Support Vector Machine Based Kernel Types in Extraction of Urban Areas in Uyo Metropolis from Remote Sensing Multispectral Image

Christopher E. Ndehedehe

Department of Geoinformatics & Surveying, University of Uyo, Uyo, Nigeria. christopherndehedehe@gmail.com

Abstract: Multi-spectral satellite data provides the potential for mapping and monitoring development in urban areas, but this would require the development and application of accurate techniques that will effectively extract spatial information from remote sensing data sets. This work examines the efficiency of SVM-based kernels for the quantification of the built environment from Landsat 7 imagery in Uyo metropolis, Nigeria. It is the first application of the use of SVM to classify remotely sensed data for urban studies in Uyo metropolis. 29 training sample points (pixels) representing urban areas was used for the signature development. Post-classification comparison was adopted to examine the performance of the various kernel types and the result showed that Sigmoid Kernel performed better than others in the quantification of built up areas. This SVM kernel trick has proved to be very useful in segmenting built environment from multispectral satellite images.
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Introduction

The mapping and monitoring of the spatial extent of the built environment, and associated temporal changes, has important societal and economic relevance (Goetz et al, 2003). Communities all over the world need spatial data to plan for expected future change and its impacts on infrastructure, as well as the surrounding environment. Multi-spectral satellite data provides the potential for mapping and monitoring development in urban areas, but this would require the development and application of accurate techniques that will effectively extract spatial information from remote sensing data sets.

Remotely sensed images are attractive sources for extracting land cover information because they represent an important, cheap and no time consuming font of data (Follador, et al, 2008), where an image classification algorithm is employed to retrieve land cover information (Debojit et al, 2011) but the classification of optical urban remote-sensing data has remain a challenging problem. Classifying urban areas in remotely sensed imageries is challenging because of the heterogeneous nature of the urban landscape resulting in mixed pixels and classes with highly variable spectral ranges (Wentz et al, 2010) and besides few classification algorithms exploit the spatial information contained in the remote- sensing data, the reason being the usually low resolution of the data (Fauvel, 2007). Different methods have been used for the classification of remote sensing multispectral images (see e.g. Goetz et al, 2003; Shafri et al, 2007; Ndehedehe et al, 2013a & c; Mmom and Fred-Nwagwu, 2013).

In order to enhance the level of accuracy in classifying the built environment, researchers and urban planners have continued to seek new mathematical models that can effectively quantify urban regions from multi spectral remote sensing image. Support Vector Machines (SVMs) were developed to solve classification problems (Goetz et al, 2003) and they are gaining popularity due to many attractive features, and promising empirical performance (Gunn, 1998). Over the years, it has proved undoubtedly to be one of the best-known methods to deal with the problem of both high-dimensional data and a limited training set (Vapnik, 1998 & Vapnik, 1999). SVMs are modern learning systems that deliver state-of-the-art performance in real world pattern recognition and data mining applications such as text categorization, hand-written character recognition, image classification and bioinformatics (Keerthi et al, 2006). SVMs have also been successful in dealing with situations in which there are many more variables than observations, and complexly structured data.

SVM first application in the region (Nigeria) was in modeling urban expansion in Lagos, Nigeria (Okwuashi, 2011). The research explored for the first time the use of the SVM-based model to calibrate a Cellular Automata model. The result showed that the use of kernel functions to overcome the problem of curse of dimensionality was a major advantage and that the predicted SVM results were better than those of the other unconventional methods. The satisfactory results from the SVM model showed that SVMs remain promising tools for modelling land use change of cities within the region that share similar characteristics. Several urban studies and land cover mapping carried out in Uyo metropolis, Nigeria have explored other supervised learning algorithms and unsupervised models and no mention made of SVM (Asuquo, 2011; Ndehedehe et al, 2013b; Ekpenyong, 2013).

This study is the first attempt of the application of SVM method in the quantification of the built environment in Uyo metropolis. It takes advantage on the robustness of this model to extract urban characteristics from a feature space using the various SVM-based kernels. Since SVM has proved to be better than conventional classifiers (Gualtieri, and Chettri 2000; Fauvel, 2007) and other unconventional methods (Okwuashi, 2011), the study takes a look at the performance of the different SVM kernel types adopted in the classification process for the study area. It is believed that SVM will produce reliable classification results that will give a boost to planning and development and will transform the present prevailing spontaneous planning to proactive and sustainable planning in the region. It will give more strength to further urban studies and researches on land use change in the study area. This work examines the efficiency of SVM-based kernels for the quantification of the built environment from Landsat 7 imagery in Uyo metropolis. It is the first application of the use of SVM to classify remotely sensed data for urban studies in Uyo metropolis. Here pixel based classification is applied to classify built up areas using a carefully-extracted training sample as a spectral signature of the specified region of interest. The SVM kernel type implementation was software-based and the results were validated using Orthophoto-derived vector of the study area.

The study is organized as follows; in Section 2, the basics of the support vector machines and the different kernel types are presented. Section 3 focuses on the study area and outline of the data and method incorporating the data preparation and analysis; section 4 is the discussion of results.

2.0 Principles of Support Vector Machines

Within the framework of the Statistical Learning Theory Vapnik and co-workers developed a new kind of classifiers, known as the Support Vector Machines (Vapnik, 1998). The support vector machine (SVM) represents a group of theoretically superior machine learning algorithms that employs optimization algorithms to locate the optimal boundaries between classes (Huang et al, 2002). They belong to the family of classification algorithms that solve a supervised learning problem (Fauvel, 2007) and also known as non-parametric statistical learning technique (Mountrakis et al, 2011). The mathematical formulation of SVM has already been detailed (see e.g. Vapnik 1995, 1998, Burges 1998) and so the basic principles are highlighted here and its implementation in Object Based Image Analysis is evaluated. Consider a supervised binary classification problem with the training data represented by $\{x_i, y_i\}$, i =1, 2……N and $y_i \in \{-1, +1\}$, where N is the number of training samples, $y_i = +1$ for class w_1 *and* $y_i = -1$ for class w_2. Suppose the two classes are linearly separable. This means that it is possible to find at least one hyperplane defined by a vector w with a bias w_0, which can separate the classes without error:

$$f(x)=wx+w_0 \qquad (1)$$

in locating this hyperplane, w and w_0 should be estimated in a way that $y_i(wx_i + w_0) \geq +1$ for $y_i = +1$ for class w_1, $y_i(wx_i + w_0) \geq -1$ for $y_i = -1$ for class w_2. Combining these 2 expressions we have equation 2 as:

$$y_i(wx_i+w_0)-1\geq 0 \qquad (2)$$

Many hyperplanes can be considered in the separation of the two classes but there is only one optimal hyperplane that is expected to generalize better than other hyperplanes (see Figure 1). A separating hyperplane refers to a plane in a multi-dimensional space that separates the data samples of two classes. The optimal separating hyperplane is the separating hyperplane that maximizes the margin from closest data points to the plane (Huang et al, 2002).

SVMs employ the principle of Structural Risk Minimization (SRM), which makes them robust and independent of underlying data distributions (Joachims, 1999). The goal of SRM is to search for the hyperplane that leaves the maximum margin between classes. In order to find this optimal hyperplane, the support vectors must be defined. The support vectors lie on two hyperplanes which are parallel to the optimal and are given by:

$$wx_i+w_0=\pm 1 \qquad (3)$$

From *figure 1.0* the unique hyperplane that has a maximum margin to separate the data is given as δ . Hyperplane H_1 separates class -1 while H_2 separates class +1. The three points of -1 and two points of +1 in the rectangles located on hyperplanes H_1 and H_2 are called "support vectors". In reality an infinite number of hyperplanes can be used to separate the data.

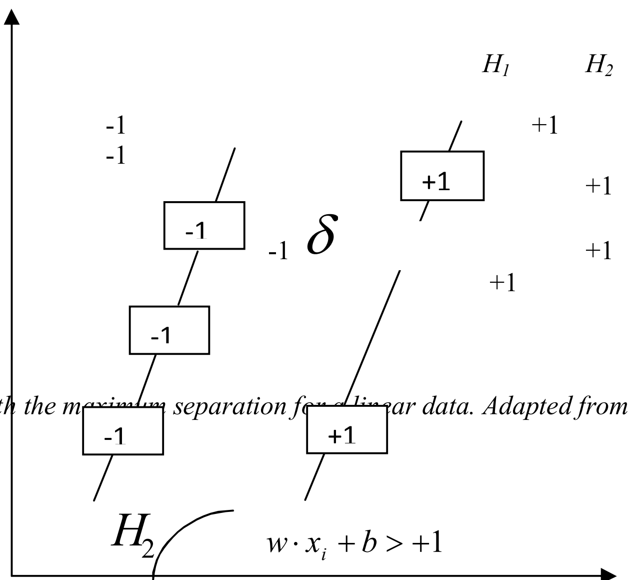

Figure 1.0 *Hyperplane with the maximum separation for a linear data. Adapted from Okwuashi (2011, p. 39)*

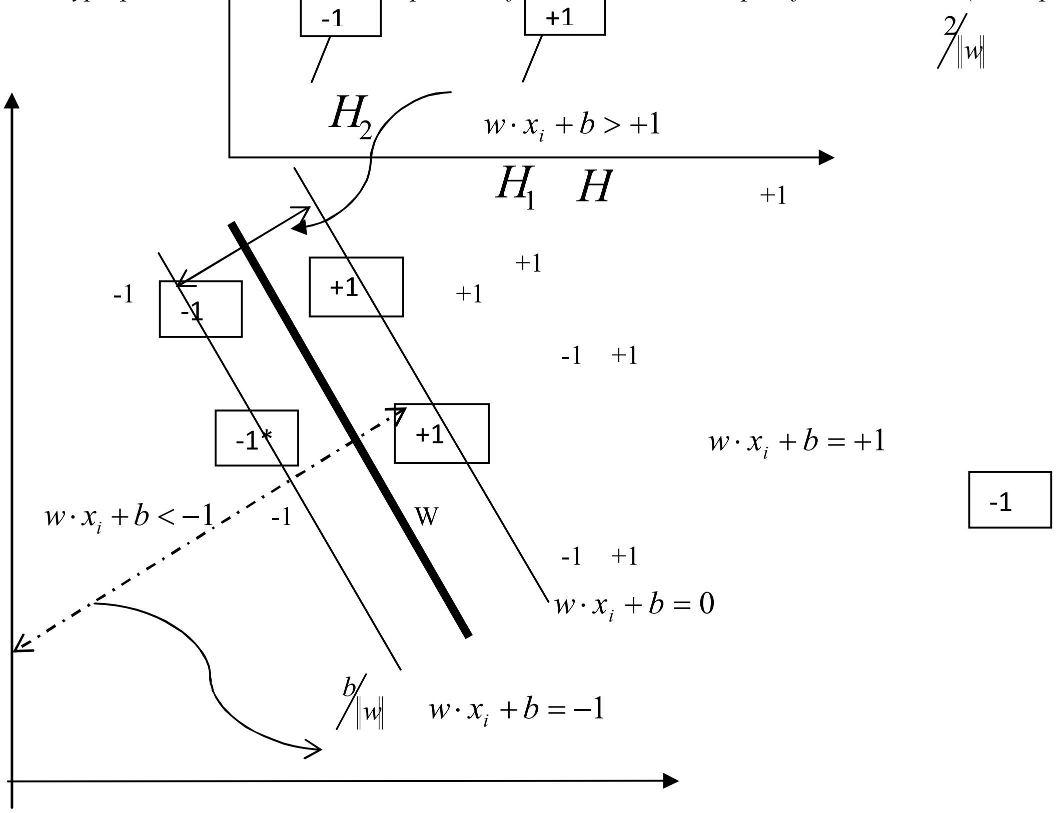

Figure 2. *The separating linear hyperplanes for a linear data. Adapted from Okwuashi (2011, p. 40)*

In figure 2, support vectors are the vectors that are non-zero that are defined by either hyperplane $w \cdot x_i + b = -1$

Support Vectors that are in class -1 or hyperplane $w \cdot x_i + b = +1$ for support vectors that are in class +1. The hyperplane H satisfies the linear classifier $w \cdot x_i + b = 0$. Other correctly classified points of -1 and +1 satisfy $w \cdot x_i + b < -1$ and $w \cdot x_i + b \geq 1$ respectively. The distance from the origin to hyperplane H is $|b| / \|w\|$. The maximum separation of $2 / \|w\|$ is required for a binary separation; b is a scalar; while w is a vector (see *details in* Okwuashi, 2011; Ivanciuc, 2007).

2.1 Support Vector Machine Kernel Types

SVMs are the most well-known class of algorithms which use the idea of kernel substitution which is referred to as kernel types in this paper. When using SVM for classification, it is important to understand how it works. In the course of training an SVM the practitioner needs to make a number of decisions ranging from how to preprocess the data, what kernel to use, and finally, setting the parameters of the SVM and the kernel. Some common examples of SVM kernel types are:

- ✓ Linear $x \cdot v$
- ✓ Polynomial $(r + x \cdot v)^d$, for some $r \geq 0$, $d > 0$
- ✓ Radial Basis Function $\exp-\gamma\|x-v\|^2$, $\gamma > 0$
- ✓ Gaussian $\exp(-1/2\sigma^2\|x-v\|^2)$

Briefly two known categories of SVM are mentioned in this work. They are linear and nonlinear classifiers.

2.1.1 Linear classifiers

Support vector machines are an example of a linear two-class classifier. One advantage of linear classifiers is that they often have simple training algorithms that scale well with the number of examples (Hastie et al, 2001 and Bishop, 2007).

2.1.2 Non Linear classifiers

The idea of linear SVM is extended to the nonlinear case when a linear classifier is not appropriate for the data set. The concept behind nonlinear SVM is to find an optimal separating hyperplane in high-dimensional feature space $\mathcal{H}$ just as we did for the linear SVM in input space (see figure 2). Examples of the nonlinear case include *Polynomial, Radial Basis Function, and Sigmoid etc.* In many applications a non-linear classifier provides better accuracy.

3.0 Study Area

The study area is a Metropolis (Uyo Metropolis) that lies within latitudes $4^0 56^1 30^{"}$ N and $5^0 07^1 40^{"}$ N, and longitudes $7^0 49^1 50^{"}$ E and $8^0 01^1 00$" E and is situated about 55 km inland from the coastal plain of South-Eastern Nigeria. The present area of Uyo Metropolis (*see figure 1*) is the capital of Akwa Ibom State of Nigeria and is about 312.6 Sq. km with a population of about 400,000 while the entire state has a population of 3.9 million. The 1991 national population census puts Uyo population density of about 1,500 people per 1 Square kilometer. Uyo local Government Area (LGA) is originally a collection of villages, now almost seamlessly joined together to form the conurbation that it is today. A nucleated settlement pattern is exhibited in the area (Ndehedehe et al, 2013). Uyo Metropolis falls within the tropical zone with a dominant vegetation of green foliage of trees, shrubs and oil palm trees.

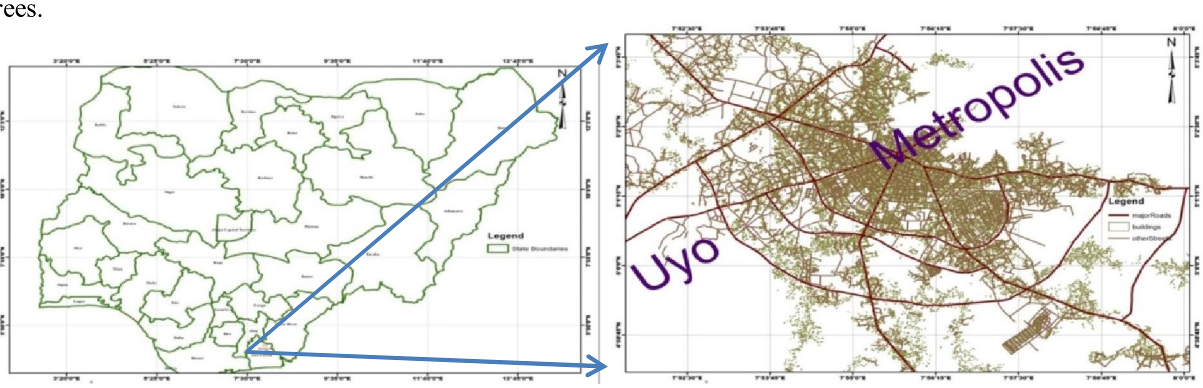

Figure 1 Location Map of the Region (Nigeria). Inset is Uyo Metropolis, the study area

3.1 Data and Method

The main focus of this study is the quantification of exact pixels representing built environment from multispectral Landsat- based imagery. An impervious surface map of the study area with very high accuracy was previously produced for this purpose. Sub-pixel estimation of Impervious Surface Areas (ISA) is done by first using the high resolution data (Orthophoto) to calculate the proportional impervious cover for the specified region of interest. Regions of Interest (ROIs) were also used to extract statistics and average spectra from groups of pixels. I created the ROIs of pixels and then examined and extracted statistics of the selected ROIs. Post-classification comparison will be adopted to examine the performance of the SVM kernel types in the quantification of urban areas in Uyo metropolis.

3.2 Data Preparation

In the present study, a processed geo-referenced remotely sensed data was used as a base for image registration. The image used for the study was extracted from Landsat 7 imagery of 2000. The image obtained was made up of three bands, viz., Band 2 (visible), Band 4, and Band 7 (infrared) which were used to create a False Colour Composite (FCC). The choice of this FCC combination is because the combination provides a "natural-like" rendition, while also penetrating atmospheric particles and smoke (Ndehedehe et al, 2013b). This combination brings out urban areas in varying shades of magenta (*figure 2b*). Pattern recognition helps in finding meaningful patterns in data (Ndehedehe et al, 2013b). Spectral pattern recognition can be improved through Digital image processing as mentioned earlier. The RGB (Red, Green and Blue) composite of band 742 was used for the classification in ENVI 4.7. *Figure 2 (a)* is an Orthophoto extraction of the study area while *Figure 2 (b)* is the Landsat 7 RGB composite of the study area.

(a)

(b)

Figure 2 (a) Extracted Orthophoto and (b) the Landsat 7 RGB composite of the study area

3.3 Data Analysis

In this study, the classified data using various SVM kernel types were vectorised and compared with the existing vector map of the same location using a GIS approach. The class statistics of the kernel methods used was extracted from ENVI 4.7 after the classification.

4.0 Results

The post classification results of the built up pixels from the 4 kernel types is indicated in Table 1. While the vectorised impervious surface maps of the study area using SVM kernel types are shown in figure 4. A classified map of the study area using the proposed SVM kernel types with the segmented map of two most performing kernel types is shown in Figure 3.

Table 1.0 Classification Results from Multi-Spectral Image

Kernel Types	*Training Pixels*	*Extracted Pixels*	*Classified Urban Segments in Hectares (Buildings and Road Polygons)*	*Percentage of Study Area (%)*	*Referenced Urban Segments in Hectares (Building Polygons only)*
Polynomial	29	28,371	1534.99	17.73	391. 33
Radial Basis Function (RBF)	29	30,256	1516.14	18.91	391. 33
Sigmoid	29	20,135	986.23	12.58	391. 33
Linear	29	31,536	1536.20	19.71	391. 33

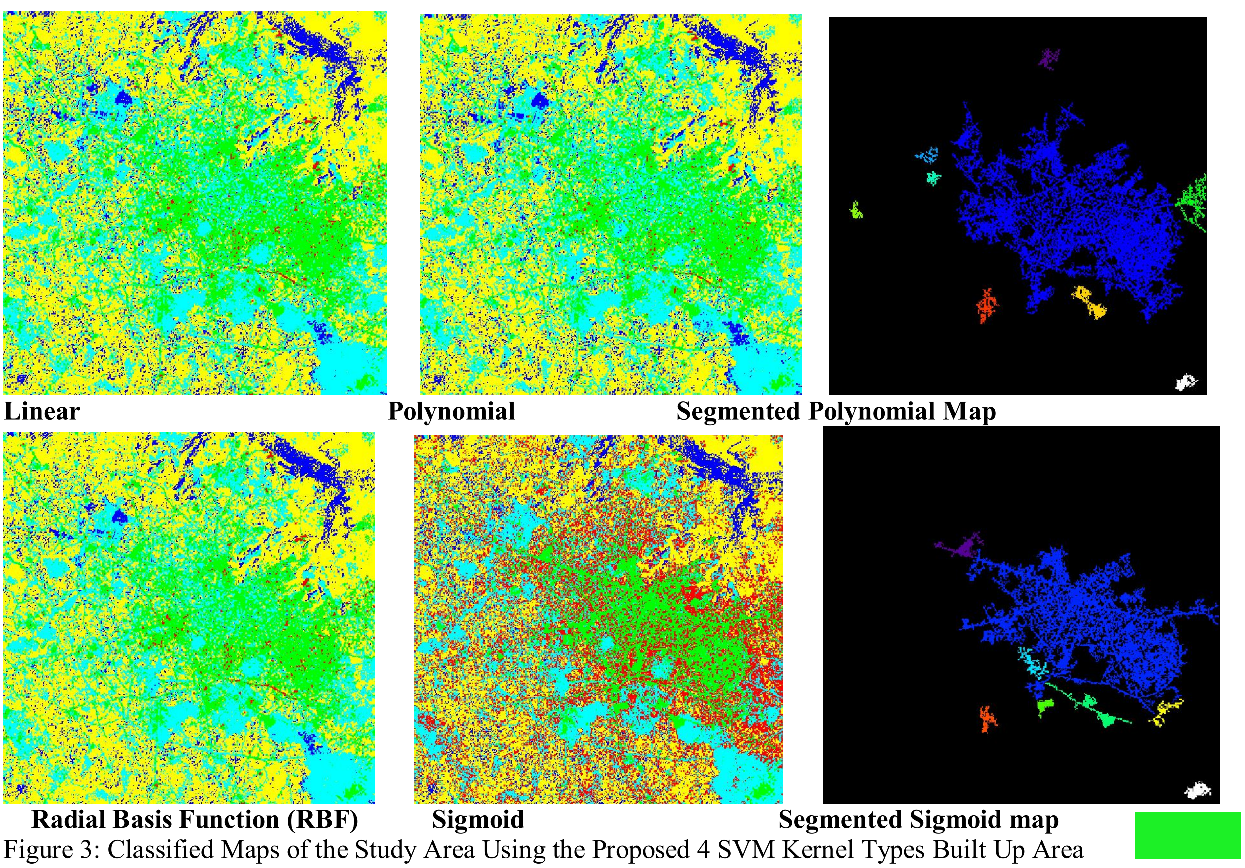

Figure 3: Classified Maps of the Study Area Using the Proposed 4 SVM Kernel Types Built Up Area

4.1 Discussion of Results

The extracted pixels from the regions of interest was examined and used for the classification of the imagery into five different classes. A total of 160,000 points representing five different land use classes were sampled for the study while the training samples used for the signature development for this study was a total of 117 randomly selected points (pixels) with 29 points representing urban areas. The previously produced impervious surface vector map sampled from a section of Uyo metropolis showed that, the total area of built up environment is 391. 33 Hectares, this area represents the building polygons only while the areas extracted by the proposed SVM Kernel methods are the impervious surface which includes building polygons and roads. The classification results of the 4 kernel types are shown in Figure 3. The classified urban segments of the various kernel types were compared with previously digitized vector of a section of the study area. The sigmoid kernel was the best because it extracted urban segment that was closer in terms of area and shape to the previously produced impervious surface vector from the Orthophoto *(see table 1.0 and figures 3.0 and 4.0)*. Nevertheless the performance of the other 3 kernels is reliable with a substantive agreement with the ground truth data *(not shown)*.

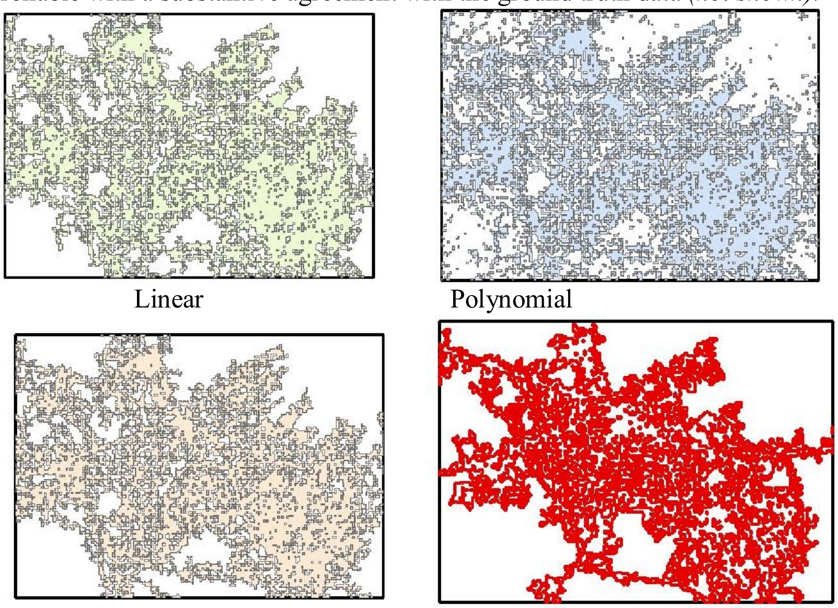

Figure 4: Vectorised Impervious Surface Maps of the Study Area Using 4 SVM Kernel Types

Conclusions

This paper looks into the performance of 4 SVM kernel types in the extraction of built up areas from multispectral remote sensing data. The classified urban segments of the various kernel types were compared with previously digitized vector of a section of the study area. The sigmoid kernel performed better than others in the quantification of built up areas. Nevertheless the polynomial, linear and RBF kernels had a good agreement with the ground truth data. The SVM Sigmoid kernel trick has proved to be very useful in segmenting built environment from multispectral satellite images.

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