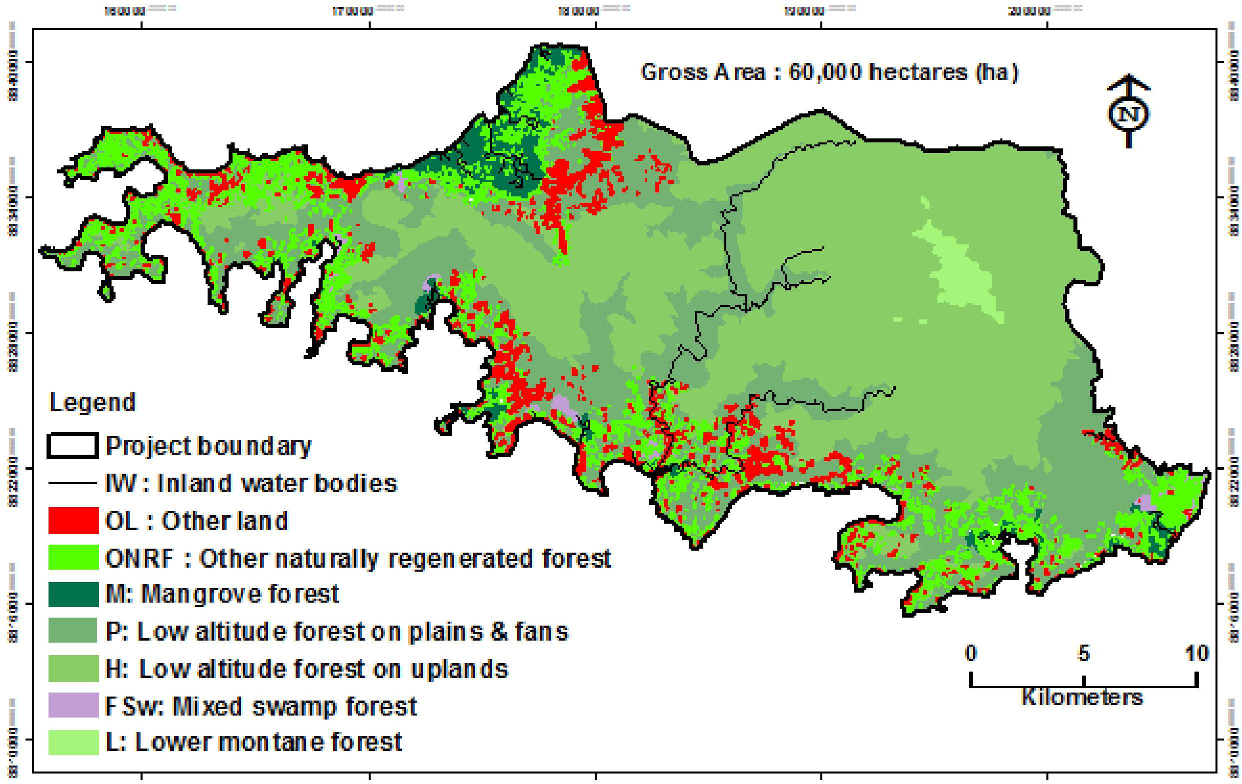

Figure 11d. *Land use/ local forest classes for year 2014 of the study site.*

5.3 Land use /forest cover change detection

Figure 12 demonstrates 2014 updated land use/land cover conversion map spatially showing other land conversion to forest degradation land (other naturally regenerated forest); forest degradation land conversion to primary forest land; primary forest land conversion to other land; primary forest land conversion to forest degradation land, and mangrove forest land conversion to forest degradation land over the 36 years study period on the site.

The detailed dynamics of the land use/local forest cover changes in Central Suau FMA from 1978 to 2014 is shown in Table 9. The table presents all the results of post classification cross tabulation matrices similar to the study done by Hanh et. al. (2015). Results show the conversion from individual class to another class. For example, considering the entire study period, 1978 to 2014, at once, 558 ha of *other land* (cultivated lands, built-up areas, small-scale logging, grasslands, bareland, unpaved roads, etc.) remained unchanged, 1335 ha of new *other land* were created at the expense of *low altitude forest on plains and fans*, but 370 ha of other land were lost to *other naturally regenerated forest* (274 ha),*low altitude forest on plains and fans* (91 ha), and *low* *altitude forest on uplands* (5 ha). *Other land, other naturally regenerated forests* and *low altitude forest on plains and fans* expanded the most over other land use/local forest classes, with 1335, 1203 and 1153 ha, respectively. During this period, the areas of *low altitude forest on plains and fans* experienced the greatest absolute reduction in area, with 1700 ha. In relative term, the reduction of *mixed swamp forest* (63%) and of *other land* (40%) is of larger magnitude than the 27% decrease in *other naturally regenerated forest* relative to the 1978 surface area of the respective land use/local forest class.

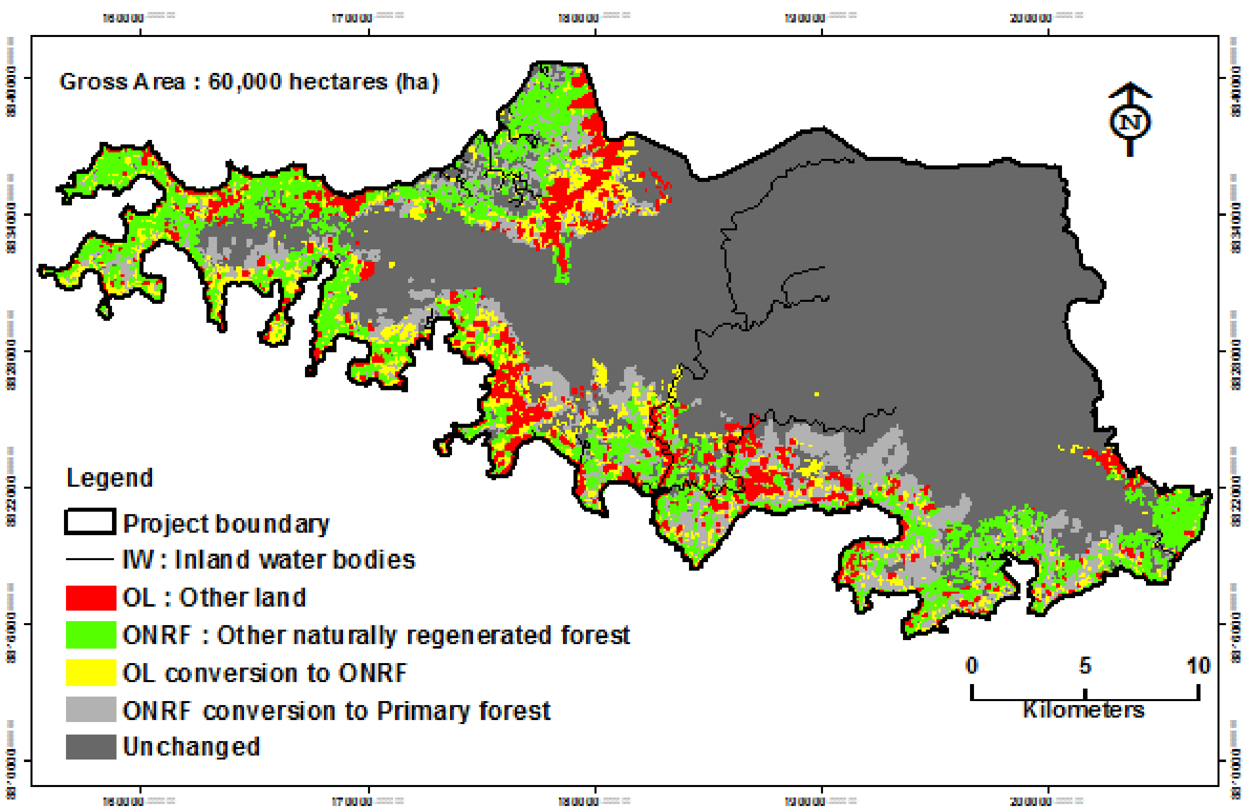

Figure 12. *The 2014 updated land use/land cover conversion map over 36 years study period in Central Suau FMA.*

Table 9. *Data demonstrate land use/local forest[6] cover changes in Central Suau FMA from 1978 to 2014 in hectares (ha.). The values on the diagonal represent the amount of each land use/local forest class that did not change, while the remaining values refer to the expansion or reduction of each class.*

1978-1997		IW	OL	ONRF	M	P	H	Fsw	L	Total	*Expans.*
	IW	**207**	0	0	0	0	0	0	0	207	0
	OL	0	**928**	0	0	1336	0	0	0	2264	*1336*
	ONRF	0	0	**1664**	134	3230	857	904	0	6789	*5125*
1997	M	0	0	0	**2596**	0	0	0	0	2596	*0*
	P	0	0	0	0	**21475**	0	0	0	21475	*0*
	H	171	0	0	0	0	**25273**	0	0	25444	*171*
	Fsw	0	0	410	0	0	0	**206**	0	616	*410*
	L	0	0	0	0	0	0	0	**609**	609	*0*
		378	928	2074	2730	26041	26130	1110	609	60000	***7042***
Reduction		*171*	*0*	*410*	*134*	*4566*	*857*	*904*	*0*	***7042***	**52958**
1978-2010		IW	OL	ONRF	M	P	H	Fsw	L	Total	*Expans.*
	IW	**272**	0	0	0	0	0	0	0	272	*0*
	OL	0	**832**	0	0	1344	0	0	0	2176	*1344*
	ONRF	0	0	**2074**	0	447	445	0	0	2966	*892*
2010	M	0	0	0	**2730**	143	0	309	0	3182	*452*
	P	0	91	0	0	**23910**	0	0	0	24001	*91*
	H	106	5	0	0	197	**25685**	0	0	25993	*308*
	Fsw	0	0	0	0	0	0	**801**	0	801	*0*
	L	0	0	0	0	0	0	0	**609**	609	*0*
		378	928	2074	2730	26041	26130	1110	609	60000	***3087***
Reduction		*106*	*96*	*0*	*0*	*2131*	*445*	*309*	*0*	***3087***	**56913**
1997-2010		IW	OL	ONRF	M	P	H	Fsw	L	Total	*Expans.*
	IW	**207**	0	0	0	0	65	0	0	272	*65*
	OL	0	**2176**	0	0	0	0	0	0	2176	*0*
	ONRF	0	0	**2966**	0	0	0	0	0	2966	*0*
2010	M	0	0	233	**2363**	0	0	586	0	3182	*819*
	P	0	88	3098	0	**20815**	0	0	0	24001	*3186*
	H	0	0	381	233		**25379**	0	0	25993	*614*
	Fsw	0	0	111	0	660	0	**30**	0	801	*771*
	L	0	0	0	0	0	0	0	**609**	609	*0*
		207	2264	6789	2596	21475	25444	616	609	60000	***5455***
Reduction		*0*	*88*	*3823*	*233*	*660*	*65*	*586*	*0*	***5455***	**54545**

[6] IW: Inland water bodies; OL: Other land; ONRF: Other naturally regenerated forests; M: Mangrove forest; P: Low altitude forest on plains & fans; H: Low altitude forest on uplands; FSw: Mixed swamp forest; L: lower montane forest

Table 9 cont...

1997-2014		IW	OL	ONRF	M	P	H	Fsw	L	Total	*Expans.*
	IW	**207**	0	0	0	0	54	0	0	261	*54*
	OL	0	**1893**	0	0	0	0	0	0	1893	*0*
	ONRF	0	275	**2447**	0	0	0	0	0	2722	*275*
2014	M	0	0	134	**2596**	0	0	13	0	2743	*147*
	P	0	91	3171	0	**21475**	274	483	0	25494	*4019*
	H	0	5	742	0	0	**25116**	0	0	25863	*747*
	Fsw	0	0	295	0	0	0	**120**	0	415	*295*
	L	0	0	0	0	0	0	0	**609**	609	*0*
		207	2264	6789	2596	21475	25444	616	609	60000	***5537***
	Reduction	*0*	*371*	*4342*	*0*	*0*	*328*	*496*	*0*	***5537***	**54463**
2010-2014		IW	OL	ONRF	M	P	H	Fsw	L	Total	*Expans.*
	IW	**261**	0	0	0	0	0	0	0	261	*0*
	OL	0	**1779**	0	0	91	23	0	0	1893	*114*
	ONRF	0	274	**2104**	233	0	0	111	0	2722	*618*
2014	M	0	0	568	**2175**	0	0	0	0	2743	*568*
	P	0	91	294	775	**22610**	1438	286	0	25494	*2884*
	H	11	32	0	0	1300	**24520**	0	0	25863	*1343*
	Fsw	0	0	0	0	0	12	**403**	0	415	*12*
	L	0	0	0	0	0	0	0	**609**	609	*0*
		272	2176	2966	3183	24001	25993	801	609	60000	***5540***
	Reduction	*11*	*397*	*862*	*1008*	*1391*	*1473*	*398*	*0*	***5540***	**54461**
1978-2014		IW	OL	ONRF	M	P	H	Fsw	L	Total	*Expans.*
	IW	**261**	0	0	0	0	0	0	0	261	*0*
	OL	0	**558**	0	0	1335	0	0	0	1893	*1335*
	ONRF	0	274	**1519**	0	365	0	564	0	2722	*1203*
2014	M	0	0	0	**2730**	0	0	13	0	2743	*13*
	P	0	91	499	0	**24341**	445	118	0	25494	*1153*
	H	117	5	56	0	0	**25685**	0	0	25863	*178*
	Fsw	0	0	0	0	0	0	**415**	0	415	*0*
	L	0	0	0	0	0	0	0	**609**	609	*0*
		378	928	2074	2730	26041	26130	1110	609	60000	***3882***
	Reduction	*117*	*370*	*555*	*0*	*1700*	*445*	*695*	*0*	***3882***	**56118**

5.4 Annual rates of forest cover change

In order to identify forest cover change in periods 1978 to 2014, the study quantified main drivers of deforestation and forest degradation. Deforestation activities were thematically represented by other land (OL) and forest degradation by other naturally regenerated forest (ONRF). To identify annual rate of deforestation and forest degradation, two equations were derived for annual rate of expansion (ARE) and reduction (ARR) of land use/land cover classes similar to cross-tabulation study results done by Hanh et.al. (2015) with slight modification from equations by Long et al. (2007a), Long et. al. (2007b) and Zakaria (2010). Equation 1 represent annual rate of deforestation and forest degradation. Equation 2 represent annual rate of conversion of other land use/local forest class to another, for example *mixed swamp forest* conversion to forest degradation or other land (Table 10), moreover, very significant finding identified in this study due to no suitable reference data available by previous studies in PNG to acknowledge. Data from Table 9 were fully utilized in these analyses.

$$ARE\ (\%/yr) = \left[\left(\frac{Expansion\ value}{\left(\frac{A_1+A_2}{2}\right)}\right) * 100\right] / (T_1 - T_2) \qquad (1)$$

$$ARR\ (\%/yr) = \left[\left(\frac{Reduction\ value}{\left(\frac{A_1+A_2}{2}\right)}\right) * 100\right] / (T_1 - T_2) \qquad (2)$$

Where:

ARE: $Annual\ relative\ percentage\ of\ expansion$ (%)

ARR: $Annual\ relative\ percentage\ of\ reduction$ (%)

A_1: $Area\ of\ land\ use\ /\ land\ cover\ class\ (ha) in\ time\ 1\ (T_1)$

A_2 : $Area\ of\ land\ use\ /\ land\ cover\ class\ (ha) in\ time\ 2\ (T_2)$

Table 10 show calculated results after employing the two equations respectively. Evidently the average annual rates of deforestation, forest degradation and local forest cover change were defined. For example present study's average annual rates of deforestation and forest degradation were 1.1 % $yr^{-1}$and 1.5% yr^{-1} respectively. Local forest classes average annual reduction rates were 4.5 % yr^{-1} (*mixed swamp forest*), 1.1 % yr^{-1}(*mangrove forest)*, 0.4 % yr^{-1} (*low altitude forest on plains and fans)* and 0.2 % yr^{-1} (*low altitude forest on uplands)* over the 36 years study period.

***Table 10[7]**. Top table, represents relative percentage of expansion and reduction of other land (OL) and other naturally regenerated forests (ONRF) land use type changes. Lower table, summarizes annual local forest cover reduction rates mainly converted to forest degradation land and other land over six sub-periods in Central Suau FMA.*

Sub-period	Other land (OL)or deforestation				Other naturally regenerated forests (ONRF) or forest degradation			
	RE (%)	*ARE (% yr^{-1})*	*RR (%)*	*ARR (% yr^{-1})*	*RE (%)*	*ARE (% yr^{-1})*	*RR (%)*	*ARR (% yr^{-1})*
1978-1997	49	2.6	0	0	65.5	3.4	5.2	0.3
1978-2010	50.9	1.6	3.6	0.1	22.3	0.7	0	0
1997-2010	0	0	2.7	0.2	0	0	60.1	4.6
1997-2014	0	0	12.3	0.7	4.5	0.3	71	4.2
2010-2014	3.8	1	13.3	3.3	14.7	3.7	20.5	5.1
1978-2014	56.6	1.6	15.7	0.4	32	0.9	14.8	0.4
Average	**26.7**	**1.1**	**7.9**	**0.8**	**23.2**	**1.5**	**28.6**	**2.4**

Sub-period	Mixed swamp forest	Mangrove forest	Low alt.forest on plains & fans	Low alt.forest on uplands
	ARR (% yr^{-1})	*ARR (% yr^{-1})*	*ARR (% yr^{-1})*	*ARR (% yr^{-1})*
1978-1997	4.06	0.18	0.70	0.12
1978-2010	0.71	0	0.18	0.04
1997-2010	4.06	0.40	0.15	0.01
1997-2014	4.04	0	0	0.05
2010-2014	12.20	5.81	0.93	0.95
1978-2014	1.99	0	0.12	0.03
Average	**4.5**	**1.1**	**0.4**	**0.2**

6 DISCUSSION

The results are both comparable and distinctive from other studies and according to Gunarso et. al. (2013) they agreed that it is an outcome that is to be expected when using different types of remote sensing data, classification methodologies, and definitional criteria when evaluating change on complex landscape mosaics.

6.1 Accuracy assessment and limitation

The field visit and consultation with the local natural resource management agency aid familiarization with major land use/local forest class characteristics. Unlike temperate countries,

[7] **Note:** RE: Relative percentage of expansion; ARE: Annual relative percentage of expansion; RR: Relative percentage of reduction; ARR: Annual relative percentage of reduction

PNG is a tropical country and experiences hot and wet climatic condition on yearly basis which does not affect plant growth and satellite image collection at any study time, but only cloud cover presence on images was very challenging in performing classification work. Ancillary data plus proficient knowledge of vegetation and land use types in PNG aided in the classification work. Many other studies discuss classifications with overall accuracies below the general target of 85% and have a large range in the accuracy with which the individual classes have been classified (Foody 2002). This study overall accuracies of land use/land cover classifications for 1997, 2010, and 2014 were 86%, 93%, and 84%, with overall Kappa coefficients of 0.81, 0.89 and 0.75 respectively. The results suggested that the classification work was exceptionally performed, although no standard exists for classification accuracy (Congalton 1991; Treitz and Rogan 2004**;** Hanh et. al. 2015). The classification errors were sometimes due to the spectral mixture between inland water body and primary forest; between primary forest and mangrove forest; between other lands and other naturally regenerated forest; between cloud/shadows and mangrove forest and between other naturally regenerated forest and primary forest. Therefore, careful selection of training samples and tedious editing after supervised classification were applied in order to reduce these factual errors.

6.2 Drivers of forest cover change

The consistent forest cover change due to deforestation (2 %, 4 %, 4 % and 3 % for 1978, 1997, 2010 and 2014 respectively) and forest degradation (3 %, 11 %, 5% and 5% for 1978, 1997, 2010 and 2014 respectively) (Table 8) was because of the traditional norm of subsistence cultivation (fallowing) system practiced in the site for ages (Filer et. al. 2009), although small-scale logging was recently introduced to the site, it didn't had immense effect to the trend which is predicted to continue. However, the 1997 land use/land cover map showed high forest degradation than 1978, 2010 and 2014 study years. This was due to drought (Bourke 2000; Ningal et al. 2008) experienced nationwide at that particular period which affected most coastal provinces and secondly, local people engagement on small scale logging (SPC and GIZ 2014a) and thirdly excessive use of forest land for cultivation of food crops (Sitango 2006), as a result of increased population. But, the general change detection analysis of spatial land use /land cover maps plus field verification confirmed subsistence cultivation, built-up areas and small scale-logging were main drivers of deforestation and forest degradation.

Low altitude forest on plains and fans experienced a lot of forest cover change in years 1997, 2010 and 2014 while *low altitude forest on uplands* experienced some change and *lower montane forest* experienced no change. Yet, cross tabulation change matrix results (Table 9) revealed accessible local forest types such as *mixed swamp forest, mangrove forest, low altitude forest on plains and fans* and *low altitude forest on uplands* experienced high relative percentage of reduction in their areal size than the inaccessible *lower montane forest*. These reductions were due to local forest class conversion to other land use/land cover classes.

6.3 Annual rates of forest cover change

Table 10 explained annual rates of deforestation, forest degradation, other land conversion to degraded lands and forest degradation lands conversion to primary forest lands or primary forest recovery experienced over the 36 year study period in Central Suau FMA. Zero value in either expansion or reduction means land use/local forest class is experiencing no change or conversion to other classes during that particular sub-period, hence a key indicator of land use change dynamics assessment.

Study of forest inventory mapping system (FIMS) of PNG by McAlpine and Quigley (1998) estimated the average annual rate of forest cover change (combined deforestation & forest degradation) between 1975 to1996 was 0.5% yr^{-1}. Shearman et.al. (2009), estimated over the period 1990 to 2002, overall rates of change generally increased and varied between 0.8 and 1.8 % yr^{-1}, while rates in commercially accessible forest have been far higher, ranging from 1.1 to 3.4 % yr^{-1}. Study by Agus et. al. (2013) in neighboring countries including PNG explained that the rate of expansion of oil palm plantations has been remarkably constant at approximately 7 % yr^{-1} from 3.5 to 13.1 million hectares between 1990 and 2010. Recent study by SPC and GIZ (2014a) in same study site (Central Suau FMA) revealed the annual deforestation rate was 171 $ha.yr^{-1}$ (7.7 % yr^{-1}) and annual forest degradation to be 154 $ha.yr^{-1}$ (7.7 % yr^{-1}) between years 2001 to 2014.

This study's average annual rates of land use/forest cover change were 1.1 % yr^{-1}(deforestation), 1.5% yr^{-1}(forest degradation), 0.8 % yr^{-1} (other land conversion to forest degradation land) and 2.4 % yr^{-1} (primary forest recovery). Local forest types annual reduction rates were 4.5 % yr^{-1} (*mixed swamp forest*), 1.1 % yr^{-1}(*mangrove forest)*, 0.4 % yr^{-1} (*low altitude forest on plains and fans)* and 0.2 % yr^{-1} (*low altitude forest on uplands)* evidently reverting back to forest degradation land and other land between study period 1978 to 2014.

The rates reported by SPC and GIZ (2014a) are far higher than present study rates and similar studies conducted in the country including neighboring countries due to two possible reasons.

Firstly, methods applied were different (Agus et. al. 2013; Gunarso et. al. 2013) thus current study used pixel-based image classification for years 1997, 2010 and 2014 while the 1978 based map was vectorized using on-screen digitizing of mosaic topographic map which was similar to SPC and GIZ (2014a) where they digitized the satellite images. Secondly, there was no accuracy assessment reported. Also their tabulated and spatial map results showed no disturbance occurring in *mangrove forest* throughout their study period which was arguably not consistent to present study results and ground truth perspective. Therefore, current study results are significant and fall within the overall rates of land use/land cover change that was reported by Shearman et.al. (2009). Importantly the study also revealed new information about annual rates of local forest cover change which is vital for relevant stakeholders to use in reporting, awareness and planning programs that relates to REDD+ activities at the project site.

7 CONCLUSION

Current study achieved its three main objectives: firstly, to map major land use/land cover classes from multi-temporal remote sensed data. Secondly, to investigate rate of forest cover change through deforestation and forest degradation activities over different periods using change detection techniques. In addition to the second objective, primary forest recovery, other land conversion to degraded forest lands and local forest area reduction rates were identified when applying the annual relative percentage of expansion and reduction equations from cross-tabulation change matrix analysis, thus very important findings in understanding forest cover change in such scenario and landscape. Thirdly, provide precise results to policy and decision makers in the relevant agencies that are responsible for REDD+ initiatives in the study site.

The 1978, 1997, 2010 and 2014 land use/land cover maps and change detection techniques help identified deforestation, forest degradation and local forest types recovery and disturbance rates. The identified drivers of deforestation and forest degradation were subsistence cultivation, built-up areas and small scale-logging. According to Hanh et.al. (2015) “land cover/land use maps and change detection may be used to help in understanding the impact of past policies and the role of several factors such as socio-economic trends and environmental changes in controlling the dynamics on land use changes. Understanding the drivers of land use change might in turn contribute to model future evolution of land use patterns and better steer future land use planning policies at the district or provincial level.”

The study's annual rates of deforestation and forest degradation were compared against other studies and proved to be significant. In addition, easy and accessible local forest types such as *mixed swamp forest*, *mangrove forest* and *low altitude forest on plains and fans* showed alarming annual rates of forest disturbances and are predicted to continue. Current study results are vital for planning, policy and decision making regarding REDD+ programs that are implemented by PNGFA and its partners. The study's methods and results will be reviewed against the *Climate Change Framework for Action 2009 to 2015* (PNGFA 2009) document so that the next review of this governmental framework is enhanced.

To conclude, there is an opportunity to extend these methods to other areas of PNG as well as other neighboring tropical countries to fully understand differences of land use and local forest cover changes at varying socio-economical and geographical scales.

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