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Expert Classification of Land Use and Land Cover in Markham, Morobe Province, Papua New Guinea

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Abstract

The expert classification approach useddata other than satellite images to improve and increase the accuracyof classificationof land use and land cover. This study was focused on understanding expert classification and formulating the rules for extracting LULC classes using 1992 and 2001 Landsat Thematic Mapper datasets. Auxiliary data of Principal Components Analysis (PCA) and Normalized Difference Vegetative Index (NDVI) were applied in order to improve the accuracy of classification using a decision tree approach for classification. A total of 7 classes, which include Dense Forest, Less Dense Forest, Agriculture, Grassland, Bareland, Built-Up Landand Water were identified and extracted with overall accuracies of 90% for 1992 and 92% for 2001 with Kappa statistics of 0.8786 and 0.8935. However, there were still issues faced with spectral similarities between classes for Landsat TM images. Despite this, the study has shown that expert classification technique can be used for acquiring useful and reliable LULC information for natural resource management in Papua New Guinea.

Keywords: *Expert Classification, Decision Tree Approach, Land Use and Land Cover, Remote Sensing, Landsat TM*

1. Introduction

Providing reliable and accurate LULC information is an important component in remote sensing and has been a point of concern for many studies (Wilkinson, 2005; Rahdarry et al. 2008). Remote sensing techniques can provide a firm basis for identifying and understanding past, current, and predict future LULC changes as it has produced important source of data for LULC and is an important tool for updating of inventories (Hans et al. 2004). By carrying out satellite image classification, LULC areas can be identified and classed depending on procedures and techniques applied.

An image classification approach can be grouped either as unsupervised, supervised, parametric and nonparametric, hard and soft (fuzzy) classification, or per-pixel, sub-pixel and per-field (Lu and Weng, 2007). More superior classification techniques have been developed and used to improve classification accuracies such as advanced statistical data modelling (Frankling and Peddle, 1989; Lauver and Whistler, 1993), integration of multitemporal and ancillary data (Middlekoop and Jansen, 1991), and multisource field data (Wu et al. 1988; Zeff and Merry 1993). However, the two advanced classification techniques commonly used at present are the object-orientated classification (Mather, 1999) and expert system classification (Chmiel and Gumbricht, 1996). Object-orientated classification requires a prior segmentation of homogenous regions (depending on shape, texture, background and spectral information) in an image and then classifying these regions (Mather, 1999).The expert classification approach, on the other hand, uses data other than spectral characteristics to improve the results of classification, thus increasing the accuracy of image classification. This is done by adding and combining an existing knowledge base with information extracted from images (Trotter, 1991). With the use of auxiliary data, the initial results of the procedures can be corrected through expert rules (Wicks et al. 2002).

Currently, in Papua New Guinea (PNG), most studies carried out on LULC and forest cover classification by the Papua New Guinea Forest Authority (PNGFA) useeCognition, which is based on object-based classification software. Expert classification, despite its potential, has not been fully utilized in Papua New Guinea (PNG) for LULC studies. Thus, this study has applied the technique of expert classification for LULC classification in an area north-east of Lae (PNG's second largest city). Landsat TM satellite images were used with auxiliary data of Principal Components Analysis (PCA) and Normalized Difference Vegetative Index (NDVI) images. The aim of this study was to apply the expert classification technique on the Landsat TM datasets with PCA and NDVI to identify, extract and classify LULC. The main objectives were:

i) To formulate rules for extracting and classifying LULC using Digital Numbers (DN), Principal Components (PC) and Vegetative Index (VI) values from satellite image bands, PCA and NDVI images;

ii) To identify and classify LULC using expert classification technique for Landsat TM 1992 and 2001; and

iii) To assess the accuracy of the expert classification technique.

2. Materials and Method

2.1. Study Area

The study area is located north-west of the main city of Lae between 6°35'00"and 6°45'00" south and 146°45'00"and 146°55'00" east with the Markham river flowing on one side and the main highway on the other side(Figure 1).

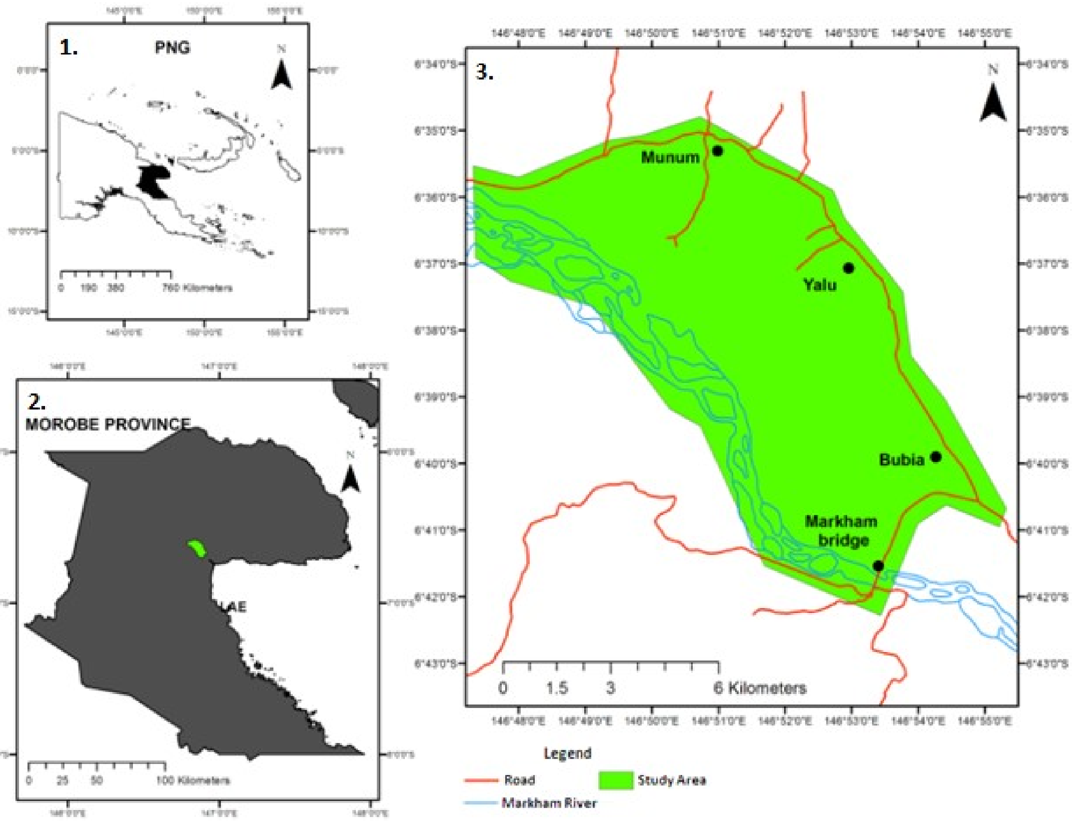

Figure1: Map showing the study area. 1). Indicating location of Morobe Province in PNG (2). Showing location of study area (in green) in Morobe Province (3). Detailed map of study area showing, the Markham River and road networks (**Source:** Authors, 2019)

2.2.Data

2.2.1. Satellite Image

The 1992 and 2001 Landsat TM images for Morobe Province were acquired from the Global Land Cover Facility's website with a spatial resolution of 30m and consisted of 5 and 6 spectral bands respectively. The images were later geometrically rectified, layer-stacked and sub-setted in ERDAS Imagine 9.1. Table 1 shows the general information about the acquired Landsat TM images. Each band has a distinct characteristic determined by the region of the electromagnetic spectrum it is taken from, thus they can be used to identify different features on the ground.

Table 1. Characteristics of Landsat TM images used in the study.

Year	Acquisition Date	No of bands	Band	Spatial Resolution (m)	Cloud Cover over AOI	Path/Row
1992	9th September	5	1,2,3,4,7	30	Zero	96, 65
2001	3rd March	6	1,2,3,4,5,7	30	Zero	96, 65

2.3.Pre-processing of Landsat TM Images

Pre-processing of Landsat TM images involved radiometric and geometric corrections, and image enhancements prior to expert classification in ERDAS Imagine 9.1. Radiometric correction processes of haze and noise reduction were performed to reduce, enhance and correct unwanted irregularities of haze and noise using the radiometric enhancement function. Geometric correction was performed using a 1:100,000 1978 topographic map by image to image registration with Band 4 of 1992. Band 4 was then used to rectify the other bands, including 2001 bands.

All images were projected to WGS 84, Zone 55, South projection. Enhancement of images was also performed to aid interpretation and identification of LULC classes for expert classification. Since the 5 bands of 1992 and 6 bands of 2001 were acquired individually, the process of Layer-stacking was performed so that image processing could be efficiently carried out with all the bands together. Figure 2 shows the flowchart of the research methodology.

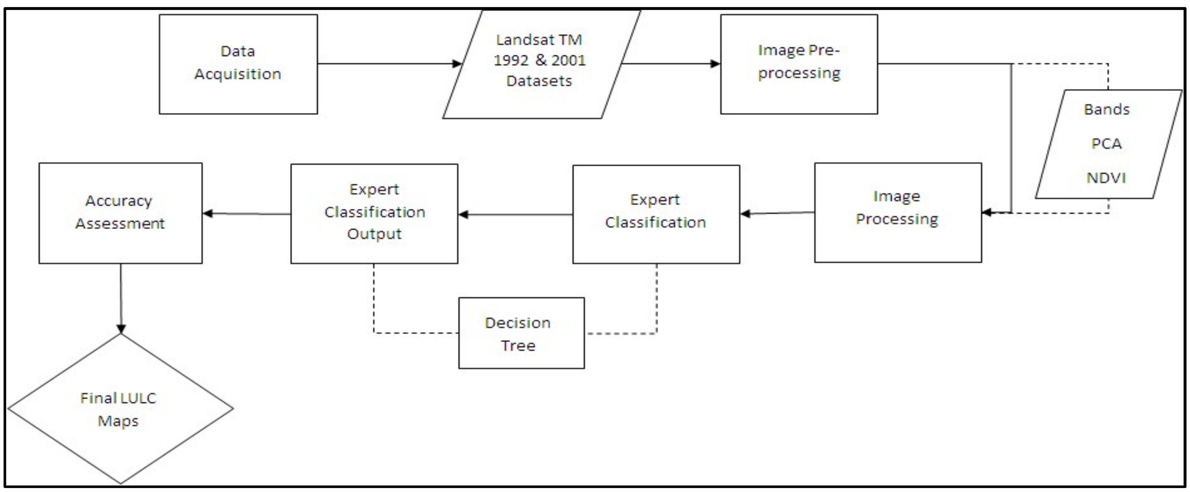

Figure 2: Methodology Flowchart

2.4.Deriving PCA and NDVI Images

In this study Principal Components 1, 2 and 3 (i.e. PC1, PC2 and PC3) and NDVI images were produced for both 1992 and 2001. These two data were then combined with Landsat TM data for the expert classification process as additional data to aid in improving classification. Both PCA and NDVI images were derived from the Landsat TM data via the spectral enhancement process in ERDAS Imagine 9.1.

2.5.LULC Classification using Expert Classification Technique

Expert classification was performed on Landsat TM datasets using the expert classifier knowledge engineering interface in ERDAS Imagine 9.1. Data used for the extraction of LULC classes were the Landsat, PCA and NDVI images, in which the rules for extracting classes were formulated using the highest and lowest DN, PC and VI values identified using the “start/update inquire curser” in ERDAS Imagine 9.1 (Figure 3). Not all bands from Landsat, PC’s or NDVI images were used in every LULC classification due to the fact that this expert classification was based on an empirical process and the final class extracted was dependent on whether the high and low values from a combination of band (s), PC (s) and/or NDVI were appropriate and produced a satisfactory classification result. Thus, in some instances, only certain bands and PC's or only PC's and NDVI were used.

2.6. Expert Classification and Decision Tree Approach

A decision tree approach (Avci&Akyurek, 2004) was used to improve accuracy by reducing the spectral variability and encouraging homogeneity and ease when differentiating between classes (Figure 4). Classification was done by a First Level, Second Level and Third Level order of extraction process. Masking was also an important process of getting individual or separate images after the first and second level classifications thus making it easy for the identification of classes. Following the decision tree approach, vegetation and non-vegetation classes were extracted first and then masked from the Landsat TM satellite, PCA and NDVI images thus creating new sets of images containing vegetation and non-vegetation areas. This was the first level of classification.

From these first level classifications, forest and non-forest areas were extracted from the vegetation images and water and non-water areas from the non-vegetation images for the second level classification. The output classification maps were then masked from the vegetation and non-vegetation Landsat TM satellite, PCA and NDVI images. For the third level classification, forest image was sub-divided into dense and less dense forest, non-forest into grassland and agriculture and non-water into bareland and built-up areas. Water was left as it was as there was no further subdivision.By the third and final level of classification, the LULC classes extracted were combined to form complete expert classification maps.

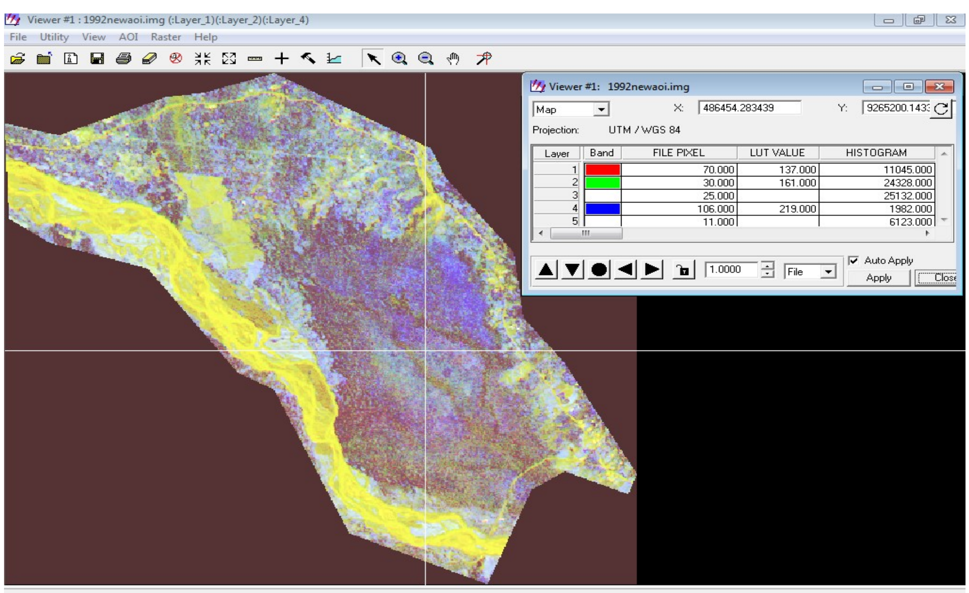

Figure 3: Expert classifier user interface in ERDAS Imagine 9.1. used for formulating the rules for expert classification showing the hypothesis or LULC classes in green, rules in yellow and conditions in blue.

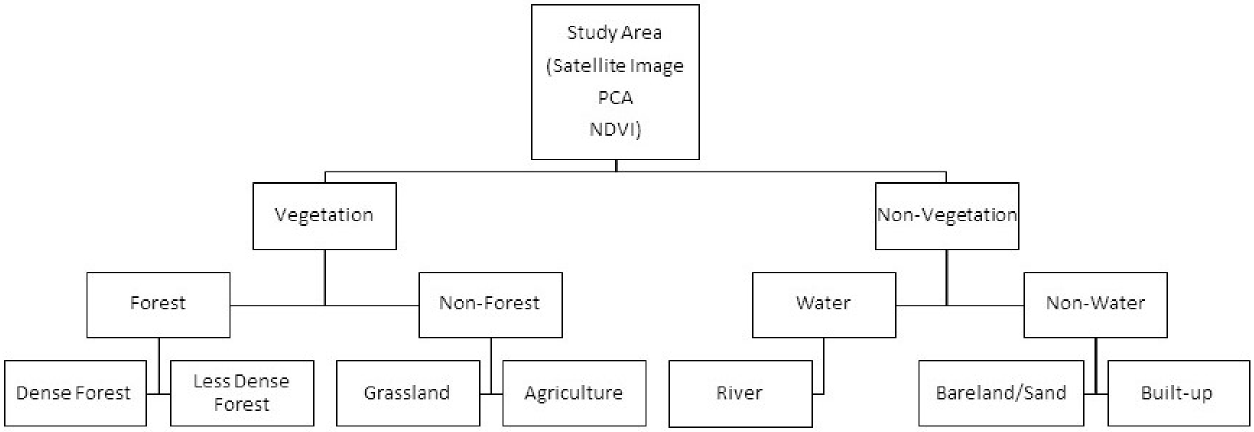

Figure 4: The Decision tree approach used for expert classification. It also shows the 3 levels of classification (1st, 2nd& 3rd levels) **Source**: Avci&Akyurek (2004)

3. Results

3.1.Formulation of Expert Classification Rules

Rules were formulated using satellite, PCA and NDVI images whereby DN, PC and NDVI high and low values were identified to create thresholds for each class for extraction following the decision tree approach. Tables 2a and 2b show the rules used for Landsat TM expert classification of LULC classes. Figure 5 (1992) and Figure 6 (2001) show the resulting first and second level classifications.

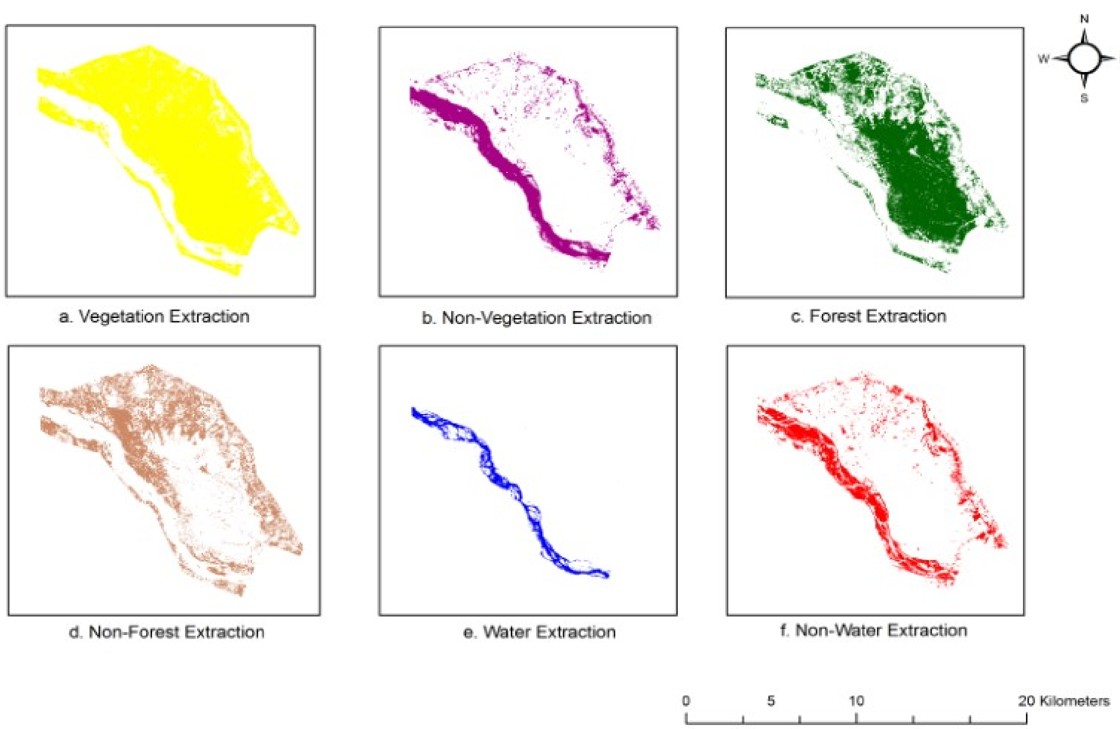

Figure 5: Landsat TM 1992 first (a, b) and second (c, d, e, f) level extractions

For Landsat 1992 expert rules (Table 2a), Principal Component 1 (PC1) was used for extracting the study area consisting of both vegetation and non-vegetation areas. This was then used in a rule to extract non-vegetation areas. The first level classification of Vegetation (V) used NDVI. Non-Vegetation (nV) class was then extracted using Sa == TRUE and V == FALSE rule, thus subtracting Vegetation from the study area to leave only Non-Vegetation areas. The second level of extraction of Forest (F) class from the Vegetation masks used Principal Component 2 (PC2), Band 4 (B4) and NDVI. Non-Forest (nF) class was extracted using V == TRUE and F == FALSE. Water class was extracted using Band 7 (B7), PC1, PC2 and NDVI from Non-Vegetation masks.

Non-Water (nW) was extracted using nV == TRUE and W == FALSE. Figure 4 shows the extracted maps for the first and second level classifications for 1992. The third level classification of Dense Forest (Df) used B4, PC1 and PC2 from forest masks and then was used to extract Less Dense Forest (LDF) using V == TRUE and Df == FALSE. Agriculture (Ag) was extracted from nF == TRUE and Gr == FALSE after Grassland (Gr) was extracted using Non-Forest masks of PC1, PC2 and B4. Bareland (Bl) used Non-Water mask of B4, B7, PC1, PC2 and NDVI. Built-up (Bu) areas used B4, B1, PC1 and PC2 from Non-Water mask subsets.

For Landsat TM 2001 classification rules (Table 2b), PC1 was again used for Sa and NDVI was used for V extraction. The rule Sa == TRUE and V == FALSE was used for extracting nV areas. From the Vegetation masks, Band 3 (B3), B4 and Band 5(B5) were used for extracting Forest areas and nF from V == TRUE and F == FALSE. Df used B3 and PC1 from forest masks. LDf was extracted using F == TRUE and LDf == FALSE. W was extracted using B7, PC1 and NDVI. nW was extracted from Non-Vegetation using nV == TRUE and W == FALSE. Figure 5 shows the extracted maps for the first and second level classifications for 2001. Ag used B3, B4 and PC1 Non-Forest masks and Gr were extracted using nF == TRUE and Ag == FALSE. Non-Water masks of B1, B2 and PC1 were used to extract Bl areas. Bu used a subset from Non-Water masks using B3, B4, PC1.

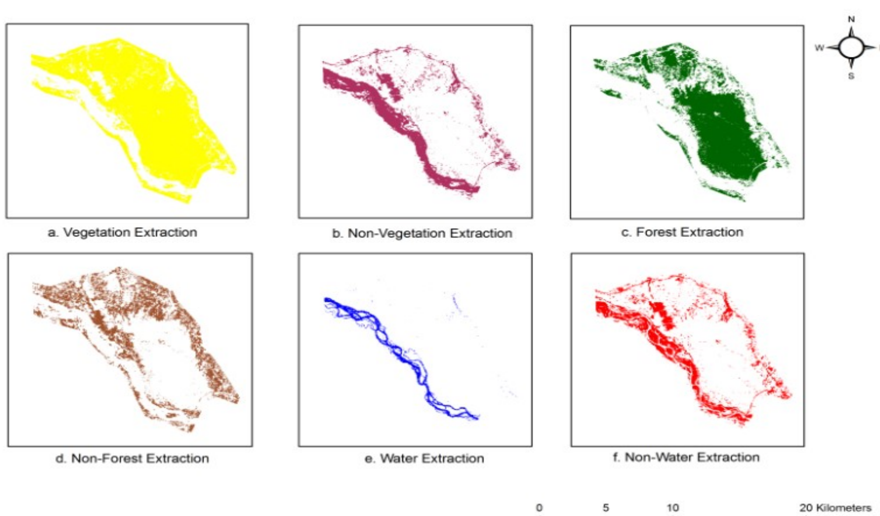

Figure 6: Landsat TM 2001 first (a, b) and second (c, d, e, f) level extractions

3.2. *Expert Classification*

In the 1992 Landsat TM classification (Figure 7a), dense forest (33%) cover is found mostly in the middle and towards the south-east with small portions in the north, east and south of the river. Less dense forest (16%) is found more in-between dense forest areas. Grassland (20%) is found around dense and less dense forest and close to built-up and agriculture areas. Agriculture (5%) is mostly found in-between the middle and northern parts of the study area. Built-up (5%) areas are found near and along the highway. Bareland (16%) areas are found in-between the river system and amongst agriculture areas. Water (7%) is from the Markham River, which runs from north-west to south-east and to the coast.

Table 2: Summary of Expert Classification Rules for Landsat TM (a) 1992 and (b) 2001

a)

Class	Description	Rule
Sa	Vegetation & Non-Vegetation	PC1 > 0
V	Plants	NDVI > 0.48
nV	No plants	Sa == TRUE V == FALSE
F	Trees	PC2_vegetation-mask > -30 PC2_vegetation-mask < 15 B4_vegetation-mask > 50 B4_vegetation-mask ><130 NDVI_vegetation-mask > 0.4 NDVI_vegetation-mask < 1
nF	No trees	V == TRUE F == FALSE
LDf	No much forest cover	F == TRUE Df == FALSE
Df	Thick forest cover	B4_forest-mask > 60 B4_forest-mask < 100 PC1_forest-mask > 100 PC1_forest-mask < 130 PC2_forest-mask > -10 PC2_forest-mask < 10
W	Water	B7_non-vegetation-mask > 1 B7_non-vegetation-mask < 25 PC1_non-vegetation-mask > 90 PC1_non-vegetation-mask < 130 PC2_non-vegetation-mask > 15 PC2_non-vegetation-mask < 70 NDVI_non-vegetation-mask > -0.5 NDVI_non-vegetation-mask < 0.25
nW	No water	nV == TRUE W == FALSE
Ag	Crop and Farmland	nF == TRUE Gr == FALSE
Gr	Little vegetation cover	PC1_non-forest > 120 PC1_non-forest < 160 PC2_non-forest > -20 PC2_non-forest < 0 B4_non-forest > 50 B4_non-forest < 130
Bl	No ground cover	B4_non-water-mask > 30 B4_non-water-mask < 100 B7_non-water-mask > 10 B7_non-water-mask < 50 PC1_non-water-mask > 20 PC1_non-water-mask < 150 PC2_non-water-mask > 20 PC2_non-water-mask < 100 NDVI_non-water-mask > -0.9 NDVI_non-water-mask < 0.5
Bu	Settlement	B4_bu-subset > 60 B4_bu-subset < 95 B1_bu-subset > 70 B1_bu-subset < 100 PC1_bu-subset > 110 PC1_bu-subset < 140 PC2_bu-subset > 5 PC2_bu-subset < 30

b)

Class	Description	Rule
Sa	Vegetation & Non-Vegetation	PC1 > 0
V	Plants	NDVI > 0.3
nV	No plants	Sa == TRUE V == FALSE
F	Trees	B3_vegetation-mask > 20 B3_vegetation-mask > 50 B4_vegetation-mask > 80 B4_vegetation-mask > 120 B5_vegetation-mask > 20 B5_vegetation-mask < 80
nF	No trees	V == TRUE F == FALSE
Df	Thick forest cover	PC1_forest-mask > 140 PC1_forest-mask < 160 B3_forest-mask > 30 B3_forest-mask < 50
LDf	No much forest cover	F == TRUE Df == FALSE
W	Water	PC1_non-vegetation-mask > 100 PC1_non-vegetation-mask < 150 B7_non-vegetation-mask > 0 B7_non-vegetation-mask < 60 NDVI_non-vegetation-mask < -0.25
nW	No water	nV == TRUE W == FALSE
Ag	Crop and Farmland	B3_non-forest-mask > 40 B3_non-forest-mask > 55 B4_non-forest-mask > 120 B4_non-forest-mask > 145 PC1_non-forest-mask > 195 PC1_non-forest-mask > 215
Gr	Little vegetation cover	nF == TRUE Ag == FALSE
Bl	No ground cover	B1_non-water-mask > 30 B1_non-water-mask < 100 B2_non-water-mask > 10 B2_non-water-mask < 50 PC1_non-water-mask > 20 PC1_non-water-mask < 150
Bu	Settlement	B3_bu-subset > 30 B3_bu-subset < 90 B4_bu-subset > 50 B4_bu-subset < 100 PC1_bu-subset > 160 PC1_bu-subset < 200

Key

Sa	Study Area	B1	Red Band
V	Vegetation	B2	Green Band
nV	Non-vegetation	B3	Blue band
F	Forest	B4	Near Infrared Band
nF	Non-Forest	B5	Mid-Infrared
LDf	Less Dense Forest	B7	Mid-Infrared
Df	Dense Forest	PC1	Principal Component 1
W	Water	PC2	Principal Component 2
nW	Non-Water	NDVI	Normalized Difference Vegetative Index
Ag	Agriculture		
Gr	Grassland		
Bl	Bareland		
Bu	Built-up Area		

In the 2001 Landsat TM classification (Figure 7b), dense forest (14%) cover is found around a large percentage of less dense forest cover with small portions of both found towards the north and along the river. Less dense forest (34%) is found in the middle and continuously to the southern part of the study area. Grassland (30%) is found around dense and less dense forests and close to built-up and agriculture areas. Agriculture (2%) is mostly found in between the middle and northern part of the study area and near built-up (11%) areas that are found again near and along the main highway. Bareland (11%) areas are found in between the river system as well as near built-up areas. Water (7%) is from the Markham and Yalu Rivers.

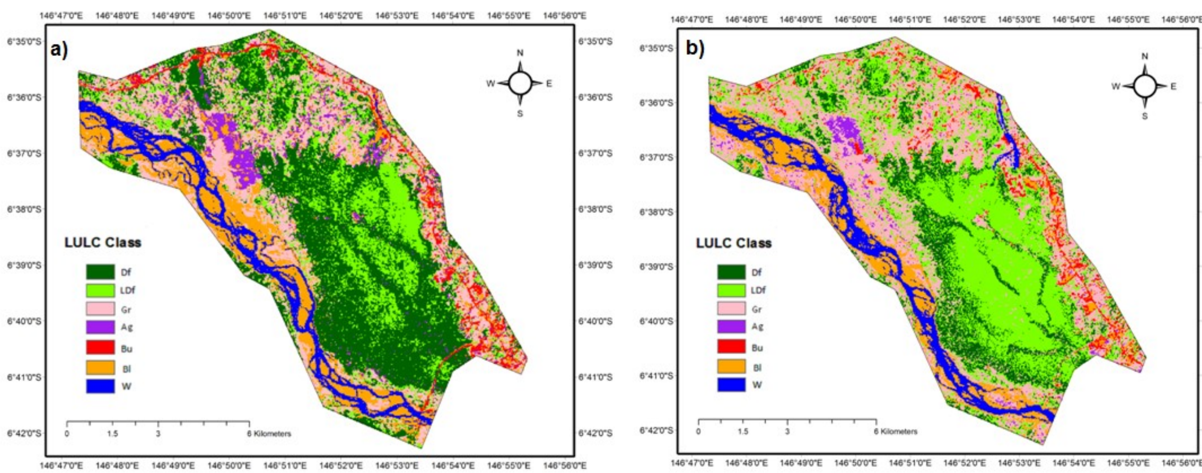

Figure 7: Resulting expert classification of Landsat TM a) 1992 and b) 2001

3.3.Accuracy Assessment

In this study, 100 random points were used for accuracy assessment, which resulted in an error matrix for each LULC map, giving rise to the producer, user and overall accuracy and the kappa statistics. Tables 3a and 3b show the summary data for expert classification accuracy assessment.

The overall accuracy for 1992 expert classification was 90% with a kappa of 0.8786. Individual class accuracy from random sampling gave a high producer accuracy assessment for dense forest and agriculture both with an accuracy of 100%. It also provided high accuracy for grassland with 96.65%. User accuracy was high for built-up and water with 100% and also high for grassland and less dense forest with 95.65% and 94.12% respectively. The 2001 classification gave an overall accuracy of 92% and a kappa of 0.8935. High producer accuracy was yielded by less dense forest, agriculture and water with 100% and 95.83% and 91.67% for grassland and water respectively. User accuracy was high for agriculture again with dense forest and water also having 100%. Less dense forest was also high with 90%.

Table 3: Expert classification accuracy assessment summary a) 1992 and b) 2001

a)

LULC Class	Reference Totals	Classified Total	Correct Number	Producer Accuracy	User Accuracy	Kappa Statistics
Df	21	24	21	100.00%	87.50%	0.8418
LDf	19	17	16	84.21%	94.12%	0.9274
Gr	23	23	22	95.65%	95.65%	0.9435
Ag	3	5	3	100.00%	60.00%	0.5876
Bu	7	5	5	71.43%	100.00%	1
Bl	15	16	13	86.67%	81.25%	0.7794
W	12	10	10	83.33%	100.00%	1
			Overall	90.00%		0.8786

b)

LULC Class	Reference Totals	Classified Total	Correct Number	Producer Accuracy	User Accuracy	Kappa Statistics
Df	17	14	14	82.35%	100.00%	0.8418
LDf	36	40	36	100.00%	90.00%	0.8438
Gr	24	26	23	95.83%	88.64%	0.8482
Ag	1	1	1	100.00%	100.00%	1
Bu	3	0	0	-----	-----	0
Bl	7	8	7	100.00%	87.50%	0.8665
W	12	11	11	91.67%	100.00%	1
			Overall	92.00%		0.8935

4. Discussion

4.1.Expert Rules and LULC Classification

Expert rules were derived from the DN's, PC's and NDVI values based on a trial and error basis following the decision tree approach. Table 4 summarizes data inputs for the first, second and third levels of class extraction. The use of the decision tree proved to have reduced the problem of spectral similarities between classes by separating and classifying individual classes on their own before combining them as one classification result as was done by Avci and Akyurek (2004).

For the first level classification, NDVI was used for the extraction of vegetation areas as it could identify and distinguish the differences between vegetation and non-vegetation areas (Hayes and Sader, 2001). Non-vegetation areas were extracted by subtracting vegetation from the study area map using the rule Sa == TRUE and V == FALSE, which was a much quicker way of extracting classes rather than extracting them separately and then combining them. In the second level classification, masked images were created from the original images (i.e. satellite, PCA and NDVI) using the vegetation and non-vegetation areas.

Creating spectrally homogenous areas within the masked images reduced spectral variability between the different classes because spectral variability present within each masked image is usually considerably less than that between classes (Avci and Akyurek, 2004). Landsat forest areas were extracted using vegetation-masked images while non-forest areas were extracted using V == TRUE and F == FALSE rule. Water was extracted using non-vegetation-masked images, which was then used to extract non-water areas (i.e. nV == TRUE, W == FALSE).

For the third level classification, forest masks were used to extract dense and less dense forest areas, non-forest masks for grassland and agriculture, and non-water masks for built-up and bareland areas. Water class was already extracted in the second level classification and there was no other sub-class to extract again in the third level. For1992 and 2001, dense forest was extracted first and then used to extract less dense forest (i.e. F == TRUE, Df == FALSE. This was due to Landsat TM data showing clear characteristics of dense forest areas then less dense.

Since grassland areas were easily distinguished for 1992, they were extracted first before agriculture, hence nF == TRUE and Gr == FALSE and vice versa for 2001. Built-up and bareland areas were extracted separately as it was quite difficult to differentiate one from the other. Landsat TM can discriminate built-up areas (Woodcock and Strahler, 1987); however, some areas had similar properties to bareland and water thus making it hard to separate and classify them.

Table 4: Summary of data inputs for expert classification

		EXPERT CLASSIFICATION	
Decision Tree Approach		Landsat TM	
Classification Level	Class Extracted	1992	2001
First Level	Vegetation	NDVI img	NDVI img
	Non-vegetation	*Sa extract *V extract	*Sa extract *V extract
Second Level	Forest	B4, PC2, NDVI Vegetation mask	B3, B4, B5 Vegetation mask
	Non-forest	*V extract *F extract`	*V extract *F extract
	Water	B7, PC1, PC2, NDVI Non-vegetation Mask	B7, PC1, NDVI Non-vegetation Mask
	Non-water	*nV extract *W extract	*nV extract *W extract
Third Level	Dense Forest	B4, PC2, PC2 Forest Mask	B3, PC1 Forest Mask
	Less Dense Forest	*F extract *Df extract	*F extract *Df extract
	Grassland	B4, PC1, PC2 Non-Forest Mask	*nF extract *Ag extract
	Agriculture	*nF extract *Gr extract	B3, B4, PC1 Non-Forest Mask
	***Built-up	B4, B7, PC1, PC2 Non-Water Mask	B3, B4, PC1 Non-Water Mask
	Bareland	B4, B7, PC1, PC2, NDVI Non-Water Mask	B1, B2, PC1 Non-Water Mask

4.2. Accuracy Assessment

Expert classification produced an overall accuracy of 90% and 92% for Landsat TM 1992 and 2001 respectively. Yang *et al*. (2007) study found that the use of PCA and NDVI improved classification accuracy; thus, use of satellite bands alone could not have obtained such results. The AA results were then compared with a supervised classification AA of the same area. Table 5 shows the overall accuracy and kappa for expert and supervised classification.

Table 5: Expert classification overall accuracy and kappa

	Overall Accuracy	Overall Kappa
	EC	EC
Landsat TM		
1992	90.00%	0.8786
2001	92.00%	0.8935

5. Conclusion and Recommendations

In this study an expert classification method was applied for LULC classification with rules formed and used with a decision tree approach. Formulation of rules and results using PCA and NDVI as additional data inputs improved classification accuracy. However, there were still difficulties in distinguishing classes such as built-up with water,bareland, grassland and agriculture at the third level of classification.

Therefore, classes such as built-up and water were sub-setted, thus additional RS data can be used to improve such classification of those classes. The quality of data and expert knowledge used to build the rules for extracting classes of a particular area of interest is important. Further studies should utilize and integrate other RS and GIS layers such as the PNGRIS (Papua New Guinea Resource Information System) and FIMS (Forest Inventory Management System), DEMs and other topographic layers.

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