Natural Science, 2016, 8, 138-151
Published Online March 2016 in SciRes. http://www.scirp.org/journal/ns
http://dx.doi.org/10.4236/ns.2016.83017

Change Detection of Land Use and Land Cover over a Period of 20 Years in Papua New Guinea

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Received 17 February 2016; accepted 14 March 2016; published 17 March 2016

Abstract

People have an inherent tenacity to throng coastal regions in pursuit of better living conditions. As such the brisk dynamism of land use/land cover activities in a coastal region becomes obvious. The former keeps changing rapidly due to burgeoning population. A digital change detection analysis is performed with the help of Geographic Information System (GIS) on the Remote Sensing data spanning over last 20 years, complemented by *in-situ* data and ground truth information. This current research briefly endeavours to find out the nature of change happening in the major three coastal cities of Papua New Guinea (PNG), namely Alotau, capital of Milnebay province; Lae, capital of Morobe province and Port Moresby, capital of Papua New Guinea. Changes in land use and land cover that took place over 20 years have been recorded using Landsat 5 thematic mapper (TM) data of 1992 and Landsat 8 operational land imager (OLI) data. Land use and land cover maps of 1992, and 2013/14, and change detection matrix of 1992-2013/14 are derived. Results show an immensely sprawling urban landscape, evincing about five times growth during 1992 to 2014. At the same time "natural forests" dwindled by 444.96 hectares in Alotau, 6977.25 hectares in Lae and "mangrove" and "grass/shrub land" decreased by 127.78 and 4859.39 hectares respectively around Port Moresby. The above changes owe to ever increasing population pressure, land tenure shift, agriculture and industrial development.

Keywords

Land Use and Land Cover, Accuracy Assessment, Change Detection, Remote Sensing

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How to cite this paper: Samanta, S. and Pal, D.K. (2016) Change Detection of Land Use and Land Cover over a Period of 20 Years in Papua New Guinea. *Natural Science*, **8**, 138-151. http://dx.doi.org/10.4236/ns.2016.83017

1. Introduction

Optical remote sensing data of the earth surface can be analyzed to generate thematic information about general land use/land cover [1]. Pixel-by-pixel basis multi-spectral image classification is one of the techniques generally used for information extraction [2]. Before the process starts rolling it is mandatory to collect multi-spectral satellite imagery of a user defined geographical area, to be followed by good geometric registration of the images. The cloud-free recent satellite images are the best option in this case. There are five (5) basic steps to be followed to acquire land use/land cover information, namely identify the nature of the problem statement and planning, collection of proper data sets, information extraction/analysis, quality validation of the classification output and generation of final product/report (**Table 1**).

High-altitude orbital remote sensor data are very useful for land use/land cover classification system [3]. The result of classification of the satellite data should meet some significant criteria for its acceptance by the third party/user. Those criteria are: 1) classification accuracy should be more than 85 percent, 2) accuracy of the individual land use/land cover categories must be approximately equal, 3) repetitive results' synchronisation from one interpreter to another and one time to another is to be ensured, 4) larger areas must be applicable for classification, 5) the classification must permit vegetation and other types of land cover as surroundings features, 6) temporal resolution and time series data should be suitable for the classification, 7) selection of subcategories can be identified from ground truth collection, 8) aggregation of subcategories must be possible, 9) comparison with future land use/land cover should be considerable, and 10) multiple uses of land should be documented if possible.

Land use/land cover mapping is very significant for resource management and planning programs of any area. Natural vegetations grow according to seasonal and annual phenological cycle. In order to capture such nuances, analyses of multi-seasonal/multi temporal satellite data are essential. As one of the historical pillars of human survival, it has become an inherent human nature to migrate towards the urban and city area in quest of financial might. It is important to understand long-term phenological cycle of urban phenomena. Coastal area is one of the most important regions where population pressure increases rapidly due to salubrious weather (maritime comfort) and other financial/industrial activities. It is necessary to monitor changes of land use/land cover emanating from demographic pressure in coastal regions, like decrease of wetlands and adjacent important ecological niche (e.g. mangrove), and waste loads as a result of competition to occupy limited space for human occupancy, industrial infrastructure/resources and all other wharf-related activities. Land use/land cover map establishes the baseline from which monitoring activities (change detection) can be performed. Land cover change is a direct measure loss or gain of natural habitat [4]. Change detection studies for environmental, urban, or other applications are normally carried out using medium resolution data sets like Landsat 5/7, TM/ETM+. Information on land use and land cover change detection studies can be used by planners as one of the essential parameters in development of multi-criteria decision support system, e.g., to assess urban growth, to determine changes of natural

Table 1. General steps of thematic information extraction from remotely sensed data.

Step	Activities	Details
1	Problem statement and planning	a. Selection of area of interest, planning ground truth b. Choice of land use/land cover classes c. Selection of the mode of accuracy analysis of the output
2	Data collection	a. Cloud free data b. Consideration of resolution: spatial, temporal, spectral and radiometric c. Collection of ground reference point
3	Information extraction/analysis	a. Geometric and radiometric correction b. Choosing a suitable image classification algorithm c. Training sites selection for supervised image classification d. Selection of appropriate spectral bands e. Training class statistics generation for supervised image classification f. Extraction of land use/land cover information
4	Quality validation of the classification	a. Obtain additional test reference data not used as training b. Accuracy assessment of the classification intern of class wise and overall accuracy, kappa statistics
5	Results	a. Digital map generation b. Error evaluation report generation

resources, and also in studies on trend analyses. The objective of this research work is to find out land use/land cover change detection in the period 1992-2013/14 using multi-spectral satellite images.

2. Materials and Study Area

The Landsat 5 and 8 are two satellite missions jointly operated by the United States Geological Survey (USGS) and the national aeronautics and space administration (NASA). The sensor on board Landsat 5 is the thematic mapper (TM) and for Landsat-8 it is Operational Land Imager (OLI). Enhanced sensor instrumentations in Landsat 5 and 8 are designed to monitor medium-scale features on the Earth's surface. Optical bands (Band 1 to 5 for TM and 1 to 7 for OLI) were used to find out the land use/land cover classes in the study area. Two sets of data (1992 and 2013/2014) were used with the spatial resolution of 30 m to find out the changes of coastal settlement in three different township areas. The radiometric resolution of TM data is 8 bit and 12 bit for OLI sensor. Details about data source, location and date of data collection are given in **Table 2**.

The present study was carried out in three coastal township area, namely Alotau, Lae and Port Moresby. The capital city of Milne Bay Province, Alotau is located in the northern shore of Milne Bay in the south-east corner of Papua New Guinea (10˚19'S, 150˚26'E). Second largest city Lae, the capital city of Morobe province is situated close to the mouth of Markham River (6˚44'S, 147˚00'E). It is also called the industrial city and also is the largest cargo port of Papua New Guinea. Port Moresby is positioned on the shore of the Gulf of Papua (9˚30'49'S, 147˚13'7.7'E). It is the capital and also the largest city of Papua New Guinea. The city is famous for trade and industrial hub of the country. The city is called as National Capital District being surrounded by Central Province.

3. Study Methods

Large area land use/land cover mapping using remotely sensed data needs careful planning of various activities. The following activities are particularly relevant to successful transformation of remotely sensed data into land use categories.

The selection of proper satellite image and change detection algorithm is important [5]. Change detection techniques can detect "from-to" information in the tabular form. The method followed in this study is "post classification comparison change detection". It is a quantitative method of change detection. It is essential to perform rectification (georeferencing) and classification of satellite data, so that pixel-by-pixel comparison could be carried out to generate final result. So the accurate image rectification and classification of individual images are very important for post classification comparison of change detection output layers [6].

The methodology for preparation of land use/land cover data set of the study area was performed in four parts, as 1) pre-field study, 2) laboratory work, 3) field observation and verification and 4) post-field laboratory work. Pre-field study comprised study of the background history of the research area *viz.* Alotau, Lae and Port Moresby, study of the attributes contributing to the development of the existing physical environment, study of the land use/land cover, collection of remote sensing and collateral data of the study area, and collection of ground control points (GCPs) for rectification. Laboratory work included geo-referencing, sub-setting, creation- of masks taking the remote sensing and collateral data. Field observation embraced ground truth collection, identification of different feature in different points and their spectral signature. Post-field laboratory work consisted of digital classification, post classification verification, modification of the classification using ground truth,

Table 2. Detail information of satellite images used for land use/land cover map preparation.

Satellite, Sensor, Scale	Name of the Location	Path/Row	Date	Source
LANDSAT-5, TM, (30 m) 1:250,000	Alotau	93/67	09-09-1992	GLCF University of Maryland
	Lae	96/65	09-09-1992	
	Port Moresby	96/66	09-09-1992	
LANDSAT-8 OLI, (30 m) 1:250,000	Alotau	93/67	26-03-2014	GIS Section, Papua New Guinea University of Technology
	Lae	96/65	16-06-2013	
	Port Moresby	96/66	04-09-2013	

recoding, generation of error matrix for accuracy assessment, statistics generation according to estimated cell size for final data set in ASCII format and finally the thematic map generation.

Process of rectification involves geo-referencing that is assigning map co-ordinates to the satellite image. This is achieved by collecting ground control points from both the raw data (satellite) and the reference map (rectified already). The transformation process is carried out by estimating a suitable transformation relation between a set of points (GCPs) on the image as well as on a map (reference). At first single map rectification for all three locations were performed using the Universal Transverse Mercator (UTM) projection system and WGS 84 datum with a RMS error range from 0.02 to 0.03. All the reference maps were rectified by this process. Then the double image (map to image) rectification was performed for all six satellite imagery (two images for each study location: 1992 and 2013/14) using the UTM projection system and WGS 84 datum with RMS error range from 0.09 to 0.1. The study area was extracted by sub-setting using area of interest (AOI) layer in Erdas imagine software. Actual geographical extension of study locations (rectangle shaped area) are shown in **Table 3**.

All the desired classes of interest were selected and defined to classify all sets of satellite image successfully [7]. Different classification schemes were developed that could readily incorporate land use/land cover data obtained by remotely sensed data. For the present study two sets of Landsat data were used to generate land use/land cover map of the study area. Each sensor has unique spectral band arrangement as described in **Table 4**.

Training sites selection is mandatory to perform a supervised classification to identify land use/land cover categories. After collection of training data combination of bands are normally ranked according to their potential ability to discriminate one class from others using multiple bands for both sensors. Statistical measures such as univariate and variance-covariance matrix are very much useful to solve the above issue. Univariate and variance-covariance matrix were generated from training data sets for all bands as shown in **Table 5**. In the overall consideration Standard false color bands 5, 4 and 3 are selected to carry out the classification [8].

Land use and land cover maps were generated for Alotau, Lae and Port Moresby based on the supervised classification using a maximum likelihood algorithm [9] in ERDAS Imagine and finally overlaid in ArcGIS to identify the major changes that had occurred during 1992 to 2013/14.

4. Result and Discussion

Different dominant land use/land cover types were selected for the classification for Alotau, Lae and Port Moresby region. They were deep sea water, shallow sea water, river water, dense vegetation, low dense vegetation, mangrove, agriculture/plantation, shrub land, open fallow or degraded land and urban and built-up area. **Tables 6-8** describes all land use and land cover classes that were selected. Their detailed statistics during 1992 to 2013/14 for all three coastal regions are shown in the **Figures 1-3**.

Table 3. Detailed information of satellite images used for land use/land cover map preparation.

Location	Upper Left (X)	Upper Left (Y)	Lower Right (X)	Lower Right (Y)	Total Area (Ha)
Alotau	199,642.50	8,861,987.50	223,897.50	8,846,912.50	36,623.43
Lae	485,750.05	9,269,211.56	508,415.05	9,251,616.56	39,939.48
Port Moresby	498,210.30	8,970,704.26	532,830.30	8,944,559.26	87,969.42

Table 4. Spectral band consideration of Landsat 5, TM and Landsat 8, OLI.

<table>
<tr><th>Bands</th><th colspan="2">Landsat 5, TM (1992)</th><th colspan="2">Landsat 8, OLI (2013/14)</th></tr>
<tr><td>1</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>2</td><td>Green</td><td rowspan="3">Used for supervised classification</td><td>-</td><td>-</td></tr>
<tr><td>3</td><td>Red</td><td>Green</td><td rowspan="3">Used for supervised classification</td></tr>
<tr><td>4</td><td>Near-infrared</td><td>Red</td></tr>
<tr><td>5</td><td>-</td><td>-</td><td>Near-infrared</td></tr>
<tr><td>6</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>7</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>8</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
</table>

Table 5. Univariate and variance-covariance matrix for 9 land use/land cover classes using OLI image.

Location-Alatau: OLI Sensor, 2014											
Univariate statistics					Variance-covariance						
Sea water											
Layer	Minimum	Maximum	Mean	Std. Dev	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
1	9747	9951	9849.00	27.59	761.33						
2	8659	8879	8748.47	24.94	510.82	622.17					
3	6914	7168	7021.01	27.85	230.97	480.20	775.62				
4	5993	6204	6074.33	24.31	327.93	482.68	586.94	591.04			
5	5366	5739	5504.98	42.27	639.70	818.18	879.07	890.85	1786.47		
6	5027	5246	5099.43	23.92	328.43	442.89	505.19	505.30	937.29	571.91	
7	4997	5140	5048.38	16.97	231.04	309.94	355.05	355.87	645.06	375.49	288.05
Dense vegetation											
1	9096	9488	9292.06	84.43	7128.83						
2	8045	8479	8259.87	94.11	7865.19	8856.35					
3	6985	7690	7341.10	121.02	8255.19	9701.78	14,646.51				
4	5978	6610	6298.31	116.30	9066.94	10,395.86	13,362.79	13,526.66			
5	11,024	15,174	13,305.40	949.50	26,329.38	36,900.24	87,747.47	67,708.69	90,1540.78		
6	7079	8732	8020.30	346.14	12,240.28	15,746.59	32,397.56	25,597.40	269,019.04	119,811.40	
7	5716	6390	6060.93	135.87	6928.74	8384.48	14,132.12	12,300.79	98,563.20	45,384.44	18,459.90
Agriculture/plantation											
1	9613	9912	9745.38	50.31	2530.90						
2	8646	8975	8767.94	50.75	2378.49	2575.77					
3	8263	8649	8437.01	72.28	2668.64	2872.53	5224.91				
4	6702	7173	6857.10	81.96	1864.37	2592.01	3097.38	6717.37			
5	24,973	33,188	30,371.83	1198.46	15,997.78	6613.09	16,057.40	−62,084.06	143,6305.42		
6	13,802	14,928	14,384.28	195.17	4545.41	4642.72	6613.91	1720.60	108,721.63	38,092.14	
7	8157	8737	8404.13	95.97	1740.45	2352.60	3060.73	4830.86	−22,082.83	13,565.77	9210.00
Lae: OLI Sensor, 2013											
Univariate statistics					Variance-covariance						
Inland water											
Layer	Minimum	Maximum	Mean	Std. Dev	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
1	9253	9662	9436.08	57.96	3359.18						
2	8349	8810	8577.26	60.24	3334.99	3629.35					
3	7604	8053	7727.76	77.38	3389.21	3458.31	5988.34				
4	6515	6942	6699.96	60.23	2908.10	3003.67	3999.60	3627.82			
5	4656	11645	6665.17	1314.76	6742.04	2022.17	51,899.32	21,383.74	1,728,600.65		
6	4921	7942	5815.01	649.47	8469.42	6490.43	32,224.51	17,020.38	803,087.55	421,815.57	
7	5159	6163	5448.17	230.58	3063.54	2334.02	11,367.49	6524.70	283,058.12	147,909.97	53,166.90

Continued

					Low dense vegetation						
1	9103	9623	9335.32	55.67	3099.23						
2	8127	8678	8375.13	61.30	3304.46	3758.07					
3	7322	8161	7761.19	95.84	3604.16	4218.52	9185.80				
4	6294	7017	6689.72	82.51	3479.45	3994.94	6935.44	6808.33			
5	15,660	20,561	18,455.43	651.71	3640.44	4445.46	34,221.07	20,934.40	424,723.74		
6	8148	9636	8912.18	176.58	5755.67	6649.71	12,624.07	9565.94	51633.73	31,181.64	
7	5958	6604	6245.04	77.11	3310.88	3755.25	4800.96	4218.55	4784.82	12,047.93	5945.61
					Urban and built-up						
1	10023	14018	11717.77	1081.31	1,169,225.69						
2	9720	14141	11433.00	1182.16	1,269,649.08	1,397,512.17					
3	9273	13982	11153.92	1234.03	1,325,397.90	1,456,827.67	1,522,827.91				
4	9021	14024	11093.54	1299.98	1,391,573.30	1,524,977.25	1,590,959.13	1,689,940.44			
5	10422	16921	14102.31	2057.25	1,868,414.83	1,904,111.08	2,009,488.78	2,100,435.57	4,232,272.06		
6	10758	16108	14065.69	1609.81	1,406,051.92	1,433,895.50	1,494,163.14	1,669,949.01	2,880,871.35	2,591,470.73	
7	9831	13795	12045.92	1093.27	948,924.65	1,000,344.33	1,044,791.99	1,194,260.63	1,642,779.28	1,644,831.14	1,195,240.74
					Port Moresby: OLI Sensor, 2013						
			Univariate statistics					Variance-covariance			
					Shrubs						
Layer	Minimum	Maximum	Mean	Std. Dev	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
1	9832	10,281	10,063.51	76.38	5833.20						
2	9063	9574	9342.37	87.07	6480.63	7580.45					
3	9425	10,476	10,129.49	171.39	6337.80	7468.48	29,375.17				
4	8086	8929	8610.14	133.72	8342.17	10,262.92	9439.80	17,880.13			
5	19,396	24,234	22,434.18	988.82	−5188.64	−9268.54	113,023.91	−43,022.71	977,756.83		
6	13,046	13,974	13,584.65	169.71	5179.11	6603.59	6481.68	12,494.49	103.21	28,801.57	
7	8249	9041	8673.60	125.47	5099.63	6347.29	−3646.06	12,044.94	−73,931.18	16,113.91	15,742.21
					Grass cover land						
1	9795	10,590	10,145.17	125.72	15,804.54						
2	9033	9925	9477.15	149.99	18,429.32	22,497.64					
3	8509	9642	9188.34	202.72	22,256.62	28,612.08	41,096.75				
4	9054	10,787	10,153.85	320.79	29,743.55	40,059.84	59,704.53	102,907.23			
5	14,393	19,201	17,291.18	897.54	49,762.12	75,041.48	134,234.77	209,439.55	805,568.25		
6	15,267	20,260	18,601.36	1013.34	54,979.08	80,349.74	129,757.34	272,655.30	622,836.63	102,6853.17	
7	10,850	14,112	12,703.28	618.44	39,087.13	52,884.82	76,796.46	163,883.77	233,808.86	567,458.46	382,467.05
					Fallow land						
1	9912	10,378	10202.32	73.48	5399.27						
2	9040	9515	9344.23	76.09	5280.86	5789.39					
3	8145	8647	8435.40	79.22	3792.41	4887.06	6276.29				
4	8027	8725	8328.74	126.44	2528.21	4721.56	8791.09	15,988.18			
5	9206	12,449	10,138.58	523.59	−15,045.29	−8994.31	13,983.22	39,757.45	274,143.29		
6	11,895	15,188	12,806.02	501.19	−14,052.68	−9817.04	9562.89	34,266.94	224,248.25	251,189.76	
7	11,493	13,368	12,248.64	271.80	4757.57	4099.85	2034.48	2659.46	−26,977.74	38,843.04	73,876.63

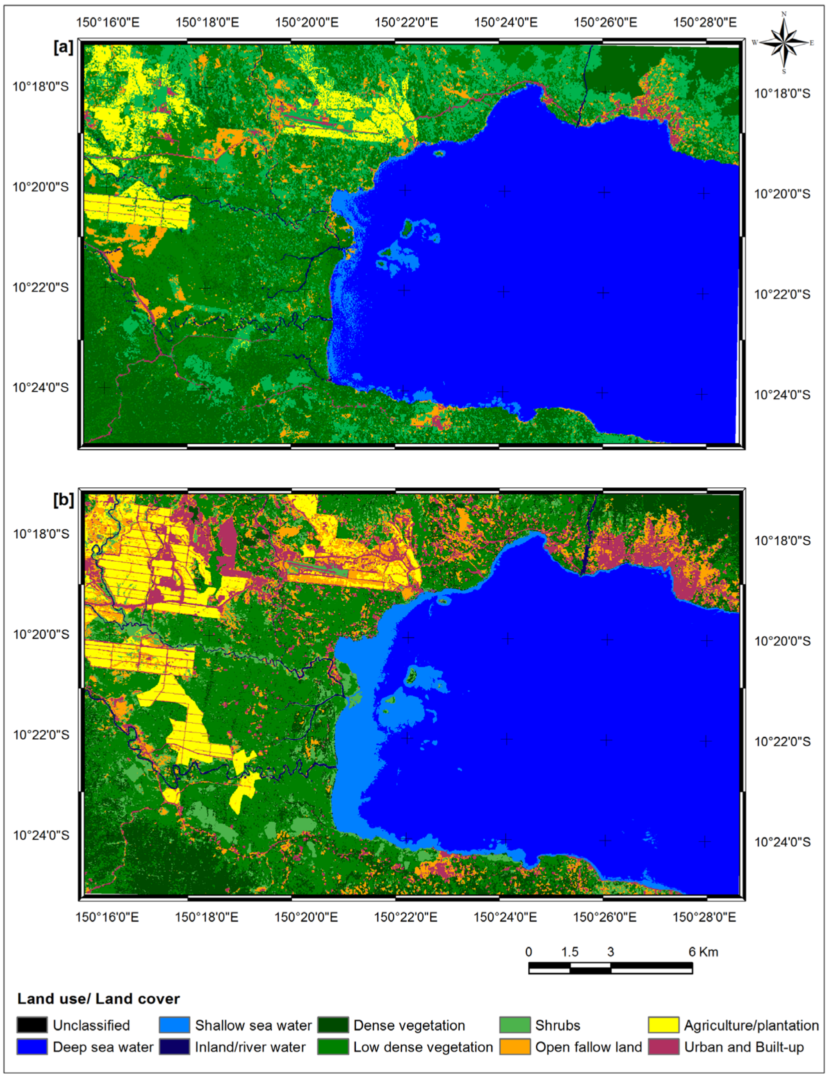

Figure 1. Land use/land cover map of Alotau, [a] 1992 and [b] 2014.

Table 6. Land use/land cover of Alotau region based on TM and OLI satellite images.

Sl. No.	Land Use/Land Cover	Area in Hectare		% of Area	
		1992	2014	1992	2014
1	Deep sea water	14,686.90	13,419.99	40.1	36.6
2	Shallow sea water	633.71	1802.30	1.7	4.9
3	River water	203.56	244.53	0.6	0.7
4	Dense vegetation	5488.47	4078.60	15.0	11.1
5	Low dense vegetation	6864.77	7829.69	18.7	21.4
6	Shrubs	5398.83	2123.33	14.7	5.8
7	Fallow land	1327.86	2461.50	3.6	6.7
8	Agriculture/plantation	1566.79	2094.39	4.3	5.7
9	Urban and built-up	452.54	2569.12	1.2	7.0
	Total	36,623.43	36,623.43	100.0	100.0

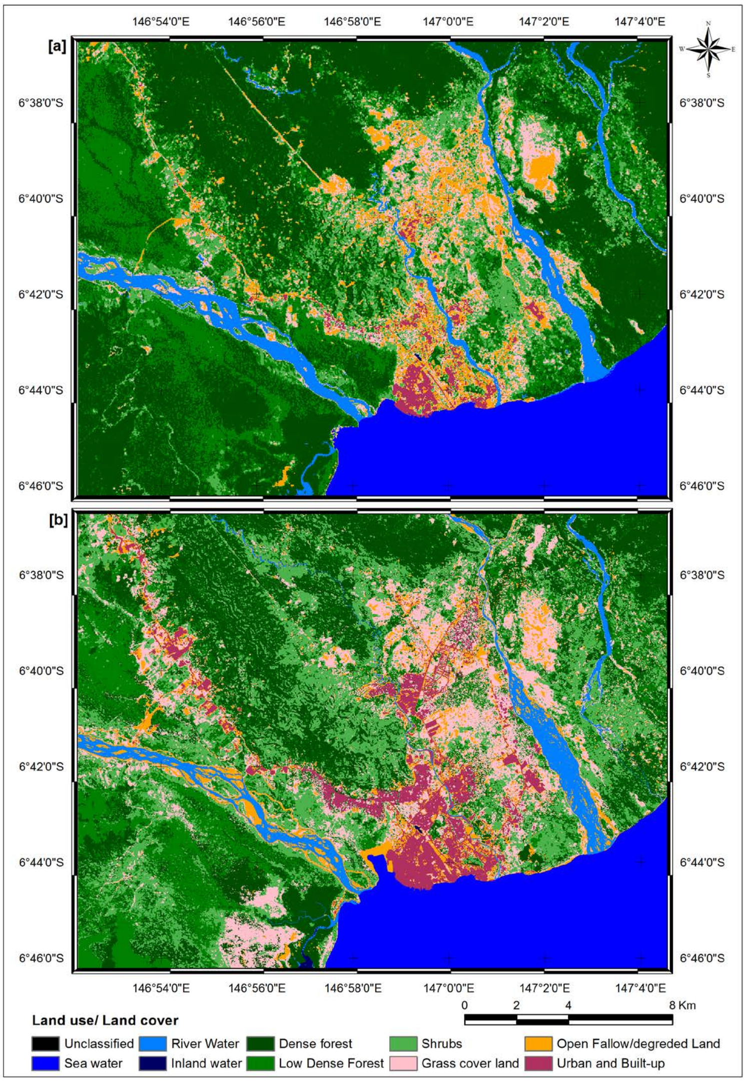

Figure 2. Land use/land cover map of Lae, [a] 1992; and [b] 2013.

Table 7. Land use/land cover of Lae region based on TM and OLI satellite images.

Sl. No.	Land Use/Land Cover	Area in Hectare		% of Area	
		1992	2014	1992	2013
1	Sea Water	5028.17	5048.03	12.6	12.6
2	River Water	1739.09	1390.55	4.4	3.5
3	Inland Water	2.93	28.82	0.0	0.1
4	Dense Forest	14,616.36	9193.59	36.6	23.0
5	Low Dense Forest	8315.78	6761.30	20.8	16.9
6	Shrubs	4742.12	8023.82	11.9	20.1
7	Grass Cover Land	2794.50	5634.38	7.0	14.1
8	Open Fallow/Degraded Land	2174.47	2100.94	5.4	5.3
9	Urban and Built-Up	526.07	1758.06	1.3	4.4
	Total	39,939.48	39,939.48	100.0	100.0

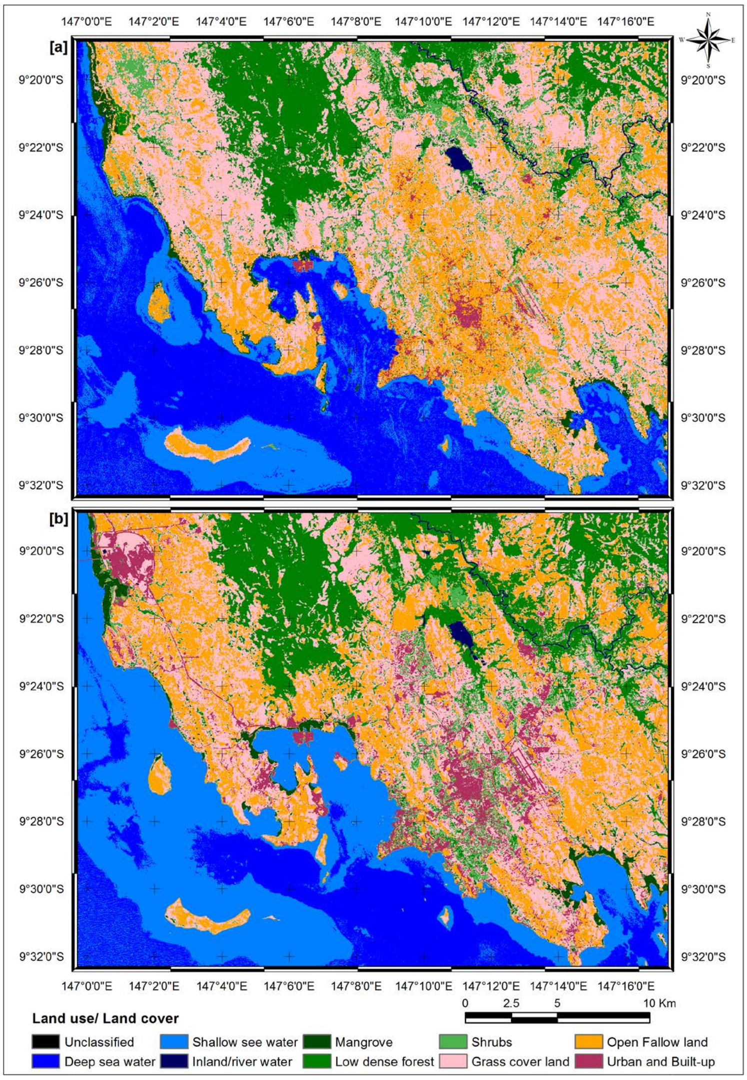

Figure 3. Land use/land cover map of Port Moresby, [a] 1992; and [b] 2013.

Table 8. Land use/land cover of Port Moresby region based on TM and OLI satellite images.

Sl. No.	Land Use/Land Cover	Area in Hectare		% of Area	
		1992	2014	1992	2013
1	Deep Sea Water	19,374.53	10,571.40	22.0	12.0
2	Shallow Sea Water	12,072.47	20,648.54	13.7	23.5
3	Inland/River Water	451.49	381.20	0.5	0.4
4	Mangrove Vegetation	1394.10	1266.32	1.6	1.4
5	Low Dense Vegetation	10,712.25	12,332.57	12.2	14.0
6	Shrubs	4052.30	3355.58	4.6	3.8
7	Grass Cover Land/Open Shrub	24,626.61	19,767.22	28.0	22.5
8	Fallow Land	14,378.04	15,144.98	16.3	17.2
9	Urban and Built-Up	907.65	4501.62	1.0	5.1
	Total	87,969.42	87,969.42	100.0	100.0

In order to assess classification accuracy, an error matrix [10] was derived that represented a square array of numbers laid out in rows and columns. **Tables 9-14** show details accuracy results of the classification. Stratified random sampling was implemented for accuracy assessment using 50 sample points for each study location. Two different measures were derived from the error matrix, namely user's and producer's accuracy [11], [12]. The overall classification accuracy of Alotau, Lae and Port Moresby region are 90.00%, 86.00%, 88.00% for 1992 classifications and 94.00%, 92.00%, 92.00% for 2014 respectively. A Kappa coefficient is usually used for judging of map accuracy [13], [14]. The Kappa statistics are derived as 0.8873, 0.8397, 0.8873 for 1992 and 0.9324, 0.9071, 0.9096 for 2014 respectively.

Classified data of 1992 and 2014 were compared on a pixel-by-pixel basis using a change detection matrix (**Tables 15-17**). Each pixel was specified whether it had changed to any other class or had remained unchanged.

Table 9. Classification accuracy and kappa statistics of 1992 classification, Alotau.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Conditional Kappa
Deep Sea Water	5	5	4	80.00%	80.00%	0.8873
Shallow Sea Water	5	5	4	80.00%	80.00%	0.8873
River Water	5	5	5	100.00%	100.00%	1.0000
Dense Vegetation	5	6	5	100.00%	83.33%	0.8148
Low Dense Vegetation	6	7	5	83.33%	71.43%	0.6753
Shrubs	8	6	6	75.00%	100.00%	1.0000
Fallow Land	5	5	5	100.00%	100.00%	1.0000
Agriculture/Plantation	6	6	6	100.00%	100.00%	1.0000
Urban and Built	5	5	5	100.00%	100.00%	1.0000
Totals	50	50	45		-	-
Overall Classification Accuracy and Kappa Statistics				90.00%		0.8873

Table 10. Classification accuracy and kappa statistics of 2014 classification, Alotau.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Conditional Kappa
Deep Sea Water	5	5	5	100.00%	80.00%	1.0000
Shallow Sea Water	5	5	5	100.00%	80.00%	1.0000
River Water	5	5	5	100.00%	100.00%	1.0000
Dense Vegetation	5	6	5	100.00%	83.33%	0.8148
Low Dense Vegetation	7	7	6	85.71%	85.71%	0.8339
Shrubs	6	6	5	83.33%	83.33%	0.8106
Fallow Land	6	5	5	83.33%	100.00%	1.0000
Agriculture/Plantation	6	6	6	100.00%	100.00%	1.0000
Urban and Built	5	5	5	100.00%	100.00%	1.0000
Totals	50	50	47		-	-
Overall Classification Accuracy and Kappa Statistics					94.00%	0.9324

Table 11. Classification accuracy and kappa statistics of 1992 classification, Lae.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Conditional Kappa
Sea Water	4	5	4	100.00%	80.00%	0.7826
River Water	4	3	3	75.00%	100.00%	1.0000
Inland Water	2	2	2	100.00%	100.00%	1.0000
Dense Forest	8	9	7	87.50%	77.78%	0.7354
Low Dense Forest	8	7	6	75.00%	85.71%	0.8299
Shrubs	7	8	6	85.71%	75.00%	0.7093
Grass Cover Land	6	6	5	83.33%	83.33%	0.8106
Open Fallow/Degraded	4	3	3	75.00%	100.00%	1.0000
Urban and Built-up	7	7	7	100.00%	100.00%	1.0000
Totals	50	50	43	-		-
Overall Classification Accuracy and Kappa Statistics				86.00%		0.8397

Table 12. Classification accuracy and kappa statistics of 2013 classification, Lae.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Conditional Kappa
Sea Water	5	5	5	100.00%	100.00%	1.0000
River Water	2	2	2	100.00%	100.00%	1.0000
Inland Water	2	2	2	100.00%	100.00%	1.0000
Dense Forest	10	10	9	90.00%	90.00%	0.8750
Low Dense Forest	8	7	6	75.00%	85.71%	0.8299
Shrubs	6	8	6	100.00%	75.00%	0.7159
Grass Cover Land	7	6	6	85.71%	100.00%	1.0000
Open Fallow/Degraded	2	2	2	100.00%	100.00%	1.0000
Urban and Built-up	8	8	8	100.00%	100.00%	1.0000
Totals	50	50	46	-		-
Overall Classification Accuracy and Kappa Statistics				92.00%		0.9071

Table 13. Classification accuracy and kappa statistics of 1992 classification, Port Moresby.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Conditional Kappa
Deep Sea Water	6	6	5	83.33%	83.33%	0.8106
Shallow Sea Water	4	4	3	75.00%	75.00%	0.7283
Inland/River Water	5	5	5	100.00%	100.00%	1.0000
Mangrove Vegetation	5	4	5	100.00%	83.33%	1.0000
Low Dense Vegetation	6	6	6	100.00%	100.00%	1.0000
Shrubs	6	5	4	66.67%	80.00%	0.7727
Grass Cover Land	8	7	6	75.00%	85.71%	0.8299
Fallow Land	4	6	4	100.00%	67.67%	0.6377
Urban and Built	6	6	6	100.00%	100.00%	1.0000
Totals	50	50	44	-		-
Overall Classification Accuracy and Kappa Statistics				88.00%		0.8873

Table 14. Classification accuracy and kappa statistics of 2013 classification, Port Moresby.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Conditional Kappa
Deep Sea Water	4	3	3	75.00%	100.00%	1.0000
Shallow Sea Water	6	7	6	100.00%	85.71%	0.8377
Inland/River Water	5	5	5	100.00%	100.00%	1.0000
Mangrove Vegetation	5	5	5	100.00%	100.00%	1.0000
Low Dense Vegetation	6	6	6	100.00%	100.00%	1.0000
Shrubs	5	5	4	80.00%	80.00%	0.7778
Grass Cover Land	8	7	5	75.00%	85.71%	0.8299
Fallow Land	5	6	5	100.00%	83.33%	0.8148
Urban and Built	6	6	6	100.00%	100.00%	1.0000
Totals	50	50	46	-		-
Overall Classification Accuracy and Kappa Statistics				92.00%		0.9096

Table 15. Change detection (cross-tabulation) of land use/land cover over 21 years, Alotau.

LU/LC	1	2	3	4	5	6	7	8	9	**2014**
1	149,067	13,807	8	178	8	119	1	0	1	163,188
2	44	6092	30	212	92	412	19	0	141	7041
3	0	1	667	256	420	512	192	2	213	2262
4	0	28	428	23,188	26,444	4919	2572	91	3314	60,983
5	0	81	709	11,194	39,203	7103	5608	6465	5913	76,275
6	0	17	513	9027	17,631	8073	10,471	4617	9639	59,987
7	0	0	323	1028	2933	1512	3952	1503	3504	14,754
8	0	0	14	0	0	723	4118	10,475	2079	17,409
9	0	0	27	236	268	220	418	119	3742	5028
1992	149,111	20,026	2717	45,318	86,997	23,593	27,350	23,271	28546	406,927

Table 16. Change detection (cross-tabulation) of land use/land cover over 20 years, Lae.

LU/LC	1	2	3	4	5	6	7	8	9	**2013**
1	55,510	144	1	10	5	7	21	131	40	55,869
2	1	9143	255	955	905	1902	1997	3873	293	19,323
3	0	0	31	0	0	0	0	1	1	33
4	210	1354	9	74,361	34,192	36,865	12,331	2749	333	162,404
5	186	1519	1	16,993	27,753	27,993	13,378	3374	1201	92,398
6	95	1571	5	5874	7415	15,874	14,675	4051	3130	52,690
7	55	1229	7	2153	3262	4253	11,732	4389	3971	31,050
8	33	486	11	1805	1594	2260	8470	4777	4726	24,161
9	0	6	0	0	0	0	0	0	5840	5845
1992	56,089	15,451	320	102,151	75,126	89,154	62,604	23,344	19,534	443,772

Table 17. Change detection of land use/land cover over 21 years, Port Moresby.

LU/LC	1	2	3	4	5	6	7	8	9	**2013**
1	149,067	13,807	8	178	8	119	1	0	1	163,188
2	44	6092	30	212	92	412	19	0	141	7041
3	0	1	667	256	420	512	192	2	213	2262
4	0	28	428	23,188	26,444	4919	2572	91	3314	60,983
5	0	81	709	11,194	39,203	7103	5608	6465	5913	76,275
6	0	17	513	9027	17,631	8073	10,471	4617	9639	59,987
7	0	0	323	1028	2933	1512	3952	1503	3504	14,754
8	0	0	14	0	0	723	4118	10,475	2079	17,409
9	0	0	27	236	268	220	418	119	3742	5028
1992	149,111	20,026	2717	45,318	86,997	23,593	27,350	23,271	28,546	406,927

According to satellite image analyses, there have been a clear reduction of forest land and concomitant increase of agriculture and urban and built-up area throughout the whole study period (1992-2013/14). Grassland (including shrubs) is decreased on an average by −155.98 hectares/year and forestland (Dense) by −67.14 hectares/year whereas agriculture (including short-time plantation) and urban and built-up area are increased by 25.13 and 100.79 hectares/year respectively in Alotau region. The total urban area in Alotau is 2569.12 hectares, which is 7.01% of the total area in 2014 and it is about 6 times of the 1992. Forestland (Dense and low dense) is decreased on average by −348.86 hectares/year whereas grassland (including shrubs) and urban and built-up area are increased by 306.08 and 61.60 hectares/year respectively in Lae area. Urban area has become 1758.6 (4.4%) hectares and thus accounts for about 3.5 times increase with respect to the situation in 1992. Mangrove vegetation has dwindled on an average by −6.39 hectares/year, grassland (including shrubs) by −277.81 hectares/year whereas urban and built-up areas have increased by 179.7 hectares/year in Port Moresby region (NCD—National Capital District). The urban area stands at 4501.62 hectares (5.12%) in 2013 and which accounts for an expansion of 4.95 times compared to 1992.

5. Conclusion and Recommendation

PNG National Census of Housing and Population indicates the average annual population growth of 3.5% in Morobe, 2.6% in Central and 2.8% in Milne Bay province. Currently (2011-Census) 71,286 persons are living in Lae urban LLG; 318,128 in Port Moresby (NCD) and 12,628 in Alotau Urban LLG with the population density of 1598, 1325 and 3237 respectively. According to the report of "The state of the forests of PNG" (2008) [15], during years 1972-2002 (30-year span), 15% (82% to 71%) of PNG's diverse rainforest had been cleared and 8.8% had been degraded to secondary forest due to human activities, like logging (48.2%), subsistence agriculture (45.6%) and mining and plantation (1.8%). In Alotau region forest and shrub land area are reduced with the corresponding increase of plantation and built-up area. Due to rapid development of industries and other settlement area primary forests have been affected. In the Port Moresby region coastal mangrove is under serious threat and shrub land area keeps diminishing due to the rapid development of urban real estate enterprises, industries and other infrastructures. Few recent developments like extension of Lae Port area, PNG-LNG (Liquefied Natural Gas) project in Port Moresby are the precise examples behind the destruction of the forest and other secondary vegetative land area. There is a need for an appropriate land use plan to be established to save the natural environment, like protection of mangrove and primary forests which are very important for a sustainable tropical ecology in Papua New Guinea.

Acknowledgements

The authors are indeed grateful to the Department of Surveying and Land Studies, Papua New Guina University of Technology for providing laboratory facilities. We are also grateful to the anonymous reviewers for their useful remarks that might have helped improve the manuscript considerably.

Author's Contribution

First author (SS) collected the data/information and performed all kinds of methodological task and drafted the manuscript. Second author (DKP) helped in drafted the manuscript and reviewed carefully. Both authors read the manuscript and agreed to be a part of the authorship.

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