Land Use and Land Cover Change Assessment from 1995 to 2015 using GIS and Remote Sensing Techniques: A Case Study in a Logging Concession

Oala Iuda[1], Sailesh Samanta[2]

[1]PNG National Forest Inventory Project, Port Moresby, PNG

[2]Department of Surveying and Land Studies, Papua New Guinea University of Technology, Private Mail Bag, Lae, 411, Morobe Province, PNG

oiuda12@gmail.com; rsgis.sailesh@gmail.com

[2] Corresponding author

Abstract

Land use and land cover mapping techniques are used in most GIS and Remote Sensing applications to understand land use patterns and changes, and to assess the quality of the environment. Classification is defined as ordering and arrangement of observed features into bio-physical properties of the earth's surface. Supervised classification is the main technique applied for data extraction in an imagery to get activity data or land use and land cover information. In this study, the key activities carried out to fulfill the classification was post-classification and accuracy assessment to get the relevant land use and land cover maps ready for calculating areas in hectares per forest type, which excluded non-forest types. It is observed that land use and land cover changes mainly due to selective logging activities, which can be investigated through the time series remote sensing satellite imagery by evaluating the difference between mapped time X activities and mapped time Y activities. Hence, a forest area that existed in year 1995 is logged in the recent year. The ultimate goal of this study is to understand the changing pattern of above ground living biomass in term of vegetation cover from 1995 to 2015. Highest forest degradation occurred in year 2000 compared to the year 1995, where there was no selective logging on the interpreted satellite imagery. The results of this research indicate the rate of degradation for the period 1995-2015 is 6.45%. Based on data availability, this kind of study may be replicated throughout Papua New Guinea.

Keywords: *Land use and land cover, Remote sensing, GIS, Classification, Forest degradation*

1. Introduction

The basis of land use and land cover (LULC) change assessment rests with the Intergovernmental Panel on Climate Change (IPCC) requirements concerning the application of GIS and remote sensing. IPCC is a scientific arm of the United Nations Framework on Climate Change Convention (UNFCCC, 2009, 2010) initiated through 'Conference of the Parties' or COP meetings between developed and developing countries on climate change agendas. IPCC provides fundamental guidelines for forest inventories and reporting carbon emissions, a process which member countries like PNG through PNG forest authority (PNGFA) and climate change and development authority (CCDA) stipulate according to several reporting templates or instruments.

A country is required to develop national monitoring systems based on IPCC Good Practice Guidelines when identifying sources of green house gasses (GHG's) under the land use and land use change and forestry (LULUCF) sector (IPCC, 2006). LULUCF is the largest sector earmarked for the non-annex1 countries (developing countries) like PNG. LULUCF covers forest degradation and deforestation as a result of anthropogenic activities on land. Objectives formulated for the study are aimed to try and achieve direct satellite imagery results and see what needs to be addressed in the near future for integration of satellite imagery and carbon information on the forests.

The key objective of the study is to develop activity data or land use and land cover type maps from Landsat annual greenest pixel (AGP) imagery of 1995, 2000, 2005, 2010 and 2015 that can be used for future climate, biomass and carbon stock assessment. Many studies have been conducted assessing change in land use and land cover change (Samanta and Pal, 2016) with trends in carbon stock (Yali and Samanta, 2014) and carbon dioxide emissions. This study aims to conduct a change assessment using optical imagery from 1995 to 2015 and evaluate areal changes in forest which can be used as a base database further for the estimation of carbon dioxide emissions.

An overview of the methods and results that provided the platform for this study is discussed, commencing with a background on PNG's early days of a fully integrated GIS system that stored land cover units or resource units. In the early seventies Papua New Guinea forest was surveyed by the Australian Army who developed 1:100,000 scale topographic maps based on aerial imagery and field patrol data. These maps contained generic level 1 and specific level 2 classifications of the land use and land cover classes. However, in the early 1990's great improvement through assistance from the Australian Government, Papua New Guinea had its digital land cover maps stored electronically in a system called the PNG Resource Information System (PNGRIS, 2008). This gradually led to the development of a fully integrated Forest Inventory Mapping System dated 1995. This mapping system applied level 2 classification defined by a lowest mapping unit called vegetation mapping unit. However, some vegetation units in remote areas covered several heterogeneous landforms (Shearman et al., 2008). Agriculture database on land use and crops about PNG was also integrated into the PNGRIS resource mapping units producing Agricultural Mapping System. This contained refined mapping units reflecting occurrences of crops and more specific land use types.

A most recent land cover and land use change mapping conducted in PNG was from 1972 to 2002 (Shearman et al., 2008) under the institutional arrangements of the University of Papua New Guinea and the European Union. The objective was to map out the land use and land cover and conduct change detection quantifying loss of forest due to deforestation and degradation. The study utilized some of the finest optical satellite imageries from SPOT and Landsat ETM+. These images were pre-processed by applying image enhancement techniques known as Tussle-cap analysis where a set of band readings are converted to composite values or ratio of: Brightness-measure of soil, Greenness-measure of vegetation, and Wetness-measure of moisture (Lillesand et al., 2008). After enhancement the satellite imagery went through object-based classification or segmentation using eCognition software. The segments were classified according to nine (9) land cover classes and one (1) land use class. The land use and land cover maps attained an accuracy of 97.7 percent for 2002 map and 96 percent for 1972 map (Shearman et al. 2008).

A site specific study conducted in the Kokada Track in Oro and Central Provinces (Williams et al., 2013) identified specific land cover classes using high resolution airborne radar (GeoSAR and LiDAR) data. Radar backscatter from tree canopy was used to determine tree height information. The difference between the first and second return values from the earth's surface were used to create a surface model depicting the height of objects above the ground. In addition, with compliments from optical image, all data were processed through an advance classification method called Support Vector Machine. This produced accurate stratifications of the forest into 'primary', 'secondary' and 'eucalypt savanna'. The three strata were further grouped into, Lowland, Lower montane, Mid-montane and Upper-montane. Forests not falling into these divisions were classed into three separate classes i.e. 'Other forest' and 'Forest (Other)' and 'Mangrove'. Mangrove was further classed into three types i.e. 'short', 'tall' and 'other'. In addition, high resolution optical imageries were also used to develop 'training data' to provide better accuracy to classification process. This study is a good example of how radar remote sensing capabilities can be applied to devise high resolution surface models to assist in classification of land cover types and measurements of aboveground living biomass in a high intensity cloud cover country like Papua New Guinea.

A study conducted by Fox et al. (2010) analysed the dynamics of carbon based on previous studies on assessment of aboveground carbon in primary and selectively harvested tropical forest in Papua New Guinea. Selective logging area was the basis of carbon stock and carbon dioxide emission estimation done for a time period of 1960-2008. Medium resolution satellite imagery applied for forest regeneration is challenging. Forest regeneration as opposed to failed regeneration is cleared area but, after a period of time recovers with new shoots appearing. This is noticeable with very light pixels seen on the following year or time 2 imagery and in this case would be after 5 to 10 years. The three key activities defining selective logging are collateral damage, deforested areas and failed regeneration areas (Fox et al., 2011; Bryan et al., 2010; Abe, 2007). Deforested areas are those linear patterns or footprints of logging roads constructed for accessibility for trucks to access log sites to load logs for dispatching to mill stations. Collateral damage is killing nearby trees during the process of cutting a large tree for timber. This accounts for branches and other smaller trees killed. This is termed as collateral damage which decomposes to residue (Fox et al., 2011). Failed regeneration is the areas cleared and assumed to recover naturally over a period of time but does not recover.

2. Study area and materials

The Vailala Block 3 forest management area which is located in the Kikori District in Gulf Province was selected to conduct this study (Fig. 1). The area is bounded by two major rivers: Purai River on the western side and Vailala River on the eastern side. The north tip, which the boundary diverts from Purari River uses the ridge tops to join Maropo Creek that flows towards Vailala River. The boundary then continues following Vailala River until it reaches the coastline. Overlay of the boundary shape file and the imagery did not align with the image coastline and the rivers described above. Therefore the boundary shape file was re-digitized to match the image coast line and rivers from the northern portion, western side and the eastern side. The area contains vast gentle slopes with lowland forests with high marketable species which makes it conducive for logging. Vailala Block 3 logging concession is approximately 195,414 hectares. This is 6% of the total land mass of Gulf Province (3.45 million ha).

Satellite images from Landsat satellite series 5, 7 and 8 with 5 year intervals from 1995 to 2015 were used to assess LULC characteristics. Enhanced sensor instrumentations like Thematic Mapper (TM) in Landsat 5, Enhanced Thematic Mapper plus (ETM+) in Landsat 7 and Operational Land Imager (OLI) in Landsat-8 are designed to monitor medium-scale features on the Earth's surface. Two TM images of years 1995 and 2000, two ETM+

images of 2005 and 2010 and one OLI image of year 2015 with the spatial resolution of 30m are used to develop LULC database for the study area. All details of the data are summarised in Table 1. ERDAS imagine 8.5 is used to perform digital image processing tasks on image data preparation, classification and interpretation.

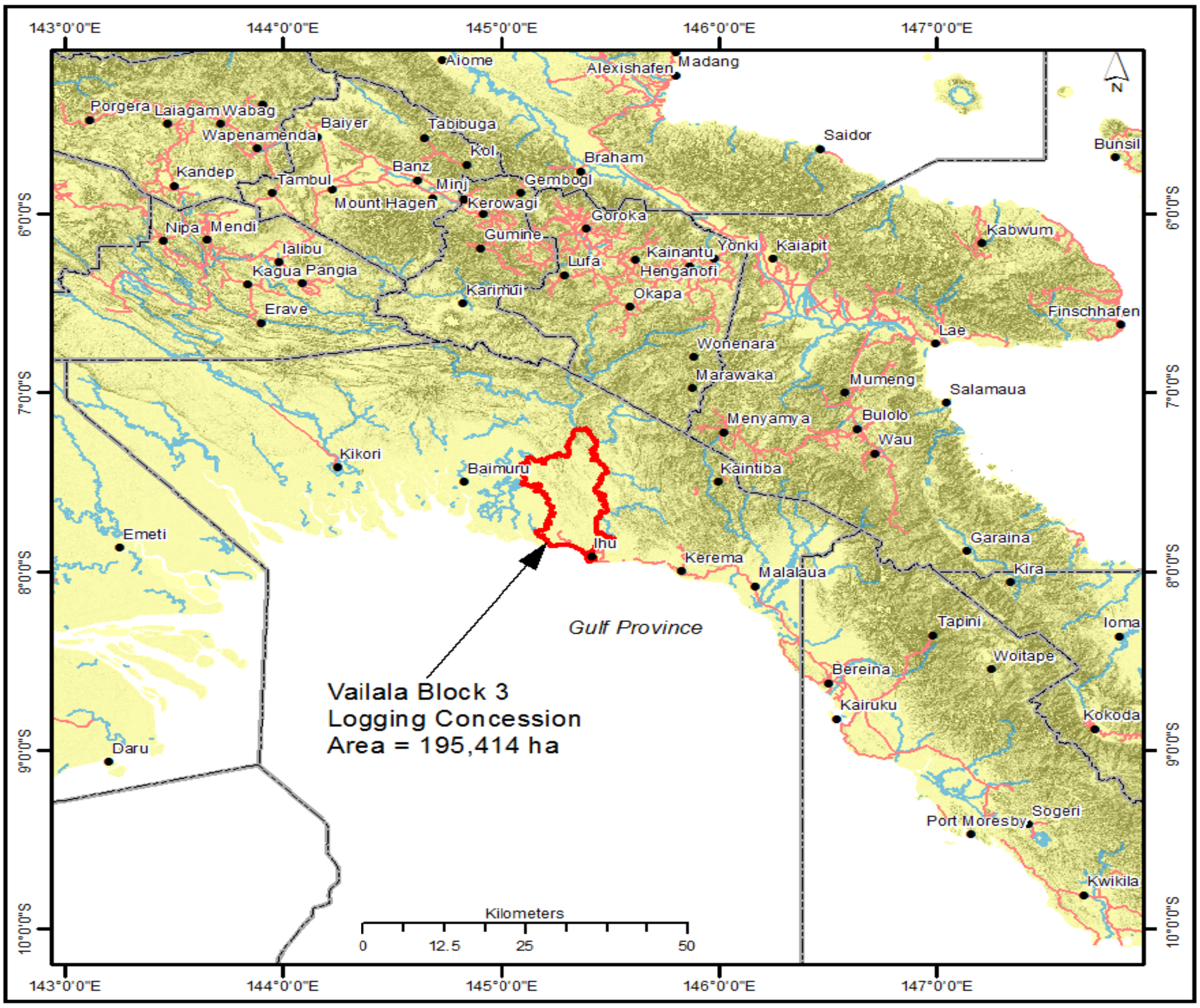

Figure 1: Location of the Study Area - Vailala Block 3 Logging Concession (PNGFA)

Table 1: Landsat satellite specification used for the assessment

Year	**Satellite**	**Standard False Colour Composite Bands**	**Bands for visual interpretation**	**Pixel size**
1995	Landsat 5 TM*	4,3,2	4,5,3	30m
2000	Landsat 5 TM*	4,3,2	4,5,3	30m
2005	Landsat 7 ETM+**	4,3,2	4,5,3	30m
2010	Landsat 7 ETM+**	4,3,2	4,5,3	30m
2015	Landsat 8 OLI***	5,4,2	5,6,4	30m

TM =Thematic Mapper, ETM+ =Enhanced Thematic Mapper, OLI = Operational Land Imager.

3. Methods

Different methods of digital image processing were successfully implemented to achieve the objective of this research. Methods are broken into three parts: preparation, interpretation and analysis (Fig. 2).

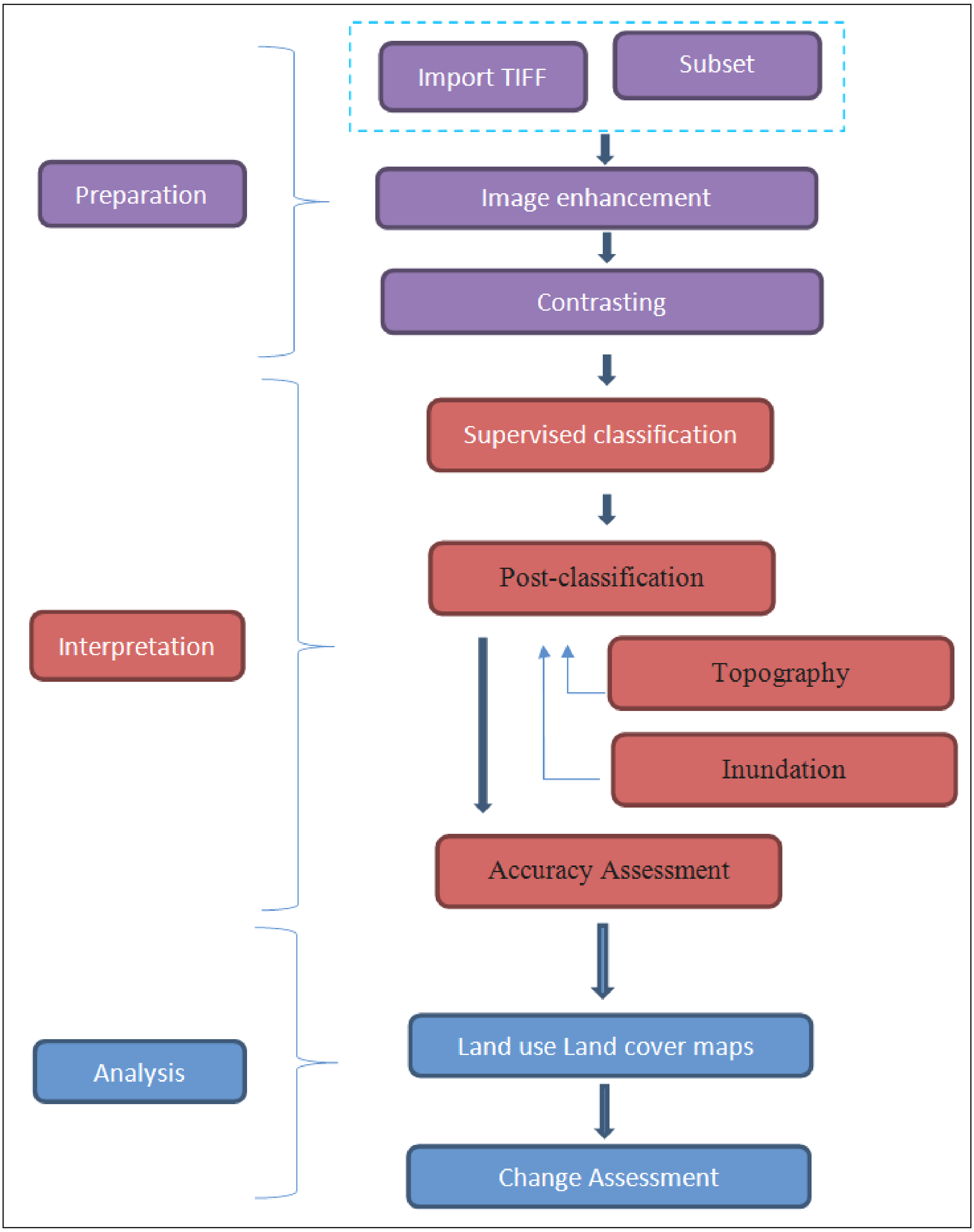

Figure 2: Workflow chart showing the various stages of processing in an image analysis stage

3.1. Preparation

Landsat AGP data have random noise that still exists after being pre-processed by Google. These are basically traces of cloud and haze edges that were not fully taken out. It was also anticipated that PALSAR and RapidEye were good data to eradicate this cloud and haze edge issue, but unfortunately were not applied due to permission of usage not being requested from PNG forestry authority. Below are steps on how the Landsat AGP data were prepared for analysis.

Landsat AGP images were properly rectified by the image suppliers. The Landsat AGP images had gone through a complex process for atmospheric correction called 'top of the atmosphere' or TOA processing by Google Inc. This was aimed at removing atmospheric reflected radiances – cloud and haze. No geometric correction was performed on the main data (Landsat AGP). However, topography and inundation layers from PNGRIS 2008 were re-projected to align with the Landsat imagery projected coordinate system – UTM Zone 55 South. Convolution filtering is a process of averaging small sets of 'noisy' pixels across an image. This process of filtering was a key technique to improve image surface reflectance. All Landsat AGP data were initially acquired from Google Earth Engine as TIFF format. Initial step was importing to Erdas Imagine software. The image was defined or cut to the extent of study site by using the subset tool in Erdas Imagine software. All seven (7) bands i.e. Bands 1, 2, 3, 4, 5, 6 and 7 were maintained to create the new image. Brightness correction was applied to improve the visual condition of all images before classifying the image into LULC subdivisions. The enhanced images were then saved as new images with new file names. After performing brightness and contrasting the images were allocated bands 4 5 3 for Landsat 5 and 7 images, while Landsat 8 was allocated a band composition of 5 6 4. This band arrangement was set to collect 'training data sets' or creation of signature file through visual interpretation.

NDVI is a spectral transformation method which is the ratio of the difference and the sum between the Near Infra-Red and Red bands. The process discriminates vegetation very well from non-vegetated areas.

The following formula was used for NDVI calculations:

$$\mathbf{NDVI} = \frac{NearInfrared - Red}{NearInfrared + Red} \qquad \text{Equation . ... (1)}$$

The NDVI values of more than 0.5 were grouped as forest cover and less than 0.5 as non-forest. Only 1995 NDVI map was a surrogate to assist visual interpretation of forest and non-forest areas with Vailala Block 3 logging concession (Table 2).

Table 2: NDVI statistics of the study area from 1995 to 2015

Year	Max	Mean	Std. dev
1995	0.842	0.739	0.068
2000	0.822	0.383	0.127
2005	0.870	0.709	0.077
2010	0.839	0.724	0.081
2015	0.871	0.787	0.072

3.2. Interpretation

Training samples or areas are sets of pixels observed to be known features on the image demarcated to drive the supervised classification (Jenson, 1996). Training samples for this study were generated in ArcGIS using base map as 1995 image. Visual interpretation bands were set to 4 5 3 in order to guide pattern recognition of the known level 2 classes. Demarcated sites were assumed to be completely contained in a class.

Signature file is a set of data that defines a training sample and featured space as in Areas of Interest or a cluster. After identifying AOI of a class the information was imported into the signature editor tool which automatically defined the pixel range covered in a sample. All samples in the same class were merged into one class. Bands used to define the signatures were set to False Colour Composite band 4 3 2. The only different arrangement of bands was the year 2015, with bands set to 5 4 3. Signature creation for 2000 – 2015 was directly compiled in Erdas using AOI tool.

Forestland, Grassland, Cropland, Wetland, Settlement and other land classes were extracted through supervised classification method. As the target class was forest, final selection of land use and land cover types was done based on forest inventory mapping system (FIMS) (McAlpine and Quigley, 1998) and connection to IPCC classes (IPCC, 2006) (Table 3).

Table 3: Land use and land cover types based on FIMS and connection to IPCC 2006 classes

IPCC	**Veg_ID (FIMS)**	**Land use and Land cover Class**
Forest	H	Lowland forest on uplands – below 1000m
Forest	P	Lowland forest on plains and fans – below 1000m
Forest	Fsw	Swamp forest
Forest	M	Mangrove
Forest	W	Woodland
Grassland	G	Grassland and Herbland
Wet land	E	Lakes and large rivers
Settlement	O	Land use intensity classes 0-4 (inclusive of agriculture)
Other land	Z	Bareland
Forest	D (own code)	Degraded forest
Forest	R (own code)	Regenerated forest

Digital Elevation Model with 90 meter resolution was used to recode top level forest classes, into (a) lowland forest on uplands (>100m) and (b) lowland forest on plains and fans (<100m). Overlay of landform type 'mangrove swamps' layer (Shearman et al, 2008) provided the separation of 'mangrove forest' in swamp forest class and in lowland forest on uplands and on plains and fans. A total of fifty (50) random stratified points were used to conduct the Accuracy assessment (Samanta et al., 2012) of the five (5) LULC maps using the Erdas imagine accuracy assessment tool. Two assessment methods applied are accuracy totals and kappa statistics: Accuracy totals to provide omission and commission errors and kappa to see whether the agreement of classes is genuine. Table 4 presents full accuracy assessment tables for each classification map from 1995-2015.

Table 4: Accuracy assessment results for accuracy totals and kappa statistics for 1995-2015

Accuracy Totals						Kappa
Class Name	Reference Totals	Classified Totals	No. Correct	Producers Accuracy	Users Accuracy	
Year 1995						
Lowland forest on uplands	8	8	8	100%	100%	1.0000

Lowland forest on plains fans	11	12	11	100%	92%	0.8932
Swamp forest	7	6	6	86%	100%	1.0000
Mangrove	4	4	4	100%	100%	1.0000
Woodland	4	4	4	100%	100%	1.0000
Grassland	4	4	4	100%	100%	1.0000
Water body	8	4	4	50%	100%	1.0000
Settlement	4	4	4	100%	100%	1.0000
Bare land	0	4	0	0	0	0.0000
Totals	50	50	45			
	90%					0.8846
Year 2000						
Lowland forest on uplands	8	8	8	100.00%	100.00%	1
Lowland forest on plains fans	8	11	8	100.00%	72.73%	0.6753
Swamp forest	12	9	9	75.00%	100.00%	1
Mangrove	4	4	4	100.00%	100.00%	1
Woodland	4	4	4	100.00%	100.00%	1
Grassland	2	3	2	100.00%	66.67%	0.6528
Water body	5	5	5	100.00%	100.00%	1
Settlement	3	3	3	100.00%	100.00%	1
Bare land	2	2	2	100.00%	100.00%	1
Logging-2000	2	1	1	50.00%	100.00%	1
Totals	50	50	46			
	92%					0.9075
Year 2005						
Lowland forest on uplands	7	7	7	100.00%	100.00%	1
Lowland forest on plains fans	10	11	9	90.00%	81.82%	0.7727
Swamp forest	10	9	8	80.00%	88.89%	0.8611
Mangrove	4	4	4	100.00%	100.00%	1
Woodland	4	4	4	100.00%	100.00%	1
Grassland	2	3	2	100.00%	66.67%	0.6528
Water body	5	5	5	100.00%	100.00%	1
Settlement	3	3	3	100.00%	100.00%	1
Bare land	2	2	2	100.00%	100.00%	1
Logging-2000	2	1	1	50.00%	100.00%	1
Logging-2005	1	1	1	100.00%	100.00%	1
Totals	50	50	46			
	92%					0.9079
Year 2010						
Lowland forest on uplands	4	5	4	100.00%	80.00%	0.7826
Lowland forest	5	5	5	100.00%	100.00%	1

on plains fans						
Swamp forest	4	4	4	100.00%	100.00%	1
Mangrove	4	4	4	100.00%	100.00%	1
Woodland	4	4	4	100.00%	100.00%	1
Grassland	5	4	4	80.00%	100.00%	1
Water body	4	4	4	100.00%	100.00%	1
Settlement	4	4	4	100.00%	100.00%	1
Bare land	2	4	2	100.00%	50.00%	0.4792
Logging-2000	3	4	3	100.00%	75.00%	0.734
Logging-2005	5	4	4	80.00%	100.00%	1
Logging-2010	6	4	4	66.67%	100.00%	1
Totals	50	50	46			
	92%					0.9127
Year 2015						
Lowland forest on uplands	5	6	5	100.00%	83.33%	0.8148
Lowland forest on plains fans	9	8	8	88.89%	100.00%	1
Swamp forest	6	5	5	83.33%	100.00%	1
Mangrove	3	3	3	100.00%	100.00%	1
Woodland	4	4	4	100.00%	100.00%	1
Grassland	4	5	4	100.00%	80.00%	0.7826
Water body	6	5	5	83.33%	100.00%	1
Settlement	3	3	3	100.00%	100.00%	1
Bare land	1	3	1	100.00%	33.33%	0.3197
Logging-2000	3	3	3	100.00%	100.00%	1
Logging-2005	3	3	3	100.00%	100.00%	1
Logging-2010	1	2	1	100.00%	50.00%	0.4898
Totals	50	50	45			
	90%					0.8894

The assessment completes the process of validating the classification, although the classification is not 100% perfect. On the other hand, there are uncertainties associated with the extent of each class in hectares. Addressing uncertainty requires a separate analysis to assess how confident the data is by determining the threshold above and below the actual areas in hectares of the forest types.

4. Results and Discussion

Accuracy totals and kappa statistics were generated separately for each year and each class. Table 4 shows two methods that were applied for accuracy checks of the five (5) years' individual maps. Before post-classification was applied the level of accuracy was very low. Upon conducting the accuracy assessment after the post-classification, all the thematic maps were above the required accuracy total cut-off mark 85% and Kappa statistics required agreement minimum of 0.4 (Table 5). A total of five classified thematic raster maps were produced for 1995, 2000, 2005, 2010 and 2015 (Fig. 3). In the year 1995 the forest cover was 96%, whereas it was 94% in 2000, 92% in 2005, 90% in 2010 and 89% in 2015 respectively (Fig. 4). The trend is that the forest stock in Vailala Block 3 is decreasing. It is notable from the charts that other land use types do not have impact on the forest due to the minute size of the activities compared to logging. The rate of degradation for the period 1995-2015 is 6.45% (Fig. 5). In year 1995 there was no selective logging based on the interpreted satellite imagery. Highest forest degradation occurred in year 2000 due to the large footprints of irregularly arranged linear bright pixels representing selective logging. Lowland forest on upland (H) and lowland forest on plains and fans (P) are highly impacted by selective logging. In year 2000 alone around 83.31% (or 3,347.87 ha) of lowland forest on plains and fans was selectively harvested for timber. The trend changed in 2005 and 2010 as loggers presumably tried to access higher ground or the upland forests. According to the records with the Society Generale de Surveillence (SGS) Group, 543.425 m3 of logs were exported between 1997 and 2003.

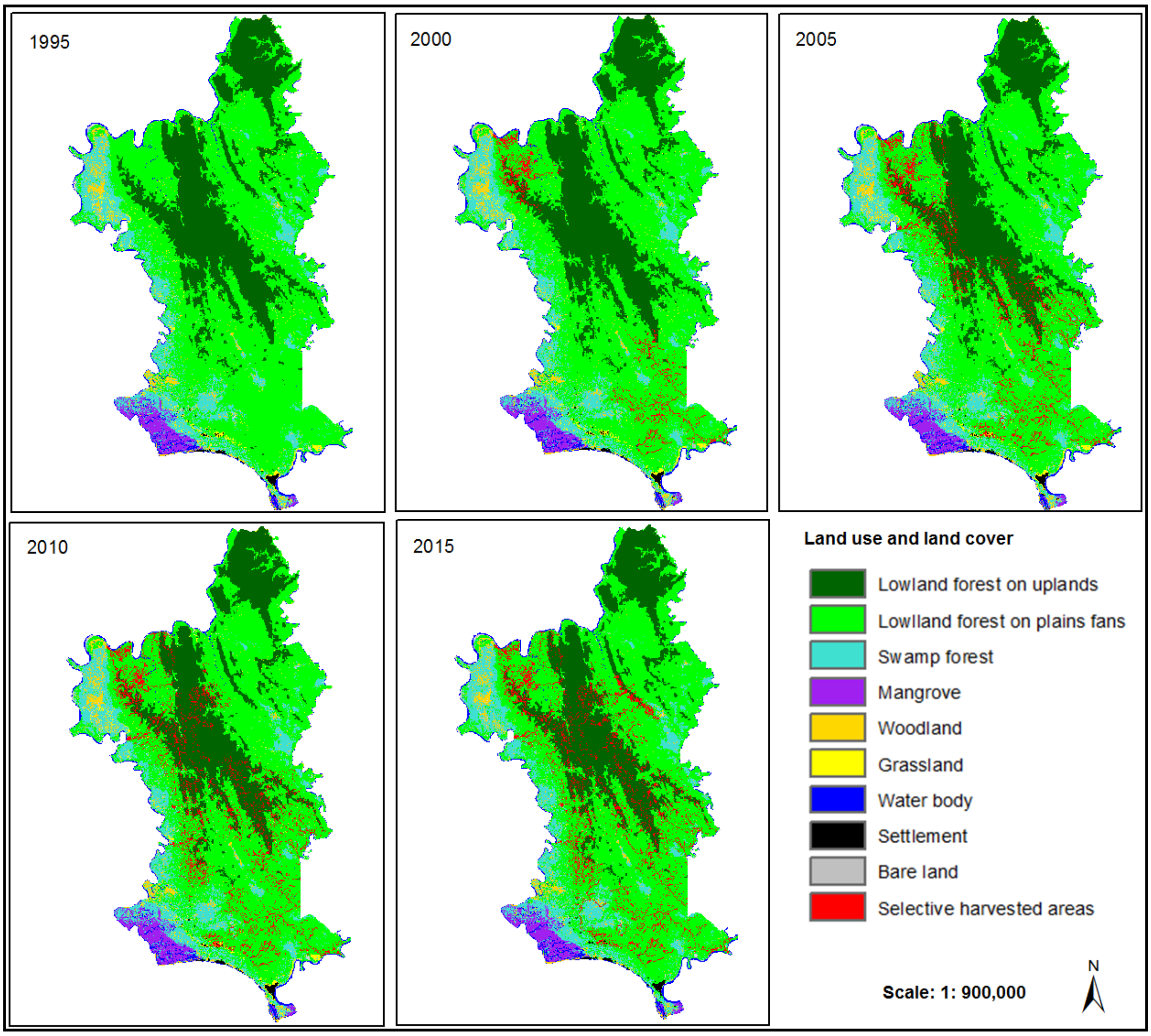

Figure 3: Classified land use and land cover maps of the study area (1995-2015)

Table 5: Accuracy assessment overall results

Year of Classified Map	Accuracy Totals		Kappa Statistics	
	Before PC	After PC	Before PC	After PC

1995	64%	90%	0.4876	0.8800
2000	82%	92%	0.8000	0.9075
2005	84%	92%	0.8232	0.9079
2010	80%	92%	0.7819	0.9127
2015	86%	90%	0.8465	0.8894

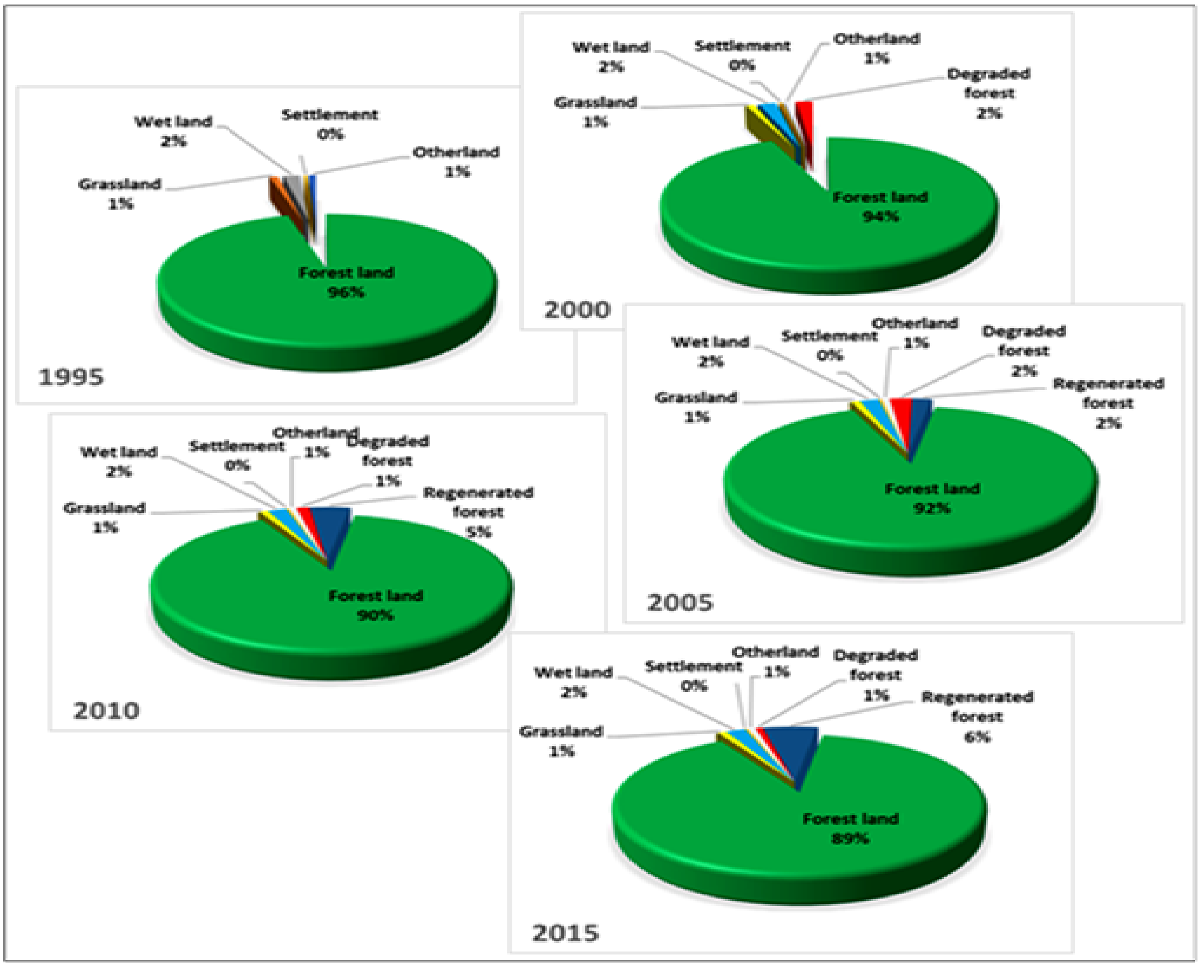

Figure 4: Characteristics of land use and land cover from 1995-2015

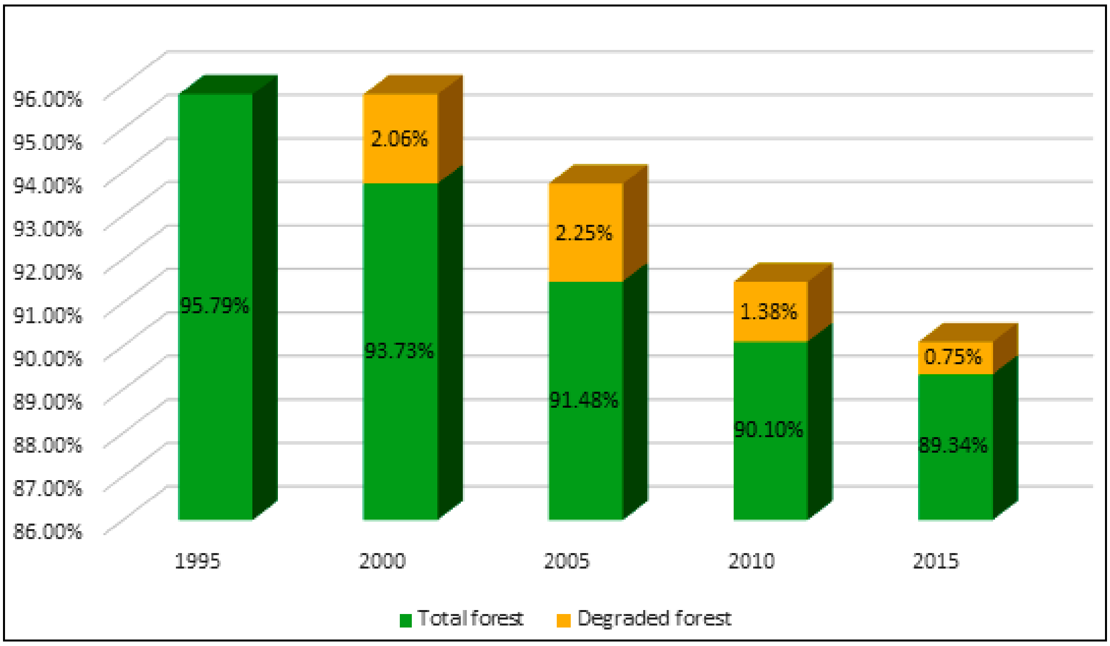

Figure 5: Amounts of remaining forest stock and degraded forest

5. Conclusion and Recommendations

A total of five (5) land use and land cover types were mapped using Landsat annual greenest pixel imagery of 1995, 2000, 2005, 2010 and 2015. These LULC maps were produced using supervised classification. After classification two land use categories were identified, namely forest degradation and forest regeneration. The classified maps went through post-classification in which the accuracy assessment results were further improved compared to the initial classification. Forest degradation rate of 6.45% is greatly affected by the deforested areas that are used for logging roads. Some portion of it is left for regeneration whilst the key linkage road connecting log ponds and other access points is continuously used throughout the operation life-span. The study has provided a new platform on how to assess forest degradation and regeneration using Landsat medium resolution imagery in a selectively harvested area. In addition, the study has provided a glimpse of how Fox et al. (2010) emission factors can be applied to satellite image assessments. Nevertheless, the final result of this study requires further validation to reduce the uncertainty from the changes of the areas in hectares and also the carbon stock changes from one point in time to another.

Conflict of Interest

The authors declare no conflict of interest.

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Author Biographies

First Author, Oala Iuda, is currently working with PNG National Forest Inventory Project. He received his M.Sc. degree in RS and GIS (GIS) from the PNG University of Technology in 2016. This paper is an offshoot of his M. Sc. research.

Second Author, Sailesh Samanta, PhD, *corresponding author,* is Associate Professor and Head of GIS Section under the Department of Surveying and Land Studies, the Papua New Guinea University of Technology, Papua New Guinea.