LAND USE-LAND COVER INFORMATION EXTRACTION FROM HIGH RESOLUTION AIRBORNE HYPERSPECTRAL DATA

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ABSTRACT: Urban areas exhibit spectral heterogeneity at smaller scales leading to inaccurate land use-land cover (LULC) classification. Detailed LULC classification requires both high spatial and spectral resolution. Hyperspectral remote sensing or imaging spectroscopy captures information in a large number of contiguous bands for each pixel in an image. High resolution hyperspectral data, rich in both contextual and spectral information, can be used to generate detailed information about various materials and entities on the Earth's surface. Traditional pixel-based classifiers fail to distinguish between different features such as building roof types or vegetation species owing to similarity of spectral signatures leading to merging of classes. This difficulty is overcome by object based classification approach which divides the image into several homogenous objects considering the textural and spatial properties along with spectral characteristics thereby yielding a more effective, efficient and accurate classification of surface features. This study assesses the potential of airborne hyperspectral data for LULC information extraction using pixel based and object-based approaches. Preprocessing steps included geometric correction of surface reflectance image following which noisy bands were removed. Spectral Angle Mapper (SAM) and Support Vector Machine (SVM) have been used for pixel based classification while multi-resolution segmentation followed by hierarchical classification using nearest neighbor algorithm has been adopted for object based approach. Ten target classes were taken and the results for both approaches have been compared using confusion matrix parameters and Pearson's Kappa Coefficient. It was found that object based image analysis gave better classification results in comparison to SAM and SVM.

1. INTRODUCTION

1.1 Background

The natural surroundings around us such as vegetation, soil, water bodies and the built-up area created after modification of the environment make up land cover while the functional use of land by humans primarily for economic activities is emphasized upon in the concept of land use. Although the two are separate terms, they are used interchangeably (Dimyati et al, 1996). Land use-land cover (LULC) characteristics tend to affect the biogeochemical cycles and provide an important source of information for bringing out policies for sustainable development.

Satellite-based remote sensing has facilitated accurate extraction of LULC information for any type of analysis. For many decades, the air-borne ad space-borne sensors have been either panchromatic or multispectral, which give limited resolving power for observing the surface of the Earth. Technological advancements in the field of data acquisition have led to the development of hyperspectral sensors. These sensors map the planet in a large number of contiguous bands for each pixel of an image thereby enabling detailed and precise characterization of objects present in the scene. Due to rich spectral information, they can even be used for material discrimination, identification of plant species and cause of disease in crops among many other applications.

The quality of the tremendous data produced by these sensors is impacted by noise and atmospheric attenuations. Multidimensionality and volume of data is no longer a constraint in hyperspectral data processing. However, data redundancy hinders the selection of minimum number of bands with maximum information. Data analysis of hyperspectral image encompasses the use of pixel reflectance values in each of the available bands for generation of spectral reflectance curves and comparison of such curves with spectra of known materials, produced through in-situ experimentations, for material identification.

The information extraction methodologies were modified for this purpose leading to the development of full pixel classifiers and sub-pixel classifiers. Spectral Angle Mapper (SAM), introduced by Kruse et al. in 1993 is one such popular algorithm incorporated in image processing software packages for classification of hyperspectral data. In SAM, the angle between the image and reference spectra is calculated, considering them as vectors in n-dimensional feature space. The spectral similarity measured in this manner allows for fast classification of the dataset. Lower the value of the angle, higher is the spectral similarity and vice-versa. The major drawback faced by this classifier is that it assumes the endmembers chosen to classify an image by representing the pure spectra of a reference material, whereas the earth's surface is heterogeneous in many ways and consists of mixed pixels (Moughal, 2013).

Efficient differentiation of LULC classes in hyperspectral data on the basis of training pixels is not an easy task for traditional pixel based classifiers. An improvement in classification results can be obtained with Support Vector Machines (SVMs). It is a supervised non-parametric method classification algorithm based on statistical learning theory given by Vapnik in 1998. SVM separates the classes by fitting an optimal linear separating hyper plane between the classes within a multidimensional feature space. The algorithm maximizes the margin between the optimal linear separating hyper plane and the training samples closed to the hyper plane are called support vectors (Vapnik 1998; Huang, Davis, and Townshend 2002). Comparison of SVM with other pixel classifiers for hyperspectral data was done by Dai et al in 2007. The study concluded that SVM gives a superior performance when compared with other classifiers and it can work even on complex data. This fact was re-affirmed by (Zhuo and Lili, 2010) whose work states that this classifier is based on optimization technology and it gives good classification results from complex and noisy data. Only a few training samples are required from classification point of view. Due to its higher accuracy and consistency, this algorithm should be applied as an optimal classifier for extraction of land use maps.

Land cover features are represented by a group of pixels rather than a single pixel in high spatial resolution airborne hyperspectral imagery. Pixel based classifiers are unable to ascertain this fact leading to merging of classes and introduction of salt and pepper effect. In such cases, the group of pixels are considered as objects for further data processing giving rise to the term object based image analysis (OBIA). The pixels identified must be spatially contiguous and composed of similar texture, tone and color (MacClean and Congalton, 2012). The objects thus reduce the increased complexity of a high resolution scene because of shadows, change in vegetation density or similar spectral signatures of dissimilar features. Noise between ground objects is also avoided through this approach and the properties of the spectral domain are also integrated (Li and Shao, 2014). The basic principle of OBIA is image segmentation, which involves the division of an image into separate homogenous non-overlapping region on the basis of gray values of an image and texture or neighbor value of pixel (Lizarazo, et.al. 2010). One of the most popular algorithms for segmentation is multiresolution segmentation. It is a bottom-up segmentation based on a pairwise region merging algorithm (Li, et al. 2009). It starts with one pixel objects, the merging decision is based on a local homogeneity criteria, describing the similarity between neighbor image objects (Li, et al. 2009). The three basic parameters of shape, size and compactness are used for the purpose (Du Fenglan, et al. 2004). Scale determines the upper threshold limit for a change of heterogeneity throughout the segmentation process (Du Fenglan, et al. 2004). Shape parameter is composed of compactness heterogeneity and the smoothness heterogeneity (Changren, 2010). Compactness heterogeneity is used to optimize image object with regard to compactness (Du Fenglan, et al. 2004). Smoothness heterogeneity is used to optimize image objects with regard to smoothness (Du Fenglan, et al. 2004). Studies conducted using OBIA over high resolution scenes (K. Tamta, et.al. 2015; Li and Shao, 2014; P. K. Garg, 2014; Z. Zhang, et.al. 2016) demonstrate extraction of dense vegetation, water, wet land, agricultural land, informal settlements with very high accuracy thereby making this method far better than pixel based classifiers.

1.2 Objective and Research Questions

The objective of the present study is to see the potential of high resolution hyperspectral data in deriving LULC information through the use of different classification techniques.

This gives rise to the following research questions, which can be addressed through this research work:

- Which classification technique is better for extraction of LULC information from high resolution airborne hyperspectral data?
- How accurate is the derived LULC information?

1.3 Study Area

The study area taken for the research is part of the city Reno, Nevada in the United States of America. It is a commercial area and a manufacturing hub containing portions of Greg Street and S. Rock Boulevard bounded by Truckee River in the south and highway no. 668 in the north. This is shown in Figure 1.

1.4 Data Used

The dataset used for this study area has been taken through airborne hyperspectral sensor ProSpecTIR developed by SpecTIR LLC, United States of America. The date and time of data acquisition are 13 September 2009 at 12:48 pm (Central Time) respectively. The specifications of the sensor are shown in Table 1.

1.5 Software Used

Following software packages were used in this study:

- ENVI 5.0
- ArcMap 10.1
- eCognition 9.1

- MS Excel 2013

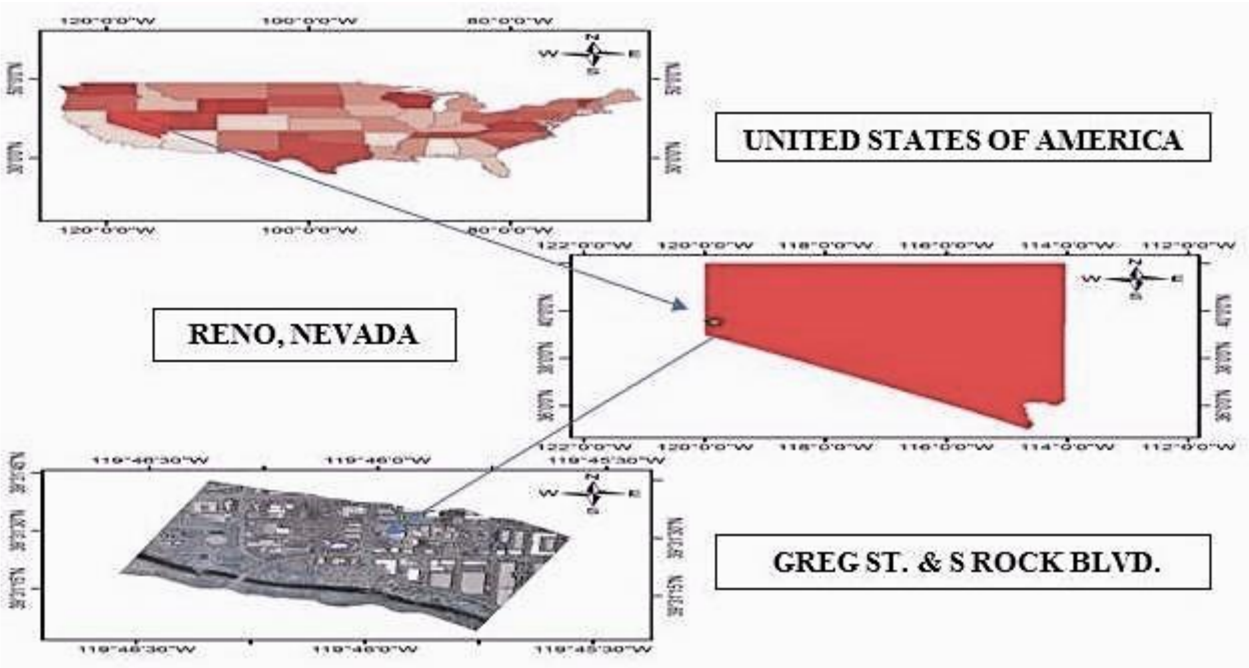

Figure 1: Study Area

Table 1: Sensor Specifications (SpecTIR Inc., 2011)

Sensor Specifications	Visible Near Infrared (VNIR)	Short Wave Infrared (SWIR)
Spectral Range	400 nm - 970 nm	970 nm – 2450 nm
Spectral Resolution	2.9 nm	8.5 nm
Spatial Pixels	320	
Spectral Channels	360 typical operation, 500 at highest operation	
Field of View (FOV)	24°	
Radiometric Resolution	12 bit	14 bit

2. METHODOLOGY

The methodology applied has the following major steps:

- Data pre-processing: Geometric Correction using Input Geometry (IGM) File; and Removal of Noisy Bands
- Classification: Feature selection; Pixel based image classification using SAM and SVM; and Object based image classification
- Accuracy Assessment

A flowchart of the methodology is shown in Figure 2.

2.1 Data Pre-processing

The dataset from ProSpecTIR has been made available after sensor and atmospheric corrections. Geometric correction was performed using the option ‘Georeference from IGM’ present in ENVI 5.0 (Harris Geospatial, 2001). Following this; bad bands were removed on the basis of visual interpretation to make the dataset ‘noise’ free. Initially the dataset contained 356 bands. Removal of Band 1, Bands 348-352 and Bands 354-356 left only 348 bands in the dataset.

2.2 Classification

Due to lack of ground truth, following LULC patterns identified from the imagery on the basis of visual interpretation were taken up as features for classification:

- Tiled Roof Structure
- Polymeric Composite Roof Structure
- Type I Metal Roof Structure
- Composite Roof Structure
- Type II Metal Roof Structure
- Road
- Parking

- Bare Ground
- Vegetation
- Water

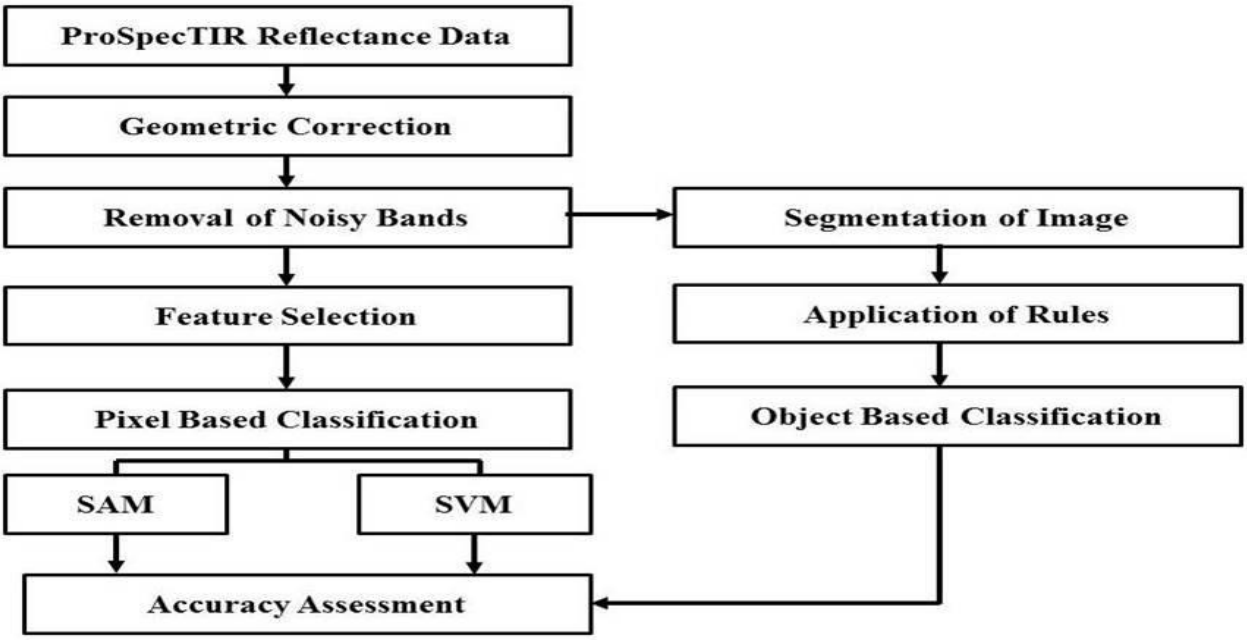

Figure 2: Methodology

Regions of interest (ROIs) of different features were taken and their characteristic spectra were plotted. This is shown in Figure 3 below.

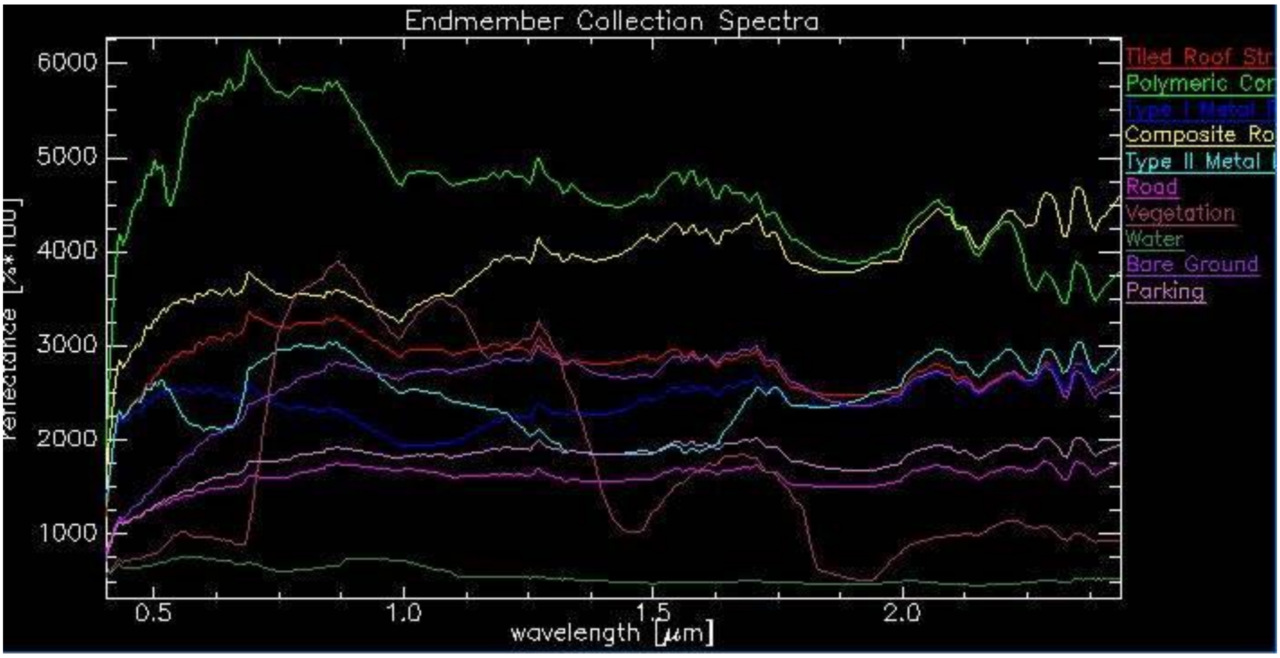

Figure 3: Spectra of Identified Features

Following this, ROIs drawn were taken as training samples for the ten target classes and pixel based classification was performed using supervised SAM and supervised SVM approach available in ENVI 5.0. Optimum classification results with maximum separability of features were obtained by keeping the angle 0.5 radians in case of SAM while in case of SVM; the best results were obtained by keeping the default parameters of radial kernel type, which are as under:

- Kernel Type: Radial
- Gamma in Kernel Function: 0.01
- Penalty Parameter:100
- Pyramid Levels: 0
- Classification Probability Threshold: 0.00

Object based image classification was performed using the software eCognition 9.1(Trimble, 2003). First of all, the image was segmented to identify image objects. The parameters taken for segmentation were:

- Scale: 130
- Shape: 0.4
- Compactness: 1.0

After this, classification was performed by applying nearest neighbor algorithm to each of the ten target classes. Mean and standard deviation of each layer have been applied as rule set for this purpose. Parameters used are sample values specifically for the study area chosen and they may vary from image to image.

2.3 Accuracy Assessment

Accuracy assessment of the thematic maps generated from the process of classification is a very important step in the process of validation of results. This was performed in the software ENVI 5.0 and eCognition 9.1. The evaluation is based on the error matrix which compares random classified pixels to reference pixels (Congalton, 1991). The metrics used are overall accuracy (OA), producer's accuracy (PA) and user's accuracy (UA). Another metric used was Pearson's Kappa coefficient, which can be defined as a multivariable statistical method and is given by (1) (Foody, et al., 2002):

$$\kappa = \frac{n\sum_{k=1}^{q} n_{kk} - \sum_{k=1}^{q} n_{k+}n_{+k}}{n^2\sum_{n=1}^{q} n_{k+}n_{+k}} \tag{1}$$

3. RESULTS AND DISCUSSION

The classified images using SAM, SVM and OBIA approaches have been shown in Figure 4, Figure 5 and Figure 6 respectively. Accuracy assessment results for SAM, SVM and OBIA approaches have been illustrated in Table 2.

Visual inspection of the classified results reveals that there is merger of water pixels with background pixels and building shadow pixels in SVM based classification causing them to be classified as water. Roads, parking area and natural features have been more effectively classified in SAM as compared to SVM. Among pixel based classifiers used, structures have been more efficiently classified in SVM. On the whole, different types of structures are more clearly distinguishable in object based classification. However, owing to high spatial resolution of the dataset, spectral signature of motor vehicles and containers have merged with that of structures rendering them as unclassified in both pixels based and object based classification.

The visual inspection results are affirmed by the accuracy assessment statistics indicating that OBIA outperforms pixel based classifiers in extraction of LULC information from high resolution airborne hyperspectral imagery.

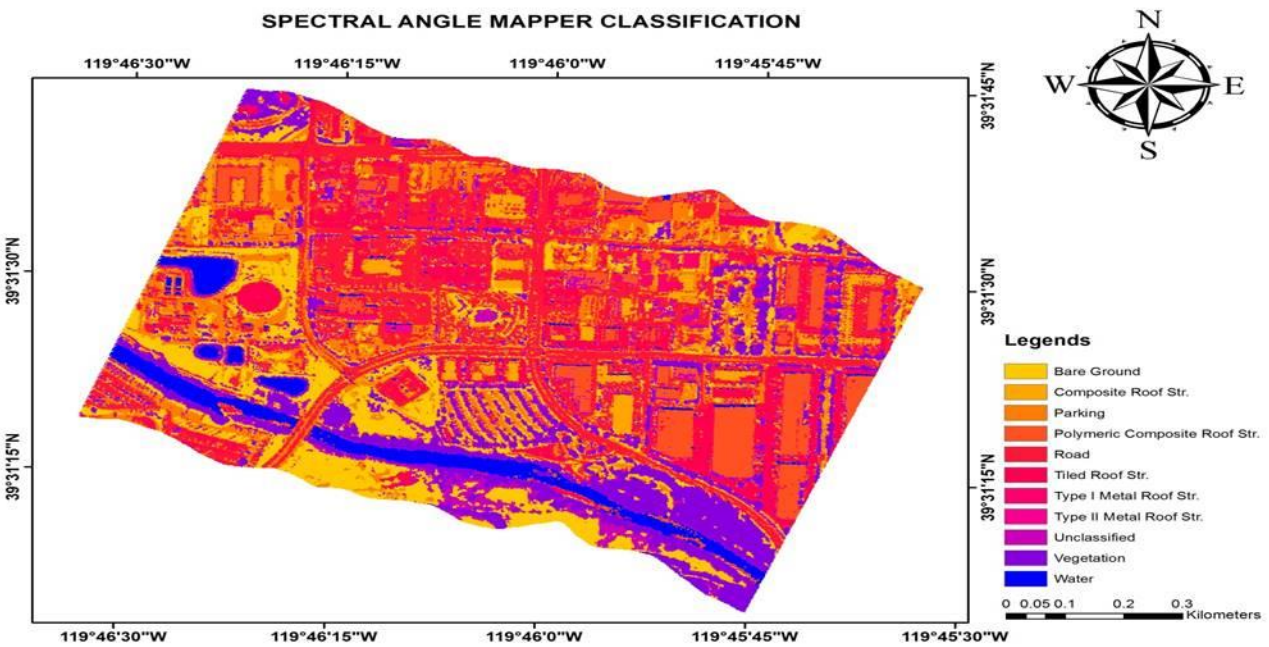

Figure 4: SAM Classification

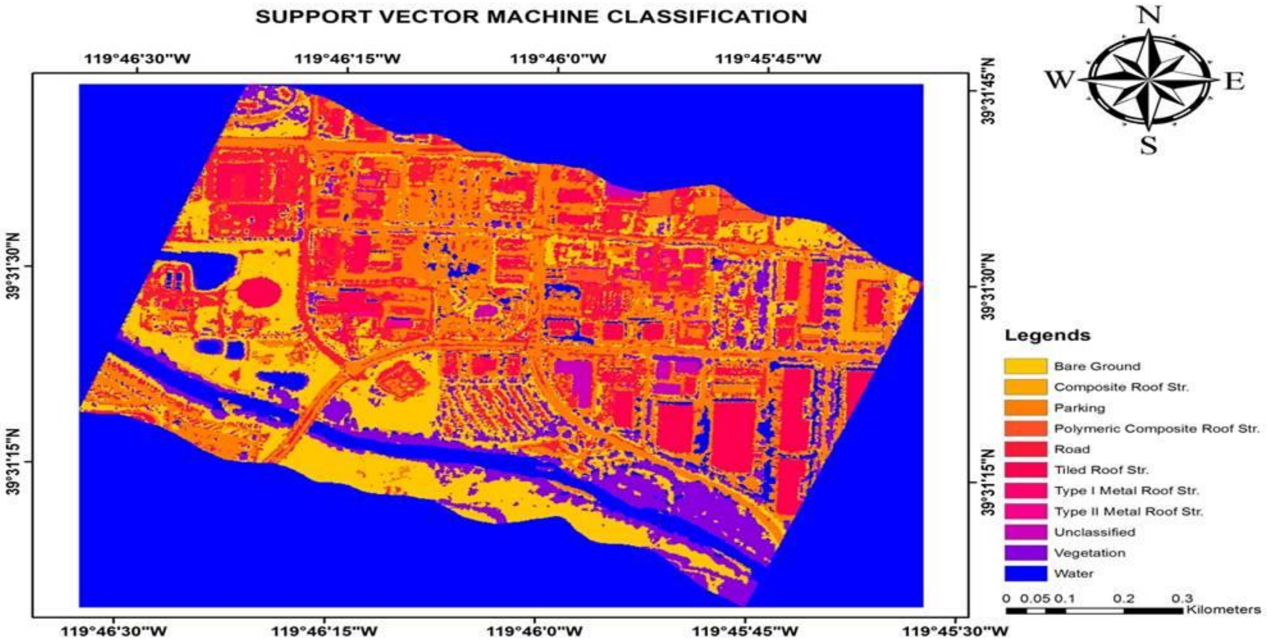

Figure 5: SVM Classification

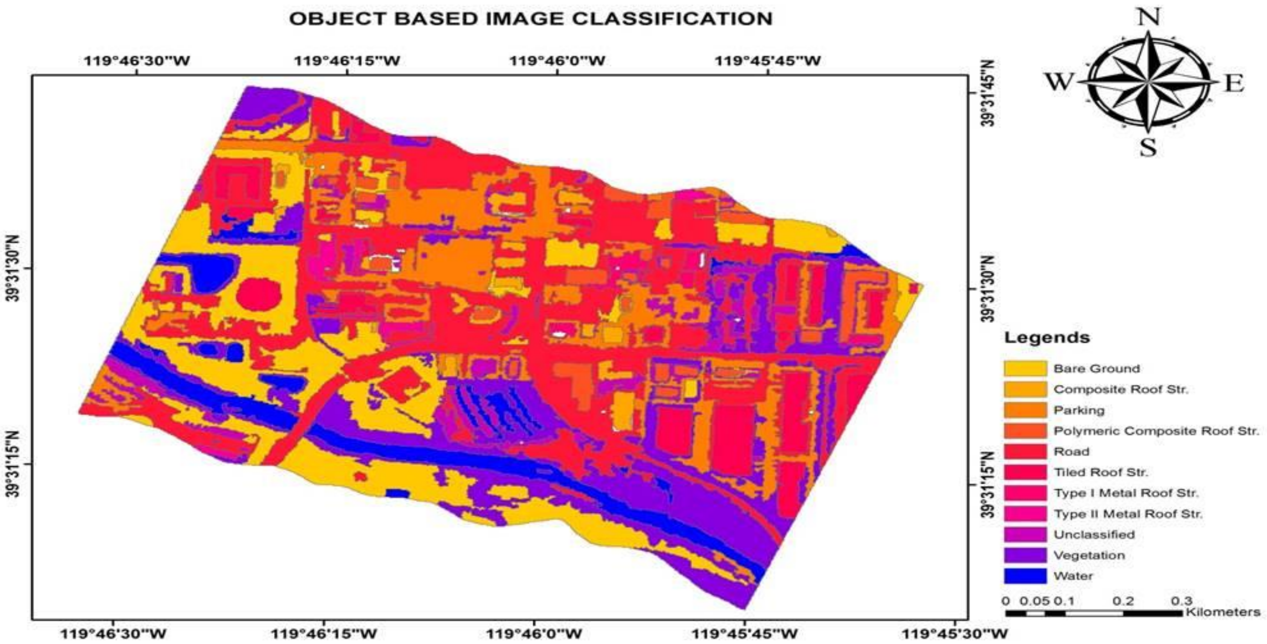

Figure 6: OBIA Classification

Table 2: Accuracy Assessment Results

Accuracy Assessment						
	SAM		SVM		OBIA	
Feature Class	**PA (%)**	**UA (%)**	**PA (%)**	**UA (%)**	**PA (%)**	**UA (%)**
Tiled Roof Str.	26.67	53.53	100	76.82	94.88	97.91
Polymeric Composite Roof Str.	80.62	21.55	48.58	91.26	96.71	98.43
Type I Metal Roof Str.	80.8	98.24	99.28	92.88	66.67	100
Composite Roof Str.	66.24	48.78	51.66	99.02	98.56	96.81
Type II Metal Roof Str.	68.42	100	71.8	100	99.87	99.04
Road	75.28	80.99	7.61	22.38	83.33	50.71
Vegetation	86.85	99.2	81.54	99.66	92.3	93.2
Water	99.54	96.42	99.91	88.39	80.11	90.65
Bare Ground	87.93	81.9	99.62	68.47	77.78	91.45
Parking	57.02	73.14	52.54	29.07	50	66.67
OA (%)	67.99		68.62		86.76	
Kappa Coefficient	0.6447		0.6455		0.852	

4. CONCLUSION

A comparative assessment of classification techniques for derivation of LULC information from high resolution airborne hyperspectral data has been performed in this work. Pixel based classifiers such as SAM and SVM and OBIA have been used to delineate ten features from the dataset and their performance has been evaluated using confusion matrix. It is found that SVM gives better results in comparison to SAM and on the whole OBIA produces the best classification results thereby displaying its potential for large scale mapping using such datasets.

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