Efficacy of Morphological Approach in the Classification of Urban Land Covers

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DECLARATION 2

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DEDICATION

To my beloved parents Olga, Charles and Grandma Koko Mmetsa and late Granddad Rakgolo Lesiba Thomas Tsoeleng, you gave me solid foundation to my upbringing.

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ABSTRACT

Understanding the often-heterogeneous land use land cover (LULC) in urban areas is critical for among others environmental monitoring, spatial planning and enforcement. Recently, several earth observation satellites have been developed with enhanced spatial resolution that provide for precise and detailed representation of image objects. This has generated new demand for enhanced processing capabilities. Thus, the need for techniques that incorporate spatial and spectral information in the analysis of urban LULC has drawn increasing attention. Enhanced spatial resolution comes with challenges for most pixel based classifiers. This include salt and pepper effects that arise from incapability of pixel based techniques in considering spatial or contextual information related to the pixel of interest during image analysis. These challenges have often contributed to the inaccuracy of heterogeneous LULC classification. Object based techniques on the other hand have been proposed to provide effective framework for incorporating spatial information in their analysis. However, challenges such as over/under segmentation and difficulty or non-robust statistical estimation hamper most object techniques in achieving optimum performance. Thus, to achieve optimum LULC classification, the full exploitation of both spectral-spatial information is essential. Hence, this study investigated the efficacy of Mathematical Morphological (MM) techniques referred to as morphological profiles (MP) in LULC classification of a heterogeneous urban landscape. The first objective of the study evaluated two MP techniques i.e. concatenation of morphological profiles (CMP) and multi-morphological profiles (MMP) in the classification of a heterogeneous urban LULC. Findings from this study indicated that both CMP and MMP provided higher accuracies in classifying a heterogeneous urban landscape. However, in evaluating their capability in preserving geometrical characteristics such as shape, theme, edge and positional similarity of image structures, CMP provided higher accuracies than MMP. This was attributed to the use of Principal Component Analysis (PCA) in the construction of MMP that resulted in the distorted edges of some of the image objects. However, in comparing the techniques in terms of the capability to discriminate image objects, MMP provided higher classification accuracies compared to CMP. This can be attributed to the former's capability to exploit both spectral and spatial information from very high spatial resolution imagery. Hence in the second objective, MMP was adopted due to its ability to deal with dimensionality problem associated with CMP and its superior object discrimination capability. The findings indicated that MMP significantly enhanced ML and SVM classification accuracies. Specifically, the use of MMP as a feature vector for SVM and ML classification increased LULC distinction of objects with similar spectral signatures in a heterogeneous urban landscape. This is due to its capability to provide an effective framework for synthesis of spectral and spatial information. Overall the study demonstrated that morphological techniques provides robust novel image analysis techniques which can effectively be used for operational classification of a heterogeneous urban LULC.

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CHAPTER 1

INTRODUCTION

1.1 Background of the study

Understanding the often-heterogeneous land use land cover (LULC) in urban landscapes is critical for environmental and spatial planning and enforcement (Blaschke, 2010). Hence, up to date LULC information is necessary for optimal and sustainable use of urban landscapes (Voltersen et al., 2014, Oleson et al., 2008). Traditionally, methods used for urban LULC classification involve enumeration, observation and field surveys. However, these methods are often costly, tedious, time consuming and unsuitable for large spatial extents (Meyer-Roux and King, 1992, Bosecker, 1988). The recent advancement in space based remote sensing technology provides the capability to acquire high spatial resolution images that provide opportunities for detailed and fast data collection and analysis for urban applications that require LULC delineation (Hu et al., 2016). In this regard, for timely mapping of urban LULC with significant accuracy, various techniques classified into pixel and object based approaches have been explored. However, whereas the adoption of pixel based techniques and object based approaches has gained popularity, generating good classification accuracies, particularly in urban landscapes often characterized by high landscape heterogeneity remains a challenge.

1.2 Commonly used approaches in urban mapping

Pixel-based image classification techniques are generally classified into supervised and unsupervised techniques; which differ in their statistical assumption made (Carrizosa and Morales, 2013, Entezari-Maleki et al., 2009). In unsupervised techniques, no training data or prior knowledge of the study area is required to perform the classification i.e. the image is divided into a number of classes based on natural groupings of image values (Lillesand et al., 2014, Puletti et al., 2014). Unsupervised classifiers includes simple classifiers such as iterative self-organizing data analysis (ISODATA), K-means (Blanzieri and Melgani, 2008) and recently, self-organising maps (SOM) and hierarchical clustering (Goncalves et al., 2008). Supervised classifiers on the other hand require training data to perform the classification. Supervised classifiers include simple parametric classifiers such as spectral angle mapper, maximum likelihood (ML), K-nearest neighbour and advanced classifiers such as artificial neural networks (ANN), support vector machines (SVM), decision trees and hybrid classification (e.g. semi-supervised and fusion of supervised and unsupervised learning).

The limitations related to traditional pixel based techniques can be attributed to two issues; the heterogeneous urban landscape and high spatial resolution imagery related to recent sensor advancement. Improved spatial information with ground sampling distance (GSD) less than 2m is inherent in current sensor advancements such as SPOT 6&7, Pleiades and IKONOS. Hence, such improved images are likely to have higher within class spectral variability. This higher within class spectral variability result in high interclass spectral confusion (Gong et al., 1991) or “salt and papper” effect, that contribute to the inaccuracy of the classification (Weih and Riggan, 2010, Campagnolo and Cerdeira, 2006). Advanced machine learning algorithms such as SVM, ANN and decision tree (DT) have been known to generate significant accuracy in urban LULC mapping (Duro et al., 2012). Although, these classifiers provide significantly higher accuracy, their dependence on statistical information does not allow for exploitation of spatial information from current sensor advancements. The inability to exploit spatial or contextual information related to the pixel reduces their ability to achieve optimum performance in a heterogeneous urban landscape (Lillesand et al., 2014). As an alternative, object-based image analysis (OBIA) techniques were developed to exploit contextual information inherent in current sensor advancements.

Object oriented classification is increasingly becoming popular in land cover classification, particularly for high spatial resolution dataset. This is due to OBIA techniques’ ability to utilise image spatial characteristics such as tone, shape, pattern and context, inherent in recent sensor development. Typically, there are two distinct methods that utilize spatial information from an image; region based such as Grey Level Co-occurrence Matrix (GLCM) and edge/window based technique such as Canny edge and Sobel operator. Commonly, edge-based and region based segmentation are used to partition discrete surface spectral characteristics. Edge based segmentation on the other hand seeks boundaries by distinguishing areas within the image and segments of complete enclosure by edge pixels (Zingman et al., 2012b). Consequently, pixels that characterise objects can either form part of the in-segment or constitute a segment as its boundary (Geneletti and Gorte, 2003). However, the limitations related to edge based techniques is that they are sensitive to noise, are edge based and therefore highly dependent on the analysis window which blurs the borders of textured regions (Zingman et al., 2012b, Gong et al., 1991).

Region based techniques on the other hand group image components by associating or dissociating neighbour pixels (Salih et al., 2018). These types of analysis methods work on the principle of homogeneity for similarity check such as grey level, colour, texture and shape, where neighbouring pixels inside a region poses either similar or dissimilar characteristics to the pixels in other regions. However, region based techniques take much more computation, determining the correct scale for analysis in advance is often not possible and often results in over segmentation. Thus, MM based techniques have been proposed to provide image analysis based on both statistical and structural analysis for analysing spatial relationships using all three levels i.e pixel, region and object.

In contrast to other spatial domain based analysis algorithms e.g. grey level co-occurrence matrix method (GLCM), simple statistical transformation (SST), texture spectrum (TS) and Getis statistics, morphological techniques not only base their analysis using edge based techniques, they also provide morphological profile techniques which use pixel similarity rule based on the morphological characteristics of connected components. This is similar to region growing, but it does not use statistical local properties as in region growing approaches (Pesaresi and Benediktsson, 2001). Moreover, the advantage of MM is its ability to process spatial information in an image using all three levels of analysis, pixel, region and object based (Dalla Mura et al., 2010b). In pixel based image analysis that focus on neighbouring pixel, regional scenes and object relations are taken into account (Valero et al., 2010, Benediktsson et al., 2003, Dalla Mura et al., 2010b).

1.3 Morphological image based analysis

Morphological image analysis techniques, generally referred to as Mathematical Morphology (MM), exploit spatial domain in images using various techniques based on set theory to estimate and measure many useful geometrical features such as shape, size and connectivity (Soille and Pesaresi, 2002, Tsoeleng et al., 2020). These techniques are developed based on concatenation of mathematical operations grounded in a set of operations such as union, intersection, complementation and translations (Soille and Pesaresi, 2002). These operators include erosion, dilation, opening, closing rank filters (including median filters) and top hat transforms (Pesaresi and Benediktsson, 2001). They are defined in an abstract structure known as infinite lattice (Pesaresi and Benediktsson, 2001), which is an assumption that an image consists of structures, which can be handled by set theory. This is unlike other image processing algorithms used in remote sensing data analysis.

1.3.1 Morphological Profiles and its application

Morphological techniques are of significant value for processing satellite remotely sensed images. They are also useful for a wide variety of image processing tasks such as image filtering (Soille and Pesaresi, 2002), feature extraction, segmentation (Navulur, 2006) and classification. The value of mathematical morphological algorithms has been evident in various fields such as urban built-up mapping (Benediktsson et al., 2003), road (Soille and Grazzini, 2007)) and urban land use land cover classification (Huang et al., 2014). Generally, the value of adopting morphological techniques include preservation of edge information, shaped-based analysis and computation efficiency (Huang and Wang, 2006).

Various morphological based techniques have been used in space based satellite remote sensing to extract urban land cover features. Specifically, morphological profiles (MPs) and its extensions such as extended morphological profiles (EMP), multi-morphological profiles (MMP), attribute profile (AP) and extended attribute profile (EAP) have been popular. MP is defined by a combination of morphological geodesic opening and closing operation of different sizes, of which opening and closing are constructed from sequential combination of erosion and dilation (Soille and Pesaresi, 2002). However, analysing an image using MPs often results in development of high dimensional vector and can only be used on a single panchromatic band, hence does not utilise the spectral information provided by other bands which limits discrimination of urban features. Other theoretical and practical problems include difficulties in statistical estimation, curse of dimensionality and redundancy in the vector components (Fauvel et al., 2008).

The development of MPs extensions such as EMP and EAP is due to limitations arising from the construction of the features vector (MP/AP), which can result in a high-dimensional vector where spectral information is not fully exploited. To compute for this problem, feature reduction techniques such as principal component analysis techniques and independent component analysis are used to provide joint spectral/spatial classifiers referred to as EMP or EAP respectively. However, the use of these feature vector reduction algorithms may limit the potential of EMP to preserve geometrical characteristics of an image, especially when using high spatial resolution imagery in urban areas, where these dimensionality problems are not specific. Huang et al. (2014), proposed multi-morphological profiles (MMP) generated by the concatenation of various EMPs to increase classification accuracies in urban areas. However, the use of MMP is normally based on the concatenation of EMPs generated using image feature reduction techniques such as Principal Component Analysis (PCA), which may limit the levels of structural information preservation.

It is revealed by Fauvel et al. (2008) that advances in morphological profiles have theoretical and practical problems such as difficulty in statistical estimation and curse of dimensionality. Thus, from a cursory review of literature, optimum classification of a heterogeneous urban landscape can be achieved when both spatial and spectral information are effectively exploited (Zhang et al., 2013). Thus, pixel based analysis technique, notably simple maximum likelihood (ML) and advanced support vector machines (SVM) provide better statistical estimation and do not suffer data dimensionality problems, hence may offer prospects of improved representation of a heterogeneous urban landscape when used together with MP techniques.

It is widely acknowledged that advances in sensor technologies, particularly those relating to sensor spatial resolution, have negatively impacted the ability of pixel paradigm to classify heterogeneous urban landscape. Hence, studies have been conducted that solely focus on the comparison of pixel based against object based techniques in classification of a heterogeneous urban landscape. These studies have commonly shown that object based techniques provide optimum classification compared to pixel classifiers. However, few studies have evaluated how object techniques can better be used as feature vectors for pixel based classifiers, since pixel based classifiers provide better statistical estimation which effectively offer prospects to improve classification of a heterogeneous urban land scape. In this regard, MMP are used to evaluate their efficacy in enhancing pixel based classifier's LULC classification accuracy in a heterogeneous urban landscape.

1.3.2 The problem

Urban LULC classification information is essential for scientific studies and for a wide variety of decision-making. Hence, accurate and reliable techniques/methods used for deriving LULC information is essential. Over the years, pixel and object based techniques have been used for classification of a heterogeneous urban LULC from remotely sensed imagery. However, advancement, such as increased spatial resolution in recent space based remote sensing technology provide opportunities for detailed data analysis, as well as challenges for traditional pixel based classification techniques used to extract urban LULC information in a heterogeneous urban landscape. This is typically because high resolution imagery provide increased geometrical analysis and fine representation of objects. Increased geometrical information is a challenge for pixel based classifiers because size of pixel may be smaller than the size object analysed, and pixels may not contain a single LULC class, but a mixture of classes such as roads, buildings and parking lots, making it difficult to classify a pixel as belonging to one class. Moreover, pixel based classifiers use only statistical information and cannot exploit scene spatial characteristics such as tone, shape, pattern and context; therefore reduces the ability to achieve optimum performance in a heterogeneous urban landscape. Typically, techniques that can exploit scene spatial characteristics such as tone, shape, pattern and context, other than 'colour', as in pixel based approaches, provide effective framework for analysing a heterogeneous landscape. Object based approaches such as region based and edge/window based techniques have been proposed to exploit spatial information. However, edge based techniques blur the borders of textured regions and are sensitive to noise, while region based techniques in heterogeneous images take much more computation and use statistical local properties, which often leads to over segmentation. Morphological based image analyses provide the potential to address challenges arising from OBIA and pixel based analysis using all three levels; pixel, region and object based image analysis. In this regard, we investigate the use of MP techniques in the classification of a heterogeneous urban landscape.

1.4 Aim and Objectives

The aim of this study was to assess the efficacy of morphological approach in classification of land use and land cover.

Objectives:

(i) To compare two morphological techniques in the classification of urban land cover.

(ii) To compare the efficacy of the morphological approach (i.e. the one with the highest classification accuracy above) vis-à-vis pixel based classifiers.

1.5 Research questions

i) Which morphological based technique provides a better geometrical/structural information preservation?

ii) Can morphological techniques improve the accuracy of pixel based techniques when used as feature vector?

1.6 The study area

A subset of very high resolution Pleiades data set covering Boksburg area within the Gauteng Province of South Africa was used for the Study (Figure 1.1). The study area presents a heterogeneous urban landscape, where households are increasingly placing a huge demand on the city's economic and social infrastructure. Residential areas range from luxurious and wooded suburbs to shanty towns and squatter settlements. Most of the developments are a result of urban sprawl. The subset area from the image is mostly residential with heterogeneous size and shape due to the presence of large industrial buildings. Shadows can be observed together with small ponds and pools within residential areas. Furthermore, the selection of classification categories was aimed to the need of analysis of object accuracy for morphological evaluation of a heterogeneous LULC.

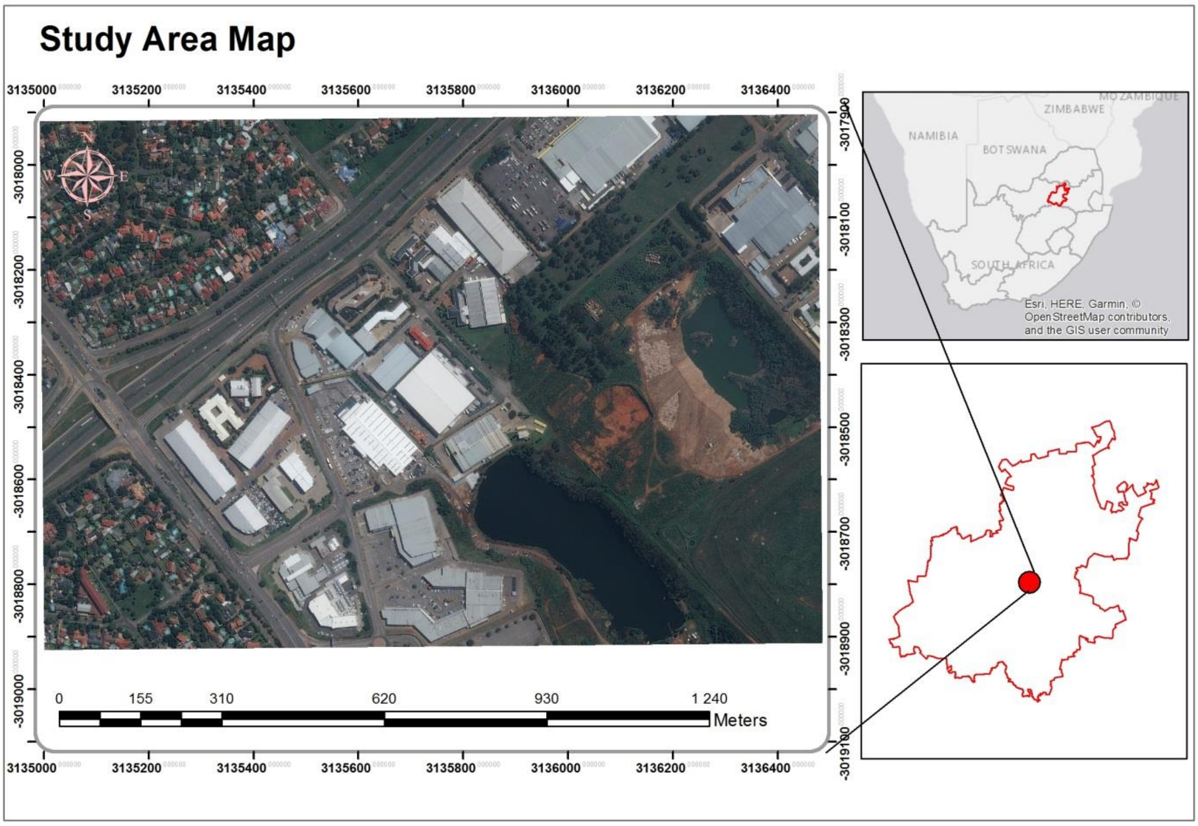

Figure 0.1: Study area map with a subset of Pleiades dataset.

1.7 Thesis Organization

Chapter 1: General Introduction

The chapter provides a general background to Mathematical Morphology, including its description, distribution and impacts, the advantages of using remote sensing data and algorithms for discriminating urban LULC. An overview of common challenges in remote sensing for pixel based classification are also briefly discussed. Additionally, research objectives, description of the study area, and the scope of the study are outlined.

Chapter 2: Literature Review

This chapter accounts for studies related to classification of a heterogeneous urban LULC. First, the chapter defines land use and land cover and gives a brief summary of traditional techniques used for LULC classification, their limitation and value of accurate LULC cover classification. It further describes the remote sensing process of capturing information about surface features, its development and the value of very high spatial resolution in classifying a heterogeneous urban area and the advantages and disadvantages of traditional remote sensing techniques. It also gives an account of the fundamental basis of Mathematical Morphological techniques used in remote sensing for various application.

Chapter 3: A comparison of two morphological techniques in the classification of urban land cover

In this chapter, two MP classification approaches are compared and results generated for the optimum classifier presented. Here, concatenation of morphological profiles (CMP) and multi-morphological profiles (MMP) classification are compared in-terms of image geometrical characteristics preservation and thematic accuracy. The one with optimum results is used in chapter four as a feature vector to enhance exploitation of spatial information for pixel based classifiers.

Chapter 4: Comparison of the performance of the Multi-Morphological Profile's effectiveness in improving urban land cover land use accuracy for Pixel based classifies

This chapter compares the use of multi-morphological profiles as a feature vector used in pixel based classifiers to perform an object based classification. This is done using two pixel based classifiers i.e. maximum likelihood and support vector machine. These classifiers are then compared with the use of maximum likelihood and support vector machine without the use of a feature vector for pixel based classification. The chapter also evaluates how MMP contributes to the enhancement in accuracy for both ML and SVM.

Chapter 5: Synthesis

This chapter presents a synthesis of the main findings of the study in chapter 3 and 4, discusses the relevance of the results, provides the limitations of the study and provide necessary recommendations for future studies.

CHAPTER 2

LITERATURE REVIEW

2 Introduction

Continuous evaluation and improvement of remote sensing techniques for urban Land Use Land Cover (LULC) classification is essential for better urban mapping, necessary for improved decision-making. Over the years, various methods generally classified as pixel or object based approaches have been used for urban LULC classification (Duro et al., 2012, Li et al., 2014). However, advancement in sensor technology, particularly image spatial resolution presents both opportunities and challenges in classifying heterogeneous urban landscapes. Hence, the role of image spatial information in land cover mapping has recently generated a lot of interest within the remote sensing community (Wang et al., 2016) . In this chapter, a review of state of the art techniques used to incorporate spatial information with emphasis on mathematical morphology is provided.

Urban areas are characterised by a complex mix of built-up and natural areas, generally referred to as urban LULC. Land cover describes the type of material or natural features of land (e.g. water, sand, vegetation, wetlands and human build structures), while land use refers to utilization of land (Barnsley and Barr, 1997). Accurate information on urban LULC is essential for urban planning and sustainable urban land-use. Hence, techniques that may optimise urban classification are necessary (Taubenböck et al., 2010).

Studies on techniques used for urban LULC classification using remotely sensed data dates back to the nineteen seventies with the launch of Earth Resources Technology Satellite (ERST1) (Blaschke et al., 2014). Since then, several earth observation satellites with improved spatial, spectral, angular, radiometric and temporal resolution have been developed. Examples of well-known earth observation missions include, Landsat TM (Thematic Mapper), SPOT HRV (High Resolution Visible), Russian SPIN, Indian IRS, Japanese Earth Resources Satellite (JERS). These developments have generated new demands for enhanced processing capabilities and stimulated new applications. Specifically, techniques that incorporate spatial information have drawn increasing attention in urban LULC mapping.

2.1 Spatial resolution and image classification

Spatial information describes how much detail can be discerned in an image. Low spatial resolution is defined by pixel with ground sampling distance (GSD) of 30 m or higher, medium 2.0-30 m, high -0.5-2.0 m and very high pixel sizes less than 0.5 m GSD (Navulur, 2006). Image Ground Sampling Distance (GSD) provides a simplification of the real world and can generally be characterized as high, medium and low spatial resolution. Typically, when the geometric resolution approaches a meter or sub-meter (high and very high resolution), spatial information of features such as geometries, texture and contextual information can be determined from images. These are valuable for urban LULC mapping (Dalla Mura et al., 2011, Prasad et al., 2011, Penn and Livo, 2002)

Generally, image classification techniques are grouped into pixel and object based approaches. Pixel based classification techniques employ pixels as the basic unit of analysis and classify individual pixels directly without taking into account the spatial or contextual information related to the pixel (Tempfli et al., 2009). Object-based classification on the other hand first aggregates image pixels into spectrally homogenous image objects using an image segmentation algorithm and then classifies the individual objects (Liu and Xia, 2010).

Table 2.1: Summary of techniques used in urban LULC classification

Classification Technique	Characteristics	Example of Classifiers	Advantages	Limitations
Pixel based	Generates individual pixels with spectral properties. Exploit scene colour.	Unsupervised (e.g. K-means, ISODATA) (Blanzieri and Melgani, 2008)	No prior knowledge of the image area is required. Relatively fast and easy to perform.	Does not consider spatial relationships in the data Can be very time consuming to interpret spectral classes. (Lillesand et al., 2014, Puletti et al., 2014)
	(Carrizosa and Morales, 2013, Entezari-Maleki et al., 2009)	Supervised parametric (e,g. Maximum likelihood, Minimum distance to means.	Generate informational classes representing features on the ground. Considers variability in the data.	Assumes Gaussianity of the data. Does not consider spatial relationships in the data.(Shalaby and Tateishi, 2007)
		Supervised Non-Parametric (e.g. Parallelepiped)	Good for non Gaussianity data and land cover features. (Duro et al., 2012)	Feature space images are difficult to interpret. (Geneletti and Gorte, 2003)

		Machine learning (e.g. simple K-nearest neighbours (KNN) & advanced artificial neural network (ANN), support vector machine (SVM), genetic algorithms(GA))	Non-parametric, pixels are classified as objects in feature space. Make no assumption about data distribution and independency. (Zhang et al., 2005, Alajlan et al, 2012)	Relies on statistical information. Therefore, does not analyse spatial information from current high resolution satellites. (Lillesand et al., 2014)
Object based	Generates image objects thorough image segmentation, exploit scene texture, shape and context. (Salih et al, 2001, Myint et al., 2011))	Edge based (e.g. standard morphology profile, morphological thinning, Canny filtering, Hough transform etc)	Algorithms are usually less complex. Edges are important features in an image to separate regions.	Dependent on window size and sensitive to noise. (Zingman et al., 2012b)
		Region based (e.g. OBIA, GLCM, morphology profiles, texture spectrum, Getis statistics)	Search for spatio-temporal patterns. Extract knowledge and relationships. (Haralick and Shanmugam, 1973, Clausi, 2002)	Depended on the accuracy of the segmentation, of which over segmentation or under segmentation can be a problem. (Liu and Xia, 2010)

Zhang et al. (2013), indicated that increased accuracy in urban LULC classification is related to an image's spatial and spectral resolution. Thus, techniques with a general framework for incorporating both spatial and spectral information in the classification process are essential. Object based techniques have been proposed by various authors (Blaschke et al., 2014, Duro et al., 2012, Myint et al., 2011) to extract spatial and spectral information in high resolution imagery, which is a limitation for pixel based techniques. However, challenges such as under and over segmentation, and difficulty or non-robust statistical estimation hamper most object based techniques in achieving optimum performance (Fauvel et al., 2008). Morphological techniques provide a viable nonlinear theory to automate the classification of urban LULC using the spatial and spectral information. Studies (Zingman et al., 2012b, Pesaresi and Benediktsson, 2001, Dalla Mura et al., 2010b, Serra and Soille) have utilised various morphological techniques for urban LULC classification. This review emphasises on mathematical morphological techniques using high resolution imagery within an urban landscape.

2.2 Spatial Domain Analysis Algorithms

Spatial domain based analysis techniques provide a new concept for urban LULC classification. Instead of considering individual pixels with spectral properties, object based methods generate image objects through image segmentation (Lillesand et al., 2014). Segmentation is the separation of one or more regions or objects in an image based on discontinuity or similarity using spectral, spatial, textural and contextual information (Myint et al., 2011). Two methods which utilise spatial information are edge and region based techniques (Gong et al., 1992). Typically, edge based technique uses point and line based detection which relies on the size of moving window. In edge based techniques, firstly, a pre-classification approach is undertaken where spatial information is used as additional band, secondly, classification procedures with logical filters are used to reduce noise in the classification results and thirdly contextual classifiers are executed (Wani and Batchelor, 1994). Region based techniques considers gray-levels from neighbouring pixels, either by including similar neighbouring pixels (region growing), split and merge, or watershed segmentation by thresh-holding (Gong et al., 1992). Region growing techniques use similarity measures by analysing the grey level difference of regions with homogeneous gray-levels, performing analysis of texture features for textured regions and shape measures for structures (Liu and Xia, 2010, Mueller et al., 2004). Compared to edge based techniques, region based techniques cover more pixels than edge based and are better in noisy images where edges are difficult to detect. In this regard, most studies have focused on region based approaches such as grey level co-occurrence matrix method (Haralick and Shanmugam, 1973, Clausi, 2002), simple statistical transformation (SST) (Gong et al., 1992), texture spectrum (TS), Getis statistics (Wulder and Boots, 1998, Myint et al., 2011, Myint et al., 2007) and mathematical morphology (Kaur and Garg, 2011).

2.3 Overview of Studies Comparing Pixel Based and Object Based Classifiers

Various studies (Li et al., 2014, Myint et al., 2011, Yu et al., 2006) have been conducted comparing pixel and object based classifiers. Yu et al. (2006), used high spatial resolution digital airborne imagery to compare pixel-based classification based on maximum likelihood (ML) with an object-based classification. Their study showed that the K-nearest neighbour (K-NN) object-based classification outperformed the pixel-based ML classification by 17%. Myint et al. (2011), tested pixel based and object based techniques in urban LULC classification using high spatial resolution imagery. The object based classifier based on nearest neighbour provided an overall accuracy of 90.40%, higher than the 67.60% using the commonly used maximum likelihood classifier. Qian et al. (2014) compared the performance of four machine learning classifiers, with an object based approach instead of using pixel based approach. The four classifiers used were support vector machines (SVM), normal Bayes (NB) and regression tree (CART) and K nearest neighbour (KNN) to classify urban land cover from WorlView-2. Four land cover types were identified i.e. impervious surfaces, vegetation, water and bare soil. Multiresolution segmentation approach embedded in Trimble eCognition was used based on the criteria of relative homogeneity. Scale, shape and compactness were customized to define the size and shape of segmented objects. SVM and NB were superior to CART and KNN in urban land classification. SVM and NB achieved the highest overall classification accuracy of 96% each, compared to 87% and 86% for CART and KNN, respectively.

Mhangara and Odindi (2013), tested the feasibility of Haralick texture based classification in urban landscapes using multispectral aerial photos. In their study, a spectral based classification was also compared to the performance of Haralick texture features for LULC classification. Grey-level co-occurrence matrix (GLCM), based on entropy, mean and angular second moment texture features were used to discriminate different LULC types. Overall accuracies of 89% and 78% were achieved for the two tests respectively. They concluded that Haralick textural features and spectral information offer great potential in mapping urban landscapes, often characterised by heterogeneous cover types. Zingman et al. (2012b), tested morphological texture contrast operator that allows detection of textural and non-textural regions to serve as an effective texture descriptor for unsupervised or supervised segmentation of textured regions. The study showed that the morphological texture contrast (MTC) descriptor is effective for localization and segmentation of high contrast textured regions. Although a single-size structuring element was used, the descriptor provides attractive segmentation of different landscapes in satellite or aerial images of half a meter resolution.

2.4 Mathematical Morphology

Mathematical morphology (MM) was first formalised by J. Serra and G. Matheron in the 1960s and is an extension of Minkowski's set theory (Soille, 2013). The approach is a non-linear method of image analysis, which can estimate and measure many useful geometric features in images such as shapes, size and connectivity based on set theory (Maragos et al., 2012, Soille, 2013, Plaza et al., 2005). Morphology refers to form and structure. In image processing, it is used to refer to the shape of a region. MM is applied to process images according to shape based on the concept of form and structure of image features. The language of MM is set theory, where set represent shapes or objects in an image (Valero et al., 2010, Dalla Mura et al., 2010b, Haralick et al., 1987).

Erosion and dilation are the two fundamental operations of MM, which essentially form the basis for all other morphological transforms (Soille, 2013, Serra and Soille, 2012, Serra and Soille, Soille, 2004, Soille and Pesaresi, 2002). Erosion shrinks image features and eliminates small objects, while dilation expands image objects (Maragos et al., 2012, Palsson et al., 2010, Serra and Soille, 2012). The several other composite relations of MM include opening, closing, conditional (geodesic) dilation, hit or miss transform, thinning and thickening and top hat transforms (Serra and Soille, 2012, Vincent and Soille, 1991). Morphological opening is defined by erosion followed by dilations using the same structuring elements and removes small or narrow elements, without affecting large ones (Dong, 1997). Morphological closing is described by a combination of dilation followed by erosion, which closes small gaps and connects sets (Shih, 2009). Most morphological operations use unique structuring element at different scales to describe an object used to probe an image to find similar objects (Soille, 2013). A structuring element is like a moving window in kernels, which is used to define a set of a known shape (e.g, square, line, circle, diamond). Mathematical operations are grounded in a set of operations such as union, intersection, complementation and translations (Soille and Pesaresi, 2002). These operators are defined in an abstract structure known as infinite lattice (Pesaresi and Benediktsson, 2001), which is more of an assumption that an image consists of structures, which can be handled by set theory. This is unlike other image processing algorithms used in remote sensing data processing, which are based on arithmetic.

Many of the morphological techniques reported in literature combine strategies of erosion and dilation in order to extract features from remotely sensed imagery. Categorizing such approaches becomes a challenge. The following section of the review present many of these different techniques starting with the fundamental properties of MM. In this section, we give a review on the use of various MM techniques in classification of urban LULC.

2.4.1 Fundamental Properties of Mathematical Morphology

The basic theory of mathematical morphology and notation of fundamental properties of morphological image transforms can also be found in the following literature (Serra and Soille, 2012, Serra and Soille, Soille, 2013, Soille, 2004, Soille and Pesaresi, 2002, Vincent and Soille, 1991, Pesaresi and Benediktsson, 2001, Haralick et al., 1987, Serra, 1986). MM techniques are commonly applied to binary (black & white, or 0&1) images. However, they are also extended to gray-scale images. A lattice theory provides a powerful tool for abstracting and understanding a number of morphological concepts and has been proven to be the foundation of MM (Maragos et al., 2012). Morphological image processing is based on two concepts of minimum $\wedge$ (infimum) and maximum $\vee$ (supremum), which are defined by the union ($\cup$) and intersection ($\cap$) operators respectively, applied within neighbourhood of every image pixel (Soille, 2013, Maragos et al., 2012, Dalla Mura et al., 2011). The only useful morphological operators are those which retain the order of images or retain their maximum and minimum order relation after transformation. A morphological filter is defined as an operator or transformation ψ, acting on a complete lattice τ, which preserves the ordering (preserve one of the basic lattice features) and is idempotent (Serra and Vincent, 1992). Hence, complete lattice is a mathematical structure that can formalise an ordering relation between image geometries, satisfying the laws of transformation ψ defined below (Serra and Vincent, 1992). A transformation ψ is (Cavallaro, 2016, Dalla Mura et al., 2010b):

- Idempotent, if is independent of the number of times is applied to an image it does not alter the results, i.e., $\psi\ (\psi\ (f) = \psi\ (f)$
- Increasing, if it does not alter the ordering relation between images. ψ
- Extensive and Anti-extensive, Extensive if, the output is always “larger” than the input and if the reverse holds then is anti-extensive. ($f \leq \psi(f)$ and $f \geq \psi(f)$
- Absorption laws. A transformation is considered an absorption property if two transformations, defined by different parameters i,j, are applied to the image, and the following relation is verified: $\psi i\ \psi j = \psi j\ \psi i = \psi \max(i,j)$.

The definitions of the laws are defined below using fundamentals of morphological operators, i.e. erosion (ε_B), dilation (δ_B), opening (γ) and closing (φ). B in both ε_B and δ_B is a structuring element. In this section, we recall the definition of opening and closing, and expand their use to include morphological profiles. All definitions are given for binary images; the set elements are members of the 2-D integer space Z^2. Where each element $f\ (x,y)$ is a coordinate of black (or white) pixel in the image. But the results can be generated for the space of gray-scale image f. In the next section morphological application is defined and its extension to grayscale image is also explained.

2.4.2 Binary and Gray-Scale Morphology

Two-dimensional digital image f is usually represented by a matrix of pixels (x, y). It is a mapping of the coordinate’s space into a space of pixel values. Let f denote a binary image Z^2 and B a binary structuring element (moving window) used to probe structures in f. Morphological erosion of set f by set B (i.e., structuring element) is defined as:

$$\varepsilon_B f = \{z \setminus (B)_z \subseteq f\} \tag{1}$$

and

This means that to perform erosion we translate B by z, if it is completely inside f erosion is anti-extensive (shrinks the input image). The basic effect of the operator on binary image is to erode the boundaries of regions

And morphological dilation is defined as:

$$\delta_{\mathrm{B}} f = \{z \setminus (B)\, z \cap f \;\neq \emptyset\} \tag{2}$$

The dilation of f by B then is the set of all displacements, z, such that B and f overlap by at least one element, which grow the structures under investigation. Dilation is extensive (expands the input image)

Using the relation between sets and images described for binary images, we can also give formulae for gray scale images. Below erosion ε and dilation δ of a digital image f with a structuring element B:

$$\varepsilon_{\mathrm{B}(f)} = \min_{(\mathrm{i,j})\in \mathrm{B}} \{f(\mathrm{x+i, y+j}) + \mathrm{B(i,j)}\} \tag{3}$$

$$\delta_{\mathrm{B}(f)} = \max_{(\mathrm{i,j})\in \mathrm{B}} \{f(\mathrm{x+i, y+t}) - \mathrm{B(i,j)}\} \tag{4}$$

2.4.3 Morphological Filtering

Filter refers to various meanings in several scientific and technological contexts. In image processing, a filter is defined as a technique for modifying or enhancing an image such as to emphasize certain features or remove other features (McAndrew, 2004). There are two types of filtering techniques used in image processing which are linear and non-linear filters (Arici and Altunbasak, 2006, Bovik, 2009) . Linear filters, namely convolution operators preserve all frequencies within a band and eliminates all others, while non-linear filters such as median filter removes the impulsive noise, without the blurring effect of linear smoothing. Two most important morphological filters are opening and closing; opening is anti-extensive and closing is extensive. Morphological filters preserve ordering relation and converge in per iteration. A filter denotes an arbitrary processing procedure having signal/image both as an input and an output. The sequential combination of erosion and dilation leads to morphological opening and closing transformations, respectively (Serra and Vincent, 1992). Morphological filters are basically object-oriented transforms; they focus on the processing of the image on areas with shape and size defined by the structural element (SE) (Dalla Mura et al., 2010b). The erosion followed by dilation denotes a morphological opening γ, and dilation followed by erosion denotes morphological closing φ. Opening generally smooth the contour of an object, breaks narrow object as defined below.

$$\gamma(f) = (f \ominus B) \oplus B \tag{5}$$

Similarly closing f by B is the dilation of f by B followed by erosion of the result by f

$$\varphi(f) = (f \oplus B) \ominus B \tag{6}$$

2.4.4 Connected Components

Connected components also referred to as "flat zone" defines a set of connected iso-intensity pixels (Dalla Mura et al., 2010b). Connected components probe an image, pixel by pixel in order to identify connected regions, i.e. regions of adjacent pixels which share the same set of intensity values for binary image. Connected components in gray-level images measure connectivity within an image using different measures of connectivity of four or eight in 2D images (Soille and Vogt, 2009, Serra and Soille, 2012, Dalla Mura et al., 2010a). Two pixels are connected according to a connectivity rule. Common connectivity rules are the four and eight connected, where a pixel is said to be adjacent to four or eight of its neighbouring pixels, respectively (Serra, 1998). Connected operators are also supremum of opening or infimum of closing.

2.4.5 Morphological Reconstruction

Morphological reconstruction, often referred to as geodesic operation is a useful method for extracting meaningful information about shapes in images. This include extracting marked objects, finding dark regions surrounded by bright objects, detecting or removing objects touching the image border and many other operations (Gonzalez et al., 2004). Reconstruction transformation involves the use of two images and a structural element (instead of a single image and structuring element). Transformations are usually applied to binary images, but can also be extended to grayscale images, where it extracts the connected components of an image which are marked by another image. The marker image illustrates the starting point for the transformation and the other image constrains the transformation. A structuring element *B* defines connectivity where either a four or eight connectivity is used. Reconstruction is presented using the notion of geodesic distance. Therefore, geodesic erosion and dilation is defined below. If g is the mask and f is the marker, the geodesic erosion is defined as the minimum ordinary erosion that constrains the restraining boundaries.

$$\varepsilon_B(f) = min\ (\varepsilon(f), g) \tag{7}$$

$$\delta B(f) = max\ (\delta B(f), g) \tag{8}$$

2.4.6 Opening and Closing by Reconstruction

Interaction of the morphological operations until stability occurs is called reconstruction by erosion and reconstruction by dilation. Opening by reconstruction $\gamma*$ of image f is the combination of erosion ε_B followed by geodesic dilation with $\delta_{B1\ (SE=B1)}$ iterated until stability is reached. If the reverse holds that is reconstruction by dilation $\varphi*$, in this case geodesic erosion as $\varepsilon_{B1\ (SE=B1)}$ is used after dilation until idempotence. Where, in opening by reconstruction, erosion typically removes small objects and dilation tends to restore the shape of the objects that remain and in closing by reconstruction $\varphi*$. Structures turn to grow at their boundaries and geodesic erosion ε_{B1} will constrain this growth in a way that structures do not grow outside the pre-defined boundaries. Therefore, the definition of opening and closing by reconstruction for grayscale discrete image f is given below.

$$\gamma B(f) = \delta_B\ [\varepsilon B(f)] \tag{9}$$

$$\varphi B(f) = \varepsilon_B\ [\delta B(f)] \tag{10}$$

Morphological opening and closing without applying reconstruction transformations lead to severe effect, where at times geometrical characteristics of the structures can be distorted or completely lost or structure grow at their boundaries, especially when a large structuring element is used with respect to structures in the image. Applying reconstruction to an operation constrains this growth in a way that structures do not grow outside of some pre-defined boundaries. The results obtained with operators by reconstruction are less dependent on the shape of the selected structuring element than in the case of morphological opening and closing (Dalla Mura et al., 2010b).

2.4.6.1 Alternating sequential filters

Alternating sequential filters are morphological transform that process an image using size distribution called granulometry by a combination of iterative morphological filters (opening and closing) with increasing sizes of structuring element. In the previous section, opening removes objects related to the size of the structuring element from an image, so it seems logical to use opening and closing of various sizes to study size distribution of an image. They extract the geometrical characteristics of objects by offering a hierarchical structure. However, in this study, alternating sequential filters are not used because operators by reconstruction produce more accurate results as compared to alternating sequential filters (Salembier Clairon et al., 1998).

2.4.6.2 Attribute filters

Morphological attribute filters represent an adaptive morphological analysis technique which transforms an image by merging its connected components, using a series of attribute thickening and thinning operators. These filters are morphological transformations that process an image according to criterion (Dalla Mura et al., 2010a). The criterion is evaluated on each connected component of the image. If the criterion is verified, then the component is preserved. If it is not verified, then component is removed. These filters belong to a family of connected components.

2.5 Studies on MM techniques used in classification of urban land use and land cover

Various morphological based classification techniques have been used in LULC mapping. Pesaresi and Benediktsson (2001), proposed the use of morphological profiles (MP) on Very High Resolution (VHR) panchromatic band images based on morphological segmentation by the derivative of the morphological logical profile. The MP was based on the use of residuals from opening and closing by reconstruction using two panchromatic bands with 5 m geometric resolution of the Indian Remote Sensing 1C (IRC-1C) data. The approach is different from standard morphological segmentation approaches, which are based on edge-detection. The approach uses pixel similarity rule based on the morphological characteristics of connected components, similar to region growing, but does not use statistical local properties as in region growing approaches. Benediktsson et al. (2003) used six classes (large buildings, small buildings, broad streets, narrow streets, open areas and residential lawns) in an urban area using high-resolution panchromatic band from Indian Remote Sensing 1C (IRS-1C) and IKONOS remote sensing data. The morphological opening and closing by reconstruction was applied in experiments, where a 17-dimensional morphological profile was created using circular morphological structuring element with an increasing diameter and included both discriminant analysis feature extraction (DAFE) and decision boundary feature extraction (DBFE) to enhance separability. A neural network was used to classify the data. The results indicated that reconstruction approach has a better shape preservation than classical morphological filters. The accuracy of the classification was 69.4% and 88% respectively. Palmason et al. (2003b), constructed morphological profile (MP) from a base image of the first principal component (PC) created from spectral information of a high spatial and spectral resolution DAIS 7915 data. The MPs were constructed based on a circular structuring element with increasing radius and applied the Decision Boundary Feature Extraction (DBFE) and Discriminant Analysis Feature Extraction (DAFE) on the morphological profile. The data was classified using neural networks, both with and without a feature extraction scheme. The classification accuracy for individual classes before and after DBFE from MPs provides significantly higher accuracies of 87.2% NOFE and 89.9% DBFE, as compared to 87.2% for MP without FE and 80.9% DAFE and 89.9% DBFE for the morphological processing of the first PC. Bellens et al. (2008), proposed a morphological profile using two structural elements of a disk-shaped and a linear structuring element with differing orientations which generated directional profiles. The proposed reconstruction approach called partial geodesic reconstruction leads to reaching a trade-off between the preservation of the objects geometries and a reduction of the over segmentation effect introduced by standard reconstruction. Panchromatic bands from IKONOS and Quickbird imagery were used for the analysis, and achieved an increase in overall accuracy of 2% and 7%, compared to standard reconstruction approach. Palsson et al. (2010), compared land cover classification accuracies of Morphological Profiles (MP) and Derivative of Morphological Profiles (DMP). The two MM techniques were tested on panchromatic (PC), 3 bands+PC, 4 bands+PC of IKONOS data and classified using support vector machine (SVM). They also used Intensity Hue Saturation (IHS) and brovey fusion techniques for testing if they could increase the accuracy. The DMP gave slightly better results than MP with PC 46. 2%, 3 bands+PC 58.7%, 4 bands+PC 66.5 % and 67.1%. However, the inclusion of IHS and brovey fusion methods did not increase the accuracy with 59.2 % and 59.6 % overall accuracies, because the fusion methods are not spectrally consistent.

Dalla Mura et al. (2009), proposed morphological attribute profiles for performing a multilevel analysis based on operators of connected opening and trivia opening, and compared them with operators by reconstruction using a VHR panchromatic image for the analysis. AP were considered computationally more efficient than operators by reconstruction, due to the fact that different attributes used in the transformation lead to different modelling of the spatial information contained in scene. This increases the flexibility with respect to filters based on structuring elements. These filters are usually constrained to perform an analysis based on the size of the structures. Fauvel et al. (2008) proposed an Extended Morphological Profiles (EMPs) based on PC from hyperspectral data Reflective Optics System Imaging Spectrometer (ROSIS-03) and used feature extraction (FE) algorithms based on decision boundary FE (DBFE) and nonparametric weighted FE (NWFE) to select informative features from spectral and spatial domain. Three principal components (PCs) were computed from hyperspectral data, and four openings and closings computed for each PC using a circular structuring element (SE) with a step wise increment of two. The use of FE improved the classification accuracy as compared to MP. EMPs outperformed other classifiers with overall accuracy of 97.69%. Cavallaro et al. (2014), compared Attribute Profiles (AP) and Self-Dual Attribute Profiles (SDAP) based on attribute area, Standard Deviation (SD) and Moment of Inertia (MI) using differing threshold values. The techniques where tested on PAN+MS, MS+AP and MS+SDAP from QuickBird satellite and data classified using random forest classifier. The SDAPs provide the capability in modelling spatial information within heterogeneous scenes, proving slightly high values for classification accuracy of 95.38 % based on area, 92.89 % MI and 94.72 % SD, as compared to 94.60% area, 92.64 MI and 93.07 % SD of AP. Huang et al. (2014) proposed a new Morphological Profile (MP) based on Multiple Morphological Profiles (MMP) of Extended Morphological Profiles (EMPs) and Extended Attribute Profiles(EAPs) using four categories to create base image for MPs, (1) Linear transforms based on Fast Independent Component Analysis (ICA) and Factor Analysis (FA) for MPs, (2) Nonlinear transforms based on kernel-based transforms, Kernel Principal Component’s Analysis (KPCA) and Kernel Nonnegative Matrix Factorization (KNMF), (3) Manifold learning based on Locality Preserving Projections (LPP) and Neighbourhood-Preserving Embedding (NPE) (4) and used a linear support vector machine classifier (LSVM). EAPs gave higher classification accuracy as compared to EMPs for university data area. However, the EAPs and EMPs results for Pavia Centre Dataset were similar in overall accuracies of PCA 98.9%, Joint Approximation Diagonalization of Eigenmatrices (JADE_ICA) 98.6%, Fast-ICA 98.8, FA 98.2%, KPCA96.8, KNMF97.3%, LPP98.0%, NPE96.9%,Multilinear Principal Component Analysis (MPCA) 98.4% for EAPS and PCA 97.8%, JADE_ICA 98.0%, Fast-ICA 98.4%, FA97.7%, KPCA97.9%, KNMF96.6%, LPP 97.9%,NPE97.3%, MPCA98.2% for EMPs. The MMPs was found to enhance the classification accuracy by synthesizing the spectral-spatial information extracted from the multicomponent base images. Song et al. (2014), proposed extended multi-attribute morphological profiles (EMAP), which are an extension of attribute profiles (APs) obtained using different types of attributes and stacked together. EMAP offer the potential to model structural information in great detail according to different types of attributes. The study was carried out using both multispectral Quick bird and hyperspectral data set Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS). A comparison with state-of-the-art classifiers showed very promising results for the proposed approach, particularly when a very limited number of training samples are available.

2.6 Conclusion

The literature review indicates various techniques used for image classification using high spatial resolution. The review shows that Morphological profiles based on MPs, DMPs and EMPs are very effective in extracting informative spatial features from images using either a compact disk or square structuring element, which proved to be effective in modelling size of objects in images. The EMPs proposed by Pesaresi and Benediktsson (2001) for application in panchromatic images using pixel similarity based on morphological characteristic of connected components with a circular SE provided significant accuracy compared to standard MP, which are based on edge detection. In the study conducted by Dalla Mura et al. (2010b), authors indicated the limitations arising from multi-scale processing of MPs, DMPs and EMPs. Although these techniques have proven to be effective in extracting informative spatial features from analysis images, the limitation of filters based on structuring element lies in their incapability to model other features than the size of the objects. Similar to the use of two SE of a circular and a linear structural element for computation of MPs, the drawback still lies on the inability to practically investigate the length of orientations within the SE. Therefore, Dalla Mura et al. (2009) proposed the attribute profiles (AP), which are based on operators of connected opening and trivial opening. The filters represent an adaptive morphological analysis technique which implements a series of attribute thickening and thinning operators on connected components (Huang et al., 2014). APs provides flexibility in-terms of processing image based on many different types of features such as purely geometric, textural, and contrast based analysis, using analysis techniques based on area, moment of inertia and the standard deviation.

Huang et al. (2014) compared the performance of different feature extraction methods for the generation of base images from hyperspectral imagery and found that both EMP and EAP provide similar accuracies when concatenation of either EMP or EAP is used to form multi-morphological profiles (MMP). However, the use of linear image transforms such as PCA in the formation of EMP has an impact on the preservation of structural objects, which may distort edges of objects. The reconstruction and connected components approaches have proved to have a better shape preservation than classical standard morphological filters based on edge-detection. However, when reconstruction and connected components analysis are combined with linear image transform, they may lead to distortion on image objects. In this regard, can reconstruction approaches without the use of PCA, perform better than reconstruction approaches combined with PCA? And secondly, can MM approach, one with the highest classification accuracy, provide improved accuracy when compared to conventional pixel and object based classification techniques used for urban LULC?

CHAPTER 3

A Comparison of Two Morphological Techniques in the Classification of Urban Land Cover

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Abstract

Understanding the often-heterogeneous land cover in urban areas is critical for, among others, environmental monitoring, spatial planning, and enforcement. Recently, several earth observation satellites have been developed with an enhanced spatial resolution that provides for precise and detailed representations of image objects. Morphological image analysis techniques provide useful tools for extracting spatial features from high-resolution remotely sensed images. This study investigated the efficacy of mathematical morphological (MM) techniques in the land cover classification of a heterogeneous urban landscape using very high-resolution pan-sharpened Pleiades imagery. Specifically, the study evaluated two morphological profiles (MP) techniques (i.e., concatenation of morphological profiles (CMPs) and multi-morphological profiles (MMPs)) in the classification of a heterogeneous urban land cover. The overall accuracies for CMP were 83.14% and 83.19% over the two study areas. Similarly, the MMP overall accuracies were 84.42% and 84.08% for the two study sites. The study concluded that CMP and MMP can greatly improve the classification of heterogeneous landscapes that typify urban areas by effectively representing the structural landscape information necessary for discriminating related land cover classes. In general, similar and visually acceptable results were produced for land cover classification using either CMP or MMP image analysis techniques.

Keywords: land cover; urban classification; morphological image analysis; morphological profiles; satellite imagery; principal components analysis.

3.1 Introduction

Understanding the often-heterogeneous land cover in urban areas is critical for environmental management, urban spatial planning, and optimal and sustainable use of urban landscapes (Blaschke et al., 2014, Oleson et al., 2008, Voltersen et al., 2014). Traditionally, methods used for urban land cover classification involve enumeration, observation, and field surveys.

However, these methods are often costly, tedious, time-consuming, and unsuitable for large spatial extents (Bosecker, 1988, Meyer-Roux and King, 1992). The recent advancement in space-borne remote sensing technology provides the capability to quickly acquire high spatial resolution images that provide opportunities for detailed analysis for urban applications such as the often-challenging urban land cover delineation (Hu et al., 2016). Hence, to increase the accuracy of urban landscapes, the recent proliferation of high spatial resolution sensors necessitates a further exploration of various techniques commonly classified into pixel and object-based approaches.

Pixel-based image classification techniques have been widely adopted for land cover delineation (Carrizosa and Morales, 2013, Entezari-Maleki et al., 2009, Lillesand et al., 2015, Puletti et al., 2014, Goncalves et al., 2008, Shalaby and Tateishi, 2007, Mhangara and Odindi, 2013, Alajlan et al., 2012, Zhang et al., 2010). Most pixel-based classification methods only utilize the spectral information in the pixels for classification of land cover. Notably, the efficacy of spectrally based pixel-based techniques is limited by landscape heterogeneity typified by urban areas and the ever-increasing suite of high spatial resolution imagery associated with recent sensor advancement. Improved spatial information with ground sampling distance(GSD) less than 2m, for instance, is inherent in current sensor advancements, such as SPOT6&7, Pleiades, and IKONOS, and is likely to increase within class spectral variability and inter-class spectral confusion, hence lower classification accuracies (Campagnolo and Cerdeira, 2018, Gong et al., 1991, Weih and Riggan, 2010). Whereas advanced machine learning algorithms such as support vector machine, artificial neural network, and decision tree have been known to generate significant accuracy in urban land cover mapping (Duro et al., 2012), their dependence on statistical information does not allow for exploitation of the rich spatial information that characterize the high spatial resolution sensors. According to Lillesand et al. (2015), their inability to exploit spatial or contextual information related to the pixel impedes optimum performance in a heterogeneous urban landscape. As an alternative, object-based image analysis (OBIA) techniques were developed to exploit contextual information inherent in heterogeneous landscapes. The increasing popularity of OBIA is attributed to their ability to utilize image spatial characteristics such as tone, shape, pattern, and context. Typically, two distinct methods utilize spatial information from an image: region-based, such as the Grey Level Co-Occurrence Matrix (GLCM), and edge/window-based techniques, such as the Canny edge and Sobel operator. Commonly, edge-based and region-based segmentation are used to partition discrete surface spectral characteristics. Edge-based segmentation, on the other hand, seeks boundaries by distinguishing areas within the image and segments of the complete enclosure by edge pixels (Zingman et al., 2012a). Consequently, pixels that characterize objects can either form part of the in-segment or constitute a segment as its boundary (Geneletti and Gorte, 2003). However, the major limitations related to edge-based techniques are insensitivity to noise and are edge-based, hence they are highly dependent on the analysis window which blurs the borders of textured regions (Gong et al., 1992, Zingman et al., 2012a).

Morphological image analysis techniques, generally referred to as mathematical morphology (MM) (Soille and Pesaresi, 2002), exploit the spatial domain in images using various techniques based on set theory to estimate and measure many useful geometrical features such as shape, size, and connectivity (Zingman et al., 2012a, Soille and Pesaresi, 2002). These techniques are developed based on concatenation of mathematical operations grounded in a set of operations such as union, intersection, complementation, and translations (Soille, 2013, Soille and Pesaresi, 2002). These operators include erosion, dilation, opening, closing rank filters (including median filters), and top hat transforms (Pesaresi and Benediktsson, 2001). They are defined in an abstract structure known as an infinite lattice (Pesaresi and Benediktsson, 2001), which is an assumption that an image consists of structures which can be handled by set theory. Morphological image analysis techniques provide useful tools for extracting spatial features from high-resolution remotely sensed images (Oleson et al., 2008, Voltersen et al., 2014, Bosecker, 1988, Meyer-Roux and King, 1992). These techniques include a family of morphological profiles (MPs) and its advances that include extended morphological profiles (EMPs), derivative of morphological profiles (DMPs), multi-morphological profiles (MMPs), concatenation of morphological profiles (CMPs), attribute profiles (APs), and extended attribute profiles (EAPs) (Bosecker, 1988, Meyer-Roux and King, 1992, Hu et al., 2016, Carrizosa and Morales, 2013, Entezari-Maleki et al., 2009). These MP techniques process images based on many different types of features such as purely geometric, textural, and contrast-based analysis (Huang et al., 2014). Morphological-based image analysis has the potential to address challenges arising from pixel-based and OBIA by integrating the pixel, region, and object-based image analysis (Manandhar et al., 2009, Lizarazo, 2014, Lizarazo and Elsner, 2009, MacLean and Congalton, 2012, Foody, 2004). Hence, the objective of this study was to test the efficacy of CMP and MMP's ability to preserve structural information as well as discriminate land cover classes in a heterogeneous urban landscape.

3.2. Materials and Methods

The experiments were carried out using Pleiades datasets over two areas: Boksburg in Ekurhuleni and Sunninghill in Johannesburg, both within the Gauteng Province of South Africa (Figure 3.1). The two cities constitute the fastest growing urban areas on the African continent, mainly attributed to migration from other parts of the country and the continent. The cities are characterized by a heterogeneous urban landscape, where households are increasing hence placing a huge demand on their economic and social infrastructure. Residential areas range from luxurious wooded suburbs to shanty towns and squatter settlements. The two subset images used in this study contain the typical urban landscape that include residential and industrial buildings, roads, and vegetation.

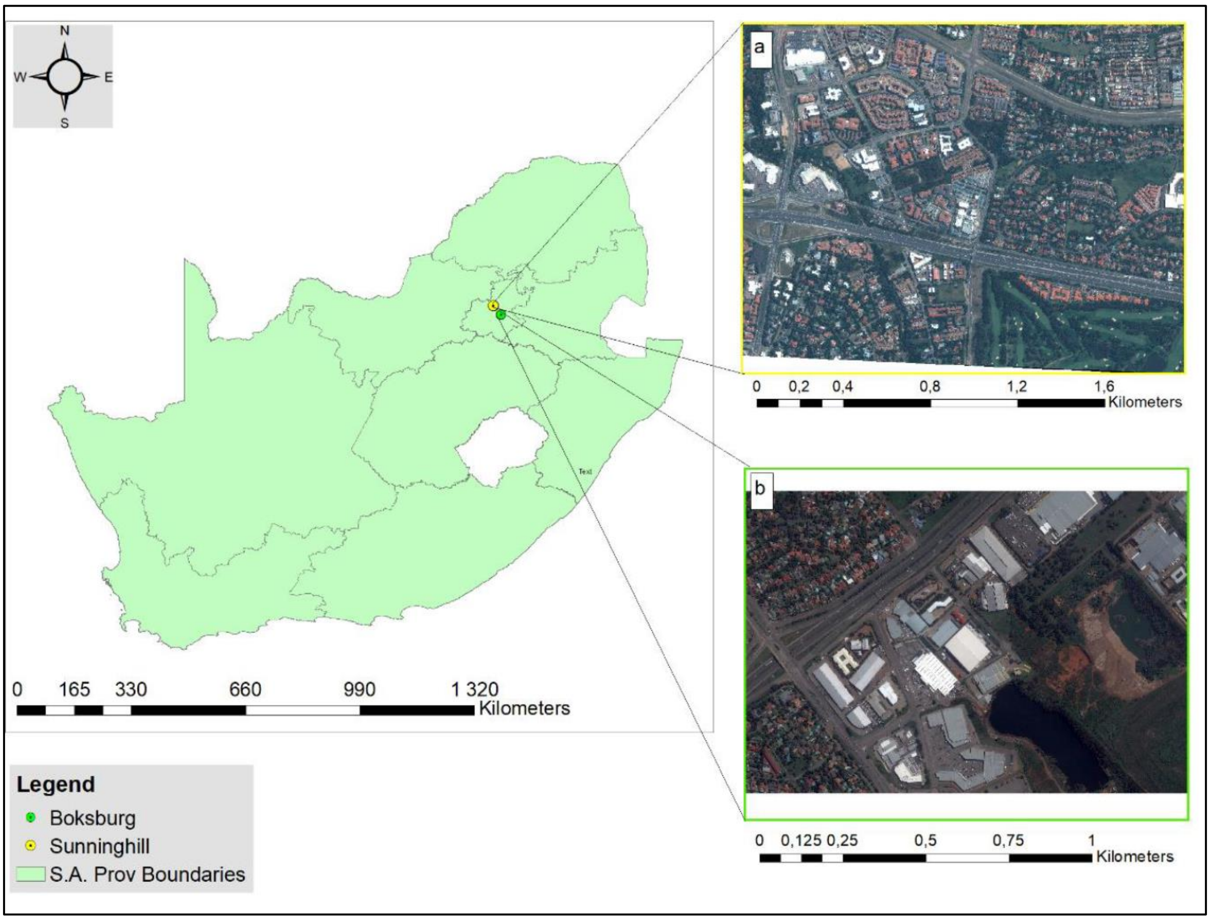

Figure 3.1. The study areas for the land-cover classification subset: (**a**) Sunninghill and (**b**) Boksburg.

3.2.1 Data set and processing

Very high-resolution pan-sharpened Pleiades (0.5 m) data were explored for the study. Table 3.1 shows the details of images acquired for the study. The imagery was acquired on 12 February and 13 December 2015, covering Boksburg and Sunninghill, respectively. The data were procured from Airbus through the South African National Space Agency (SANSA). The Pleiades imagery comprises four spectral bands from the visible (430) to the near-infrared region (950 nm). The datasets were received already stored in 11 bits per pixel and delivered as 16 bits Geo Tiff, hence allowed for increased discrimination of subtle spectral differences among objects. The images were received already georeferenced and corrected for off-nadir acquisition and terrain effects. The pan-sharpened imagery was used for the analysis. The aerial photos obtained from the National Geo Spatial Information (NGI) in South Africa were used for validation. Given that the satellite images were acquired in 2015 and the aerial photos were captured in 2012, a ground validation was undertaken in 2016 to confirm samples of existing land cover classes extracted from the aerial photos and to update samples where inconsistencies existed due to land cover change. This approach was used due the unavailability of high-resolution reference data for 2015.

Table 3.1. Very high-resolution Pleiades spectral combinations.

Panchromatic (Pan)	Multispectral (MS)	Pan-sharpened (PMS)
0.5 m	2m	0.5 m (fusion)
Pan: 450m-745nm	Blue: 430 - 550 nm Green: 490 - 610 nm Red: 600 - 720 nm Near-infrared: 750 -950 nm	Blue: 430 - 550 nm Green: 490 - 610 nm Red: 600 - 720 nm Near-infrared: 750 -950 nm

The land cover classes were grouped into seven major urban classes: Vegetation (grass), Vegetation (trees), Roads, Building, Water, Shadow, and Bare Land (Table 3.2).

Table 3.2. Land cover classes and their description.

Land Cover Classes	Cover type	Description
Bare land	Open land	Mining activities and/or dumps
Buildings	Industrial/commercial and settlements	Urban man-made structures such as buildings
Roads	Tarred roads, tarred open areas	Car parking lots and pavements
Shadows	Shadows	Shadows from industrial buildings and trees in urban areas.
Grass	Grass cover	Crop fields, conservation fields, game fields.
Shrubs	Shrubs/thicket/woody cover and	Dense tall tree dominated by forest or shrubs
Water	Wetlands and dams	Natural/man-made ponds

3.2.2. Morphological Profiles Methods

A morphological profiles is composed of repetitive transformation of opening profile $\prod\gamma$ and closing profile $\prod\varphi$.The morphological opening profile of an image f is an array of n openings performed on the original image using a series of structuring element (SE) with increasing sizes of radius λ, and is defined as:

$$\prod\gamma\ (f) = \{\prod\gamma\lambda(f),\ \forall\lambda\ \in [0, n]\}$$
(1)

Where $\prod\gamma\lambda$ is the opening by reconstruction with a SE of radius size λ and n is the total number of openings. By duality, the morphological closing profile of an image f is an array of n closing performed on the original image using a series of SE with increasing sizes of radius λ, composed by n levels can be indicated by

$$\prod\varphi\ (f) = \{\prod\varphi\lambda(f),\ \forall\lambda\ \in [0, n]\}$$
(2)

Where $\prod\varphi\lambda$ is the closing by reconstruction with SE of radius size λ and n is the total number of openings. By collating opening profile and closing profile, a morphological profile (MP) is realised.

Opening and closing profile are generated from gray level images using opening and closing by reconstruction operators, where λ represent the radius of disk-shaped or weighned square-shaped SE of fixed shape with increasing structuring element (SE) which is commonly used in literature (Huang et al., 2014, Dalla Mura et al., 2010b). When joining opening and closing profile, both of the same size n, a morphological profile is obtained (Dalla Mura et al., 2010b, Soille and Pesaresi, 2002). An MP is generally applied to analysis of single band image (e.g. panchromatic) and its extension to multispectral images is referred to as Extended Morphological Profile (EMP). An EMP is constructed by a series of MPs built on base images which contain few bands but represent most of the information that is relevant for discrimination purposes (Dalla Mura et al., 2010b, Huang et al., 2014). Therefore, EMPs of first principal component (PC) can be formalized by:

$$EMP\ (I) = \{MP_{PC^1}(I1),\ MP_{PC^1}(I2), \dots, MP(In)\} \tag{3}$$

where I comprise a set of the n-dimensional base images derived using principal component. Multi-morphological profiles (MMPs) are an extension of EMP obtained using different types of morphological profiles stacked together. The filtering operation implemented in EMPs is based on the evaluation of how a given image is computed for every connected component of a gray scale image I for a given value.

$$MMP\ (I) = \{EMP(I1),\ EMP(I2), \dots, EMP(In)\} \tag{4}$$

Where EMP ($I1$) comprise a set of the n-dimensional base images derived using principal component (Huang et al., 2014, Dalla Mura et al., 2010b).

A morphological profile based on the concatenation of MPs is defined by a combination of morphological geodesic opening and closing operations of different sizes. A CMP is constructed differently from EMPs and MMPs. Both EMP and MMP analyses rely on PCA transformation to reduce dimensionality, and CMPs are based on the analysis of an image without the addition of linear or non-linear data dimensionality reduction techniques. The concatenation of various MPs without the use of image transform techniques can be defined as follows:

$$CMP = \{MP\ (f1), MP(f2), \dots, MP(fn)\}$$
(5)

where f comprise a set of the n-dimensional original base images not filtered by PCA. Both CMP and EMP morphological profiles, aimed at multiscale decomposition of satellite imagery and scene simplification, were implemented in this study. Principal component analysis (PCA) was used for the transformation of multispectral and pan-sharpened Pleiades imagery to identify patterns in the data and reduce the dimensionality. A EMP was constructed by a series of MPs built on base images which contains few bands but represent most of the information which is relevant for discrimination (Meyer-Roux and King, 1992). Principal component analysis generates base images by analyzing the covariance matrix of the original multispectral images (Meyer-Roux and King, 1992, Goncalves et al., 2008). A MMP is an extension of EMP obtained using different types of morphological profiles stacked together. The filtering operation implemented in EMPs is based on the evaluation of how a given image is computed for every connected component of a greyscale image for a given value. A morphological profile based on the concatenation of MPs was defined by a combination of morphological geodesic opening and closing operations by reconstruction of different sizes. The implementation of the methodology is described in Section 3.2.3 below.

3.2.3 Image Processing and Parameter Settings

The multispectral and pan-sharpened imagery was transformed into a single component using algorithm PCA to derive EMPs for each band. The PC was used, because it contains more than 99% of the total variance of the data set. The analysis for the images was performed using a set of MM algorithms developed within the MATLAB environment and classified using the maximum likelihood algorithm in the ENVI software. The morphological filters' opening and closing based on reconstruction were calculated using a square structural element, and the same analysis was performed using a disk structural element with a radius range from two to nine with a step of one pixel. The same analysis was performed using morphological reconstruction based on sequential application of differing structural element size but using the same shape, either a square or a disk, respectively. The square implementation of the filter was separable and incremental, while the circular implementation was incremental. The algorithm for opening and closing by reconstruction were used to construct MPs. In both experiments, an 18 dimensional morphological profile(MP) was created using a disk structuring element and a square structuring element for each band. Then, the 18 dimensional

MPs were transformed into a few image bands using PCA algorithms for multispectral and the pan-sharpened data set. To extend the morphological profile to a multispectral and pan-sharpened image, the first PCA component was used to generate a base image to run EMP on the images. The EMP transforms were based on the ordering of connected components that best represented each object in the scene. The MMP was constructed based on the concatenation of various EMPs (Figure 3.2 B), while the second CMP was constructed based on the concatenation of MPs without using PCA. This was compared with MMP based on the concatenation of EMPs and maximum likelihood used for classification of the data to generate results.

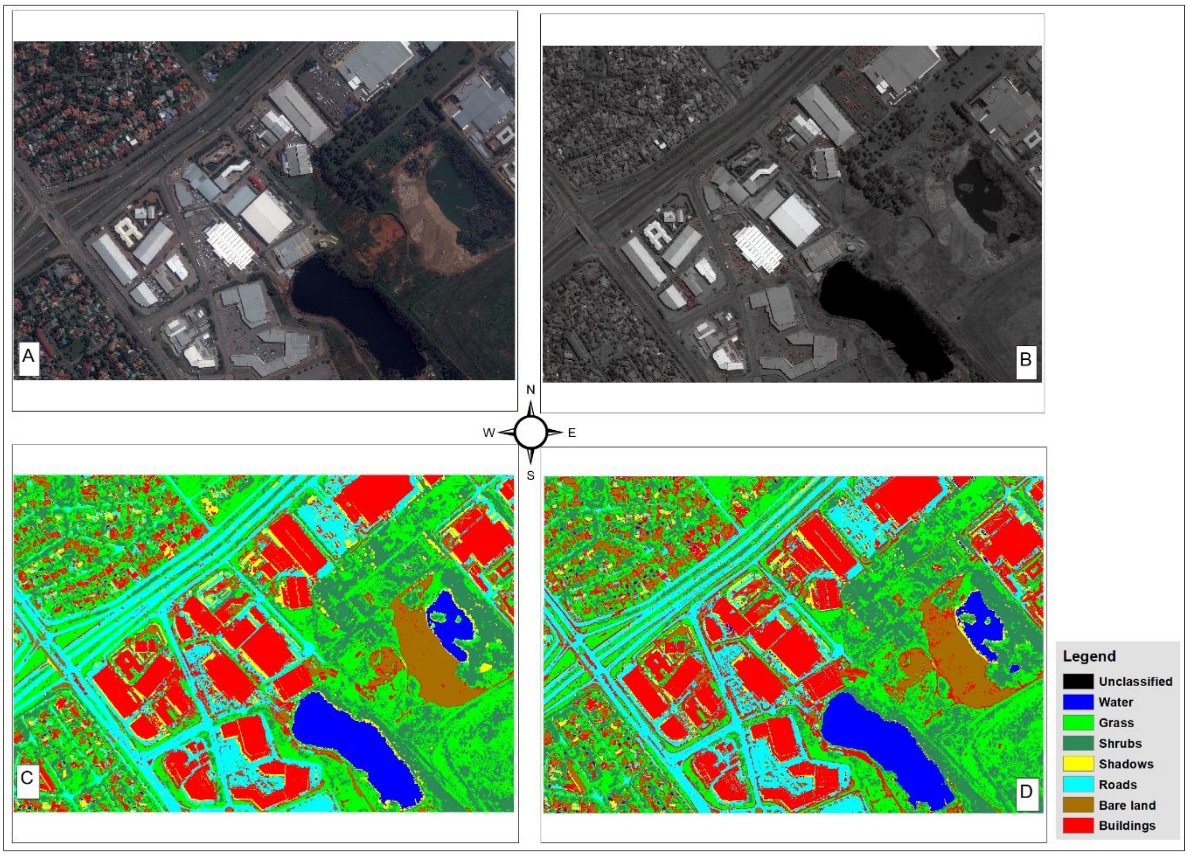

Figure 3.2. Pleiades image and classification results (A) Represents Pleiades original imagery (B) filtered imagery using MP; (C) CMP classified imagery; (D) MMP classified imagery.

3.2.4 Accuracy assessment

Firstly, Shape, Thematic, Edge and Position (STEP) similarity matrix and the confusion matrices were used to assess the accuracy of the results. Secondly, a confusion matrix was used to assess how well the classifiers performed by deriving a series of descriptive-analytical statistics (Alajlan et al., 2012). Lastly, to test the performance of the classifiers, a McNemar test of comparison was performed.

The accuracy of the classification was assessed based on geometric and thematic accuracy using Shape, Thematic, Edge and Position (STEP) similarity matrix as suggested by Lizarazo (2014). This was done to determine which technique produced the most accurate similarity matrix and structural information preservation of LULC objects. Thematic and geometric accuracy assessment was done to validate how both methods perform in preserving the structural information of LULC objects without distorting edge information. The reference sample units were the same as the segments (i.e. polygons), rather than pixels so that the units are directly comparable to the map segments (Table 3.3). To select a region of interest (ROIs) for reference objects, points were randomly extracted from a 0.5 m aerial imagery acquired from the South African Chief Directorate: National Geo-Spatial Information. One hundred points were randomly generated using QGIS 2.16.1 and spatial objects containing these random points digitized (reference polygon) at a scale of 1:600 to increase the level of object shape delineation (Figure 1). A field survey was conducted to resolve ambiguities resulting from photo-interpretation.

Table 3.3 Number of samples per class for training and test set for the two data sets.

Land cover	Points	Polygons
Water	8	3
Grass	22	15
Shrubs	19	12
Shadows	2	2
Roads	23	18
Bare land	4	2
Buildings	22	20
Total	100	72

The STEP similarity matrix assesses the thematic and geometric accuracy by measuring the geometric form, thematic attributes, exterior and interior boundaries, centroids position of classified and reference objects using shape, thematic, edge, and positional accuracy (Campagnolo and Cerdeira, 2018). The STEP system uses the correspondence between sampled and referenced objects which is established by overlaying reference object(s) (digitized polygons) and their corresponding classified object(s). When a reference object matches one or several classified objects, such a classified object is a correctly classified object (CCO). This is considered a shape, theme, edge, and positional similarity to a given reference object(s). Otherwise, the classified object is referred to as misclassified object (MCO). In this regard, MCO has a shape, thematic, edge, and positional similarity with a reference object equal to 0%.

3.2.5 Comparing classifier performance

The area weighted error matrix and McNemar test were used to compare accuracy measurements received from the STEP similarity matrix and the confusion matrix. The accuracy results measured using the STEP similarity matrix were weighted. An area-weighted error matrix, as suggested by MacLean and Congalton (2012), takes into account the area rather than the count of polygons used in STEP. An area weight error matrix was used instead of the actual area to compensate for unequal probability sampling proposed in the method. In the area weight error matrix, the individual cells reflect the weighted area of the reference units that fall into such cells, similar to how the overall accuracy is computed in the error matrix (Gong et al., 1991). Lastly, the McNemar test was used instead of the commonly used z test on kappa coefficient to evaluate/or determine the map with the highest classification results. Kappa coefficient was not used for this study, because the reference samples used were the same for both CMP and MMP. Therefore, it was not appropriate to use the kappa coefficient, because it assumes that independent samples are used in their calculations (Weih and Riggan, 2010).

3.3. Results

A STEP similarity matrix was used to determine the potential of MMP and CMP in discriminating a heterogeneous urban land cover. Specifically, the study sought to discriminate heterogeneous urban land cover types as well as preserving geometrical characteristics of the structures. This was done by comparing thematic and geometric properties of classified objects on a cell-by-cell basis. Each cell was split into quarters to store in a Morton order the four similarity metrics for each classified object which were shape, thematic, edge, and positional similarity of the classified objects. The classification accuracies were obtained by considering the thematic and geometric properties reported in Tables 3.4–3.7.

Table 3.4. Overall thematic and geometric accuracy results of (a) CMP and (b) MMP over Boksburg.

Category	a. CMP				b. MMP			
	Shape	**Theme**	**Edge**	**Position**	**Shape**	**Theme**	**Edge**	**Position**
Bare Land	0.3028	0.8944	0.0636	-0.5295	0.2788	0.7451	0.0928	-0.373
Buildings	0.8636	0.8557	0.7441	0.7855	0.2241	0.4781	0.1332	0.1486
Roads	0.6281	0.4297	0.0516	-2.3204	0.121	0.4602	0.0494	-2.2017
Shadows	0.2617	0.2735	0.1197	0.2279	0.1065	0.1721	0.0435	0.1435
Grass	0.132	0.7572	0.1007	-1.9369	0.1289	0.6989	0.0919	-1.5907
Shrubs	0.2285	0.7046	0.1617	-1.2183	0.2175	0.6818	0.0993	-0.034
Water	0.7713	0.8348	0.6088	0.7915	0.8212	0.6885	0.5068	0.4236
Overall accuracy	0.4554	0.6756	0.0917	-0.7934	0.1997	0.5321	0.1224	-0.3911

Table 3.5. Overall thematic and geometric accuracy results of (a) CMP and (b) MMP over Sunninghill.

Category	a. CMP				b. MMP			
	Shape	**Theme**	**Edge**		**Shape**	**Theme**	**Edge**	**Position**
Bare Land	0,3296	0,9758	0,0402	-0,465	0,2791	0,7467	0,0811	-0,369
Buildings	0,7467	0,8292	0,8226	0,0713	0,2632	0,5286	0,1622	0,2264
Roads	0,6518	0,317	0,6316	-1,431	0,1262	0,4492	0,0788	-1,811
Shadows	0,3543	0,437	0,0036	0,0903	0,1079	0,1733	0,0417	0,1264
Grass	0,1774	0,7855	0,1246	-5,219	0,1446	0,757	0,1328	-1,735

Shrubs	0,2112	0,5443	0,0985	-1,145	0,2144	0,6749	0,1189	-0,006
Water	0,7607	0,0012	0,0000	0,0011	0,3378	0,5116	0,0467	0,4347
Overall Accuracy	0,4617	0,5557	0,2459	-1,157	0,2105	0,5488	0,0946	-0,448

Table 3. 6. CMP and MMP classification accuracy results over Boksburg.

Category	**a. CMP**		**b. MMP**	
	PA (%)	**UA (%)**	**PA (%)**	**UA (%)**
Water	94,9	98,9	92,6	99,8
Grass	57,9	89,2	62,7	88,2
Shrubs	79,9	6,9	81	7,6
Shadows	40,4	1,4	58,7	1,3
Roads	69	67,7	72,9	78,5
Bare Land	84,9	53,3	82,6	51,1
Buildings	90,3	96,8	91.4	98,5
OA	**83.14**		**84.42**	
CMP and MMP		=	p>0.05	

Table 3.7. CMP and MMP classification accuracy results over Sunninghill.

Category	**a. CMP**		**b. MMP**	
	PA (%)	**UA (%)**	**PA (%)**	**UA (%)**
Water	94,9	98,9	92,4	99,8
Grass	58,0	89,4	60,1	88,8
Shrubs	79,9	6,9	7,2	82,1
Shadows	42,8	1,5	1,4	62,9
Roads	69,5	68,0	80,8	73,3
Bare Land	53,5	84,8	50,3	83,4
Buildings	96,76	90.3	98,5	91,7
OA	**83.19**		**84.08**	
CMP and MMP		=	p>0.05	

The major visual difference interpreted among the thematic maps produced by CMP and MMP algorithms was the amount of thematic misclassified buildings with bare land (Figure 3.3 A, C, D). Observation, based on field survey and available aerial imagery, revealed that this area is predominantly covered by impervious surfaces, bare land/mining dumps, and eucalyptus trees. Small dams also exist in the area. Figure 3.3 C shows that CMP misclassified small water bodies with shadows, whereas Figure 3.3 D shows that MMP discriminated small water bodies from shadows. However, bare lands/mine dumps were often mixed with buildings in both classified maps (Figure 3.3 C, D). Similar results are shown for an alternative study site (Figure 3.3).

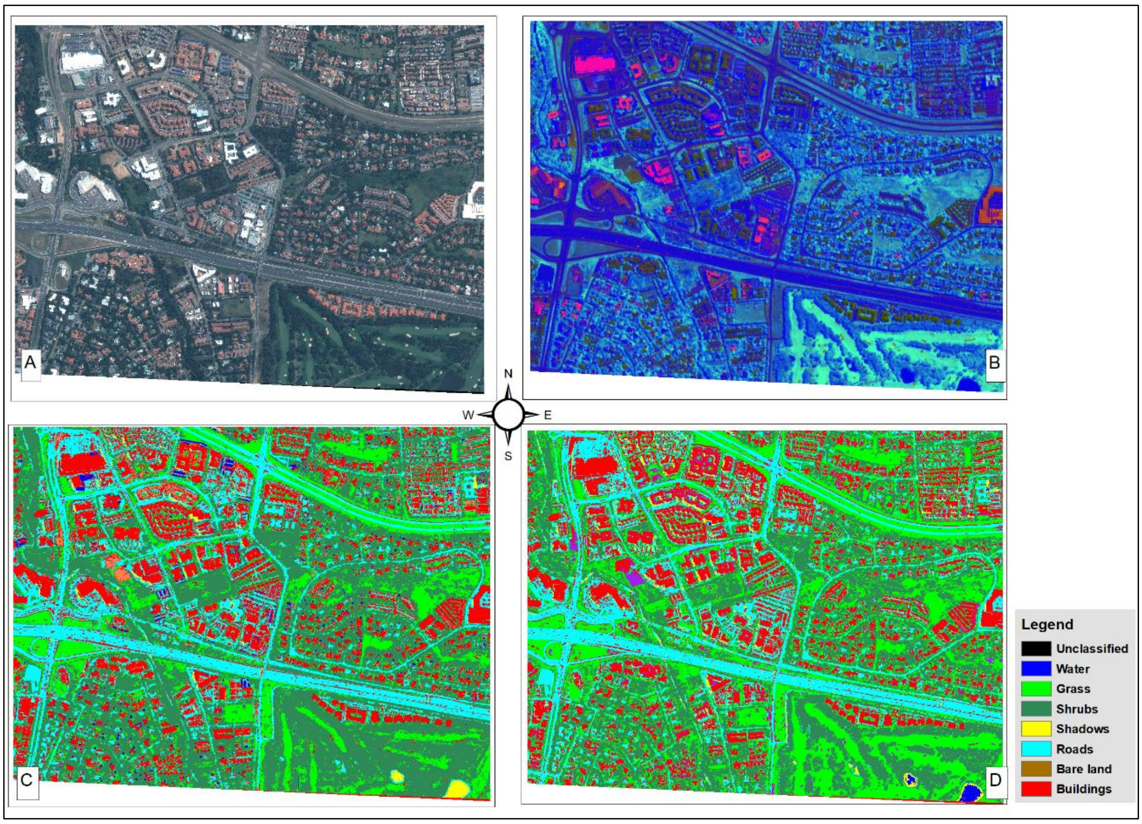

Figure 3.3. Pleiades image and classification results (A) Represents Pleiades original imagery (B) filtered imagery using MP; (C) CMP classified imagery; (D) MMP classified imagery.

The overall weight error matrix classification accuracies obtained for CMP and MMP to evaluate thematic and geometrical characteristics accuracy of objects in the classification of a heterogeneous urban land cover are reported in Table 3.4. Thematic and geometrical characteristics were evaluated by considering the shape, thematic, edge, and positional similarity of classified image features. The overall area weight error matrix results were calculated using the STEP similarity matrix. In a STEP similarity matrix, a value of 1 indicates a correctly classified object, while a value of 0 indicates a misclassified object (MCO), hence it suggests a poor shape, thematic, edge or positional similarity of objects.

Tables 3.4 and 3.5 show the overall thematic and geometric accuracy for CMP and MMP computed on the test set. From the analysis in Tables 3.4 and 3.5, it is evident that CMP outperformed MMP in terms of shape, thematic, and edge accuracy for most artificial features. However, for natural features or features without clear boundaries, both CMP and MMP achieved poor shape, edge, and positional accuracy. In terms of shape accuracy, most artificial features, such as buildings/roads and natural features with clear boundaries, such as water, were correctly classified by CMP, achieving high accuracies of 0.86 for buildings, 0.85 for roads, and 0.77 for water, compared to MMP reaching poor shape overall accuracies of 0.22 for buildings, 0.47 for roads, and 0.68 for water. Similar occurrences for edge and thematic accuracy were evident, where artificial features were correctly classified by CMP compared to MMP. However, when evaluating accuracy for the natural features or features without clear boundaries, such as grassland, trees, and shadows, both techniques indicated a poor shape, edge, and positional accuracy. Most low classification accuracy for MMP arise from the geometrical accuracy, which indicates poor preservation of features by MP after its extension to MMP.

The second accuracy assessment was performed for each classification map produced in the study. To evaluate how well both algorithms correctly classified the thematic categories in a heterogeneous urban landscape (i.e., the percentage of correctly classified samples), analysis of the categories was performed to evaluate how well both CMP and MMP utilized statistical information from the dataset to discriminate land cover classes. Tables 3.6 and 3.7 show detailed confusion matrices of classification accuracies for CMP and MMP, respectively. The CMP and MMP classification accuracy results over Boksburg and Sunninghill were similar as shown in Tables 3.6 and 3.7. Overall, accuracies for CMP were 83.14% and 83.19% for Boksburg and Sunninghill, respectively. Similarly, the MMP overall accuracies were 84.42% and 84.08% for Boksburg and Sunninghill, respectively. Overall, both CMP and MMP performed almost similarly for artificial objects, such as buildings and roads, in terms of overall classification accuracy. The accuracy assessment shows the overall accuracies of 83% for CMP and 84% for MMP classification. Producer accuracy for water and built-up areas were highest in comparison to other classes in both classifiers, where CMP produced 94% and 90% as compared to 92% and 91% for MMP. Producer accuracy for shadows and grassland was lower for both classifiers, with CMP achieving 40% and 57%, respectively, and MMP achieving 58% and 62%, respectively. However, a relative difference existed among the classifiers when evaluating the individual classes. Individual class type’s producer accuracy indicated fairly high classification accuracy for MMP compared to CMP. A 95% confidence limit revealed a wide variability and overlap in overall accuracy reported between CMP and MMP classification results. Based on this result, the lowest-performing classification model, CMP, was within the range of the best performing MMP. Based on a comparison among predictions made with optimized feature transformation techniques based on the use of PCA and without the use of PCA, the McNemar test indicated that the difference between CMP and MMP was not statistically significant ($p > 0.05$).

3.3. Discussion

This study evaluated the performance of two MM techniques, MMP and CMP, based on a reconstruction approach. The two techniques were evaluated in terms of their ability to distinguish as well as preserve geometrical characteristics of image features in a heterogeneous urban landscape. Morphological profiles based on a reconstruction approach and its extension have been proven in the literature to provide better shape preservation (Pesaresi and Benediktsson, 2001, Huang et al., 2014, Foody, 2004, Huang and Zhang, 2011b, Huang et al., 2007, Dalla Mura et al., 2010b, Palmason et al., 2003a) and classification techniques for land cover classification. The aim of comparing concatenation of morphological profiles by reconstruction transform (CMP) against its extension (MMP) in urban land cover classification was to determine the effects of image dimensionality reduction techniques, such as PCA, to construct MMP geometrical characteristics during urban land cover classification. Specifically, the study sought to evaluate characteristics, such as shape, thematic, edge, and positional similarity, of image objects from very high-resolution data sets. In general, similar and visually acceptable results were produced for land cover classification using either CMP or MMP image analysis techniques. By visual comparison, both classifiers achieved a fairly significant distinction of heterogeneous urban land cover classes. The MMP provided a better distinction of features, especially separating water bodies from shadows as compared to CMP (Figure 3.3). The enhanced classification accuracy is due to the development of MMP which synthesizes spectra-spatial information extracted from multicomponent base (Huang et al., 2014, Huang and Zhang, 2011b, Palmason et al., 2003a, Pesaresi et al., 2013). The MMP is constructed based on the use of PCA to decrease the curse of the dimensionality problem in standard mathematical profiles which then provide effective separation of the distribution of the classes in the transformed multispectral and panchromatic band. The CMP is challenged in analyzing multispectral bands or statistical information on the imagery, compared to MMP. However, comparing the classifiers in terms of geometrical characteristics preservation and thematic accuracy, CMP out-performed MMP in preserving geometrical characteristics during the classification of features in a heterogeneous urban landscape. This may be because an MMP is constructed from concatenation of EMPs based on PCA. Essentially, PCA is an edge-based image dimensional reduction algorithm which may blur object boundaries. Both CMP and MMP can be used to accurately classify a heterogeneous urban landscape. However, preservation of geometrical characteristics during classification may be challenging, especially for natural boundaries. Objects with natural boundaries may not have crisp edges and are usually affected by boundary blur which results in classification error (Lizarazo, 2014, Lizarazo and Elsner, 2009, Yurtseven et al., 2019). Hence, classifying artificial boundaries, such as buildings, may reach high levels of similarity due to the use of very high-resolution imagery and shapes for natural objects that have crisp edges. Previous studies evaluated MM techniques based on the comparison of morphological filters using reconstruction transform and standard morphological transformation. Similar results have been observed in related studies (Huang et al., 2014, Huang and Zhang, 2011a, Huang and Zhang, 2011b, Dalla Mura et al., 2010b, Pesaresi et al., 2013) and indicated that morphological profile based on a reconstruction approach had better shape preservation than classical morphological filters. However, extending MPs to MMPs using PCA for dimensionality reduction may decrease the overall capability of MMPs to provide better shape preservation, although it increases its ability to analyze statistical information, which has been a curse for MP. Overall, the results indicate that the use of MP techniques and its extension based on reconstruction provides better capabilities in classifying a heterogonous urban landscape using very high-resolution imagery. The CMP and MMP techniques address challenges such as speckle or salt and pepper effects from classical remote sensing classification techniques. The results indicate that CMP provides better shape preservation than its extension MMP. However, MMP provides better thematic or class discrimination capability compared to CMP due to the fact of its ability to synthesize spectral–spatial information from current sensor development. The effect of geometrical shape preservation from MMP is due to the use of PCA, which is an edge-based technique that blurs image objects' shapes.

3.4. Conclusions.

This study evaluated the efficacy of two morphological techniques, one based on the concatenation of MPs(CMP) and the other based on its MMP extension which used PCA to reduce the dimensionality reduction problem associated with MP. The CMP produced an overall accuracy of 83.14% and 83.19% over the two study areas, while MMP produced 84.42% and 84.08% over the two study sites. The study also established that the CMP technique produced better shape accuracy results for artificial land cover features such as buildings/roads and natural features with clear boundaries (e.g., water). This was attested to by high accuracies of 0.86 for buildings, 0.85 for roads, and 0.77 for water. In contrast, MMP produced relatively poor overall classification accuracies in terms of shape. The MMP overall accuracies for shape were 0.22 for buildings, 0.47 for roads, and 0.68 for water. Similar occurrences for edge and thematic accuracy were evident, where artificial features were correctly classified by CMP compared MMP. However, when evaluating accuracy for the natural features or features without clear boundaries, such as grassland, trees, and shadows, both techniques indicated a poor shape, edge, and positional accuracy. Most of the low classification accuracy for MMP arose from the geometrical accuracy which indicates poor preservation of features by MP after its extension to MMP. The study therefore ascertained that that the CMP technique provides an effective tool for analysis of very high spatial resolution remotely sensed images that produce better shape preservation compared to MMP.

The study concludes that CMP and MMP can greatly improve the classification of heterogeneous landscape that typify urban areas by effectively representing the structural landscape information necessary for discriminating related land cover classes. In general, similar and visually acceptable results were produced for land cover classification using either CMP or MMP image analysis techniques.

However, concerning the overall classification accuracy, MMP produced slightly higher classification results compared to CMP. Nevertheless, the difference was not statistically significant, with a p-value greater than 0.05. In terms of visual inspection from the thematic maps, MMP could separate features, such as water from shadows, when compared to CMP. Separating water from shadows is commonly a challenge for most remote sensing algorithms. Therefore, MMP can effectively be used for classification of a heterogeneous urban land cover. In summary, it can be concluded that both CMP and MMP techniques are effective in classifying land cover in heterogeneous urban landscape and are particularly effective in discriminating spectrally similar land cover classes.

CHAPTER 4

Comparing the performance of the Multi-Morphological Profile’s in urban land use land use mapping using pixel based classifiers

This chapter is based on: Tsoeleng L. T., Odindi J, Mhangara, P. and Malahlela, O. (2020). Comparing the performance of the Multi-Morphological Profile’s in urban land use land use mapping using pixel based classifies. ***Under preparation.***

Abstract

Improved spatial and spectral resolution from recent sensor advancements provides opportunities for detailed and enhanced accuracies in the classification of a heterogeneous urban landscape. The classification of a heterogeneous urban landscape and analysis of high spatial resolution images has been a challenge for most pixel based techniques. Object based techniques have proved effective in classifying heterogeneous urban landscapes by providing an effective framework for analysis of high spatial resolution images. However, challenges such as under/over segmentation and non-robust statistical estimation hamper most object based techniques in achieving optimum performance for classifying a heterogeneous urban landscape. Therefore, it is imperative that effective classification is related to the effective utilization of both spatio-spectral characteristics of image objects. Morphological techniques especially multi-morphological profiles (MMP) provide an effective framework for analysis of both spectral and spatial information from very high resolution satellite imagery by performing image analysis based on features such as geometric, texture and contrast. In this chapter, we compare the performance of MMP used as a feature vector for Support Vector Machines (SVM) and Maximum Likelihood (ML) techniques against the SVM and ML without the use of MMP as a feature vector. The results from this chapter indicate that the use of MMP as a feature vector for object based classification using ML and SVM produced significantly higher classification results with accuracies reaching, 84.8% and 82.2% respectively, compared to 75.77 and 77.6 for ML and SVM classification without the use of MMP as a feature vector. In addition, the overall results for both classifications indicated that MMP has the potential to increase classification accuracy of a heterogeneous urban LULC.

4.1 Introduction

Improved spatial and spectral resolution from recent sensor advancements provides opportunities for detailed and enhanced accuracies in the classification of a heterogeneous urban landscape. High spatial and spectral information enhances the identification of small features e,g. narrow streets, buildings, shrubs and grassland in a heterogeneous urban landscape. Identification of small image features is essential for detailed classification of a heterogeneous urban landscape with improved precision. Various classification methods and algorithms exist in remote sensing for LULC classification. Generally, they can be categorized as pixel or object based classification approaches (Duro et al., 2012). However, with many advances in the classification methods or algorithms, delineation of heterogeneous urban landscapes and analysis of very high spatial resolution data from recently developed sensors remains a challenge for most pixel based classification algorithms. To overcome the problem, object based techniques have been effectively used in classifying a heterogeneous urban landscape by providing an effective framework for analysis of high spatial resolution images (Zhang et al., 2010, Myint et al., 2011, Malinverni et al., 2011). However, challenges such as under/over segmentation and non-robust statistical estimation hamper most object based techniques in achieving optimum performance for classifying a heterogeneous urban landscape (Fauvel et al., 2008). Therefore, it is imperative that effective classification of a heterogeneous urban landscape is related to the effective utilization of both spatio-spectral characteristics of image objects (Zhang et al., 2013).

Pixel based classifiers such as maximum likelihood (ML) and support vector machine (SVM) provide an effective framework for statistical analysis. Hence, increased accuracy in the classification of urban LULC is related to effective use of an image's spatial and spectral resolution (Zhang et al., 2013). In this regard, classifiers that can optimally utilise both spatial and spectral information in the classification process are important in achieving reliable classification results. In this chapter, we propose the use of an object based filtering technique using Multi-Morphological Profile as a base image for pixel based classification algorithms (SVM and ML). We then compare results generated from the filtered imagery against classification of non-filtered imagery (without the use of a feature vector) for pixel based classification using SVM and ML.

Morphological techniques, especially a family of morphological profiles (MP), have been used in analysis of urban structures (Palmason et al., 2005). MP provides an effective framework for analysis of very high spatial resolution satellite imagery, by performing image analysis based on features such as geometric, texture and contrast. However, the limitation of MP is that it can only be applied to a single panchromatic band, and cannot fully utilise the multispectral channels from most remote sensing images (Tsoeleng et al., 2020). Therefore, MP is not sufficient to achieve optimum performance for classification of a heterogeneous urban landscape. Benediktsson et al. (2003), proposed the use extended morphological profiles (EMP), which is an extension of MP for application in hyperspectral data to effectively deal with the dimensionality problem related to MP. In EMP, the multidimensional data is reduced through a principal component analysis (PCA), to few informative dimensions (Huang et al., 2014). A multi-morphological profile (MMP) is constructed based on the concatenation of EMPs. MMP provides an effective framework for analysis of both spectral and spatial information from very high resolution satellite imagery by performing image analysis based on features such as geometric, texture and contrast. Furthermore, MMP process an input image at different scales that include filtering, feature extraction, segmentation and classification. In this chapter, MMP is used to determine image structural components by filtering process.

An image filter is important for modifying or enhancing an image so as to emphasize or remove certain features (McAndrew, 2004). The morphological filters are object-oriented transforms that focus on processing of the image on areas with shape and size defined by a structural element (Dalla Mura et al., 2010b). The MMP filter is based on morphological reconstruction transformation, which is useful for extracting meaningful information about shapes in images (Gonzalez et al., 2004). The transformation comprises the use of connected components which measure connectivity within an image using different measures of four or eight connectivity in 2D images (Serra, 1998). In this chapter, MMP is used as an object based feature vector to provide a base image for classification based on Support Vector Machine (SVM) and Maximum Likelihood (ML) algorithm. The results obtained are then compared against SVM and ML classification using Pleiades data without the use of an object based feature vector (MMP filtered imagery).

4.2 Methods

4.2.1 Data description

A Pleiades sensor pan-sharpened imagery in concert with SVM and ML were used to evaluate the effectiveness of MMP as a feature vector in improving LULC classification. A Pleiades imagery was captured on 16 February 2015 was used in this study. The datasets are stored at 11bits per pixel and delivered as 16 bits Geo Tiff, giving it a dynamic range that allows increased discrimination of subtle spectral differences between objects. The images were received already geo-referenced and corrected from off-nadir acquisition and terrain effects. The LULC classes were grouped into seven major urban classes, Vegetation (grass) and Vegetation (Trees), Roads, Building, Water, Shadow and Bare ground (Table 4.1).

Table 0.1: The distribution of test samples.

Land cover	Points	Polygon
Water	8	3
Vegetation (grass)	22	15
Vegetation (tree)	19	12
Shadows	2	2
Roads	23	18
Bare Land	4	2
Buildings	22	20
Total	100	72

4.2.2 Training and validation data

Training samples were manually digitised in an ENVI software environment. One hundred validation data points were randomly sampled in a QGIS environment. This was followed by selection of region of interest (ROIs), where spatial objects containing these reference points were digitized. The polygons were digitized at a scale of 1:500 to increase the level of shape delineation (Figure 4.1). The randomly generated training samples were verified in the field. Ambiguities were resolved using a 0.5 m aerial photo acquired from the South African Chief Directorate: National Geo-Spatial Information.

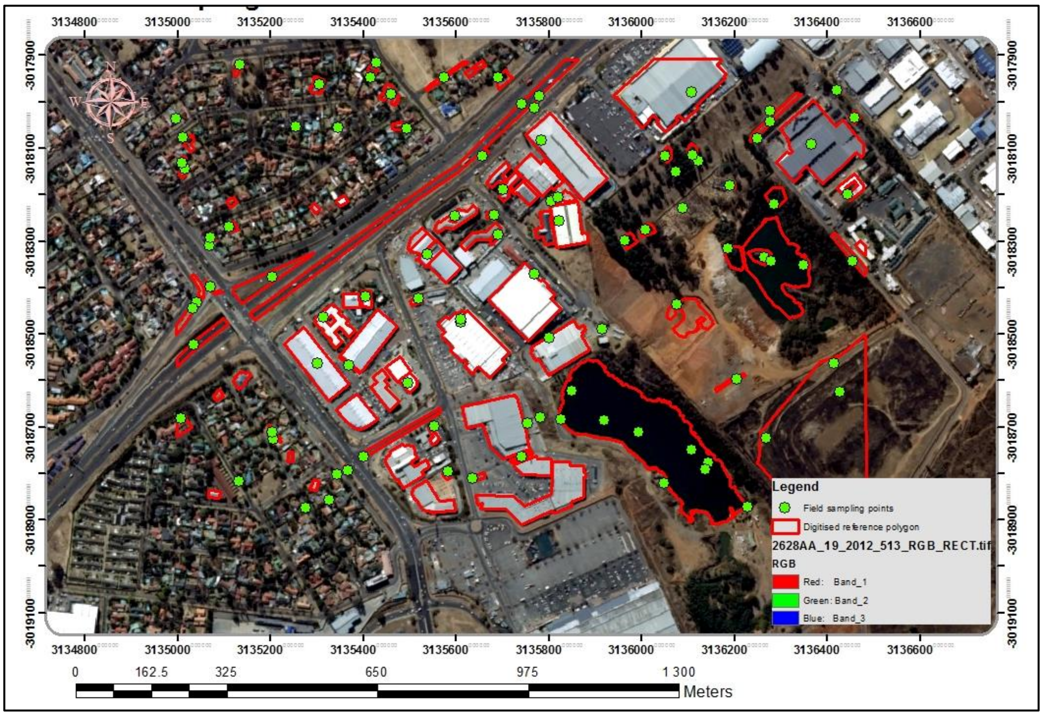

Figure 0.1: Study area field sampled reference objects points and polygons for the land-cover classification subset. The green points represent sampled points and the red polygons represent digitized polygons.

4.2.3 Image classification

A pan-sharpened imagery was used for the classification. The first stage of the analysis involved the filtering of a pan-sharpened Pleiades imagery by MMP algorithm in a Matlab environment. MMP was used to synthesize the spectral-spatial information extracted from multicomponent base image. This is crucial for exploiting spatial information from the sensor and to emphasize image structural components (McAndrew, 2004). Reconstruction transformation MMP filters were used in this study. After filtering, base imagery were classified using ML and SVM. According to Zhang et al. (2013), filtering the imagery using MMP exploit image spatial characteristics and classifying the base imagery using ML and SVM provides effective statistical estimation to analyse spectral information. The last stage of the analysis was to classify the pan-sharpened imagery using the ML and SVM algorithms, without the use of MMP filtered imagery. This was done to assess the effectiveness of MMP in increasing the accuracy of urban LULC using very high resolution imagery.

4.2.3.1 Maximum likelihood

Maximum likelihood classification is a parametric supervised classification method commonly used for LULC classification in remote sensing. ML uses two principles for analysing dataset, firstly, it assumes that cells in each class samples are normally distributed (Gaussian distribution in the datasets) and secondly, it uses Bayes theorem for decision making (Ahmad and Quegan, 2012). In this study, the probability threshold was not specified for classification based on ML algorithm for MMP base layer and non MMP transformed Pleiades data. The idea was to let the classifier use the default parameters to calculate the probability of the transformed MMP base image. The advantage of maximum likelihood is that it takes into account the covariance within the class distribution and normally distributed data (Guide, 1999). However, with non-Gaussian data, the results may be unsatisfactory (Blaschke, 2010).

4.2.3.2 Support Vector Machine

Support vector machine is a non-parametric supervised statistical learning technique (Mountrakis et al., 2011, Qian et al., 2014). It is a discriminative classifier that minimizes misclassification in the dataset by finding a decision boundary/hyperlane that separates data into predefined number of classes. In cases where the data or image objects are inseparable, a kernel function is used to project the data into high dimensional space features that solve the inseparability problem (Wang et al., 2016). Kernel functions commonly used are Gaussian radial basis function (RBF), polynomial, linear and sigmoid function (Wang et al., 2016, Chang and Lin, 2011, Schölkopf et al., 2002). In this study a radial basis function (RBF) kernel was used for SVM classification on both the MMP filtered Pleaides data set and the non-filtered Pleaides data set in ENVI 5.1 software. The default setting was used for gamma parameter setting, which is an inverse of the number of bands in the input image.

4.2.4 Accuracy Assessment

In order to validate the reliability of each of the four classified LULC maps, statistical comparison based on error matrix and McNemar test were executed for each of the four generated thematic maps. Two maps were generated using SVM and ML using MMP filtered Pleaides dataset, and the other two based on SVM and ML classification maps using non filtered Pleaides dataset. McNemar test was used instead of kappa statistics as the training reference samples used were the same for all four classified maps.

4.3. Results

4.3.1 Visual examination of land cover maps

Based on visual inspection, figure 4.2 (c) shows that shadows (represented in yellow) were misclassified as water bodies within residential areas. In figure 4.2 (d) water bodies (shown in blue) were correctly classified. However, figure 4.3 (c) shows that shadows were misclassified as smaller water bodies such as pools within residential areas, while in figure 4.3 (d), small water bodies within residential areas were misclassified as shadows and buildings misclassified as water bodies. By visual inspection, figure 4.3 (d) indicate improved classification of a heterogeneous urban LULC.

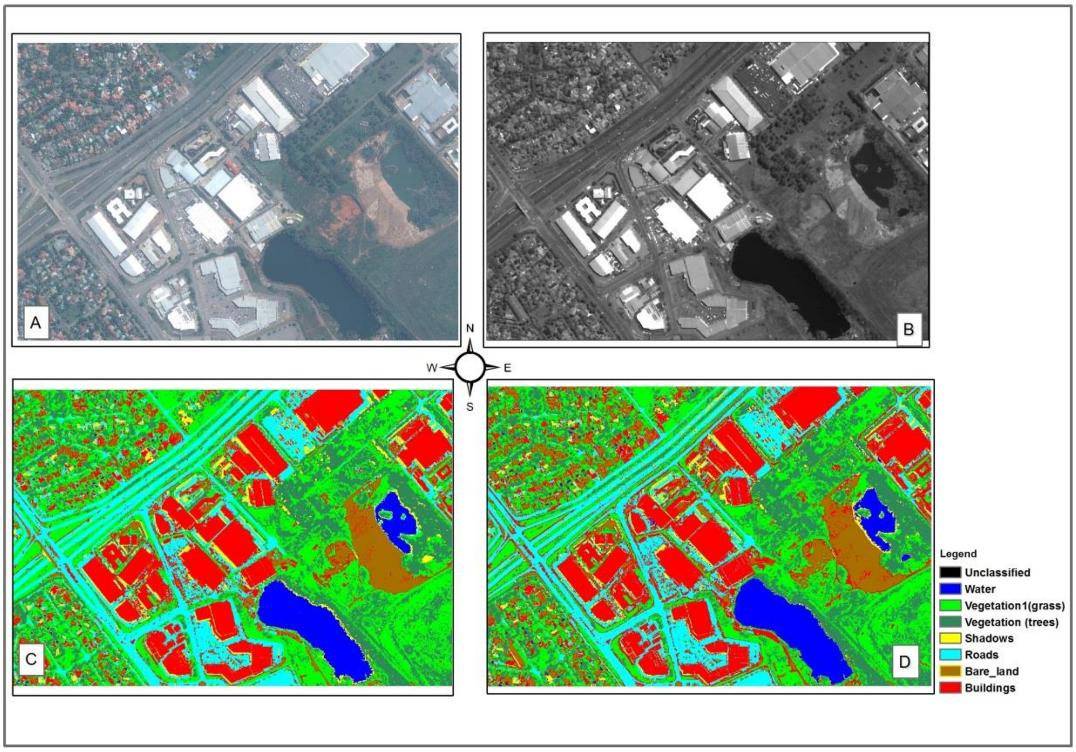

Figure 0.2: Pleiades image and classification results using ML (a) Pleiades RGB imager (b) MMP filtered Pleiades imagery (c) Classification based on Maximum likelihood from a non-filtered image (d) ML classification using imagery filtered using MMP.

The classification of MMP transformed imagery using SVM algorithm (figure 4.3 d) shows an error of commission for water bodies classification when compared to classification based SVM without the use of filters (figure 4.3 c), while an error of omission was observed for buildings when filters were used. However, when classifying bare land, MMP filtered imagery produced promising results. This error of commission and omission for both classifiers can be attributed to the kernel function's inability to provide optimal configuration for the classification. Zhu and Blumberg (2002) and Mountrakis et al. (2011) have for instance documented the shortcoming of RBF.

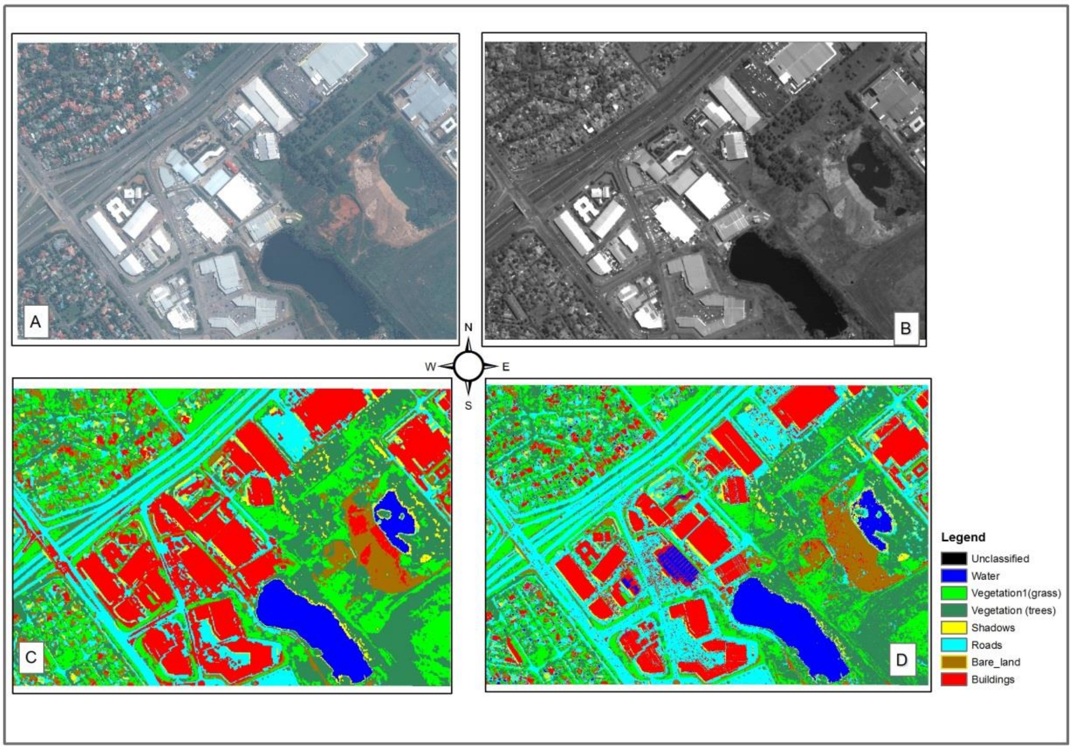

Figure 0.3: Pleiades image and classification results using ML (a) Pleiades RGB data (b) MMP filtered Pleiades dataset (c) Classification based on SVM from non-filtered Pleiades data (d) SVM classification using imagery filtered by MMP.

4.3.2 Accuracy assessment

Tables 4.2 indicate ML results obtained using non-filtered and ML MMP filtered Pleiades image, respectively. The tables show that the filtered image generated better classification accuracy i.e. 84.8% compared to 75.8%. The use of MMP as feature vector enhanced the classification accuracy by approximately 9%. A class to class assessment showed a high error of omission for water bodies with accuracies ranging from 64.3% for ML classification to 92.4% from ML classification based on MMP filtered image. However, the performance of ML based on MMP filtered Pleiades data and ML classification were similar for built-up, bare land and impervious (roads) surfaces.

Table 0.2: LULC ML classification using pan-sharpened Pleiades imagery; b. LULC ML classification using MMP filtered imagery.

Category	ML		MMPML	
	PA (%)	UA (%)	PA (%)	UA (%)
Water	64.3	100	92.4	99.8
Grass	45.8	89.9	64.1	89.8
Shrubs	79.0	5.2	82.3	8.9
Shadows	48.0	0.4	61.1	1.1
Roads	63.5	86.1	75.1	76.8
Bare Land	97.6	39.2	82.8	51.6
Buildings	92.7	99.4	91.3	98.5
OA	**75.77**		**84.8**	
MMPML and ML		=	**p>0.69**	

Table 4.3 indicates SVM results obtained using MMP non-filtered image and MMP base/filtered image. The overall accuracy for SVM classification based on MMP filtered imagery was slightly higher (82%), compared to SVM classification (77%) without the inclusion of a filtered imagery. In this case, the use of MMP as a feature vector before classification enhanced the classification accuracy by approximately 5%. Evaluating individual classes, based on respective user and producer accuracy, it is evident that water bodies and built-up areas were better classified than shadows and other classes.

Table 0.3: LULC classification from pan-sharpened and MMP filtered imagery using SVM.

Category	PANSHARPENED SVM		MMP SVM	
	PA (%)	UA (%)	PA (%)	UA (%)
Water	92.9	98.9	93.6	99.9
Grass	31.4	90.7	44.4	93.4
Shrubs	76.6	4.2	74.4	4.7
Shadows	58.6	1.9	36.0	1.7
Roads	83.3	58.1	76.1	72.6
Bare Land	80.9	49.3	90.6	43.4
Buildings	88.7	98.9	93.1	98.9
OA (%)	**77.6**		**82.2**	
MMP SVM and SVM		=	**p>0.68**	

The above tables show that the use of MMP as a feature vector for ML and SVM classification significantly improved the classification results. However, there was no statistically significant difference between the overall classification accuracy of the ML and SVM classification method using MMP as a feature vector (p-values > 0.07) (table 4.2 and 4.3). Generally, SVM provided significantly better overall classification accuracy results (77.6%), compared to ML (75.8%). However, the results were not statistically significant (*p*-value> 0.05).

4.4 Discussion

This study evaluated the efficacy of MMP as a feature vector in enhancing the LULC classification accuracy of pixel based SVM and ML classifiers. These were evaluated in the classification of a heterogeneous urban landscape using very high resolution satellite imagery. The MMP filtered Pleiades image was used as a base image for SVM and ML classification and compared with SVM and ML classification based on non-filtered Pleiades imagery.

Results demonstrated the value of MMP as a feature vector used as a base image for classification. As shown in figure 4.2 (d) and 4.3 (d), both ML and SVM classifications based on the use of MMP base image offered more generalized visual appearance compared to ML and SVM without the use of MMP as base layer. In evaluating performance, there was a significantly higher classification accuracy for SVM and ML classification based on the use of MMP as a feature vector than ML and SVM classifications without the use MMP as base image. This can be attributed to the fact that MMP exploit image spatial characteristics such as size, shape, geometry, and morphology of geospatial objects (Huang et al., 2014). These image spatial characteristics are valuable for analysing very high resolution imagery (Blaschke et al., 2014, Myint et al., 2011, Liu and Xia, 2010, Myint et al., 2007, Benediktsson et al., 2003, Fauvel et al., 2012). The use of SVM and ML classification without MMP as base image rely on pixel and spectral signature for classification, hence fail to incorporate spatial information from high resolution images and results in the mixed pixel problem (Jones and Sirault, 2014, Cracknell, 1998, Fisher, 1997).

Despite the low sample size of the test set and associated wider confidence limits, the McNemar test revealed that utilizing MMP as a feature vector did not influence the classification accuracy using the SVM and ML classifiers. This finding suggests that to achieve better overall classification accuracy, there is no statistical basis for preferring support vector machine over maximum likelihood. However, when using MMP as feature vector, SVM out-performs ML. Typically, SVM classification takes longer time on image analysis than ML. Hence, the use of ML with MMP as base image would be preferred.

The use of MMP filters in the image helps to extract invariant features, re-arranges the image objects into connected groups of the neighbourhood set and removes noise from the image by reducing the speckle pixel from an image (Huang et al., 2014). This morphological processing effectively manages the spatial information for pixel based classifiers. When classified using SVM or ML, it improves the accuracies in a heterogeneous urban landscape.

4.5 Conclusion

This chapter evaluated the capability of MMP algorithm used as a feature vector for ML and SVM algorithm for heterogeneous urban LULC classification. Results from the study indicate that the use of MMP as a feature vector for object based classification using ML and SVM produced significantly higher classification results for urban areas and vegetation, compared to ML and SVM classification without the use of MMP as a feature vector. In addition, the overall results for both classifications indicated that MMP has the potential to increase classification accuracy of a heterogeneous urban LULC. Therefore, MMP can be used effectively as a feature vector for pixel based classifiers SVM and ML for urban land use land cover classification.

Important conclusions drawn from this study are:

1) MMP combined with pixel based classifiers ML and SVM can greatly improve LULC classification of a heterogeneous urban land scape and effectively reduce or eliminate the mixed pixel problem associated with pixel based classifiers.

2) MMP can be used to improve classification performance by exploiting image spatial characteristics such as modelling the spatial context, extraction based on structures of image objects and accounting for object level thematic characteristics and relation between structures. This provide a better framework for management of spatial information for SVM and ML which is essential for discrimination of objects with similar spectral signatures.

3) The use of SVM and ML statistical classifiers provide robust statistical analysis during the classification which is essential for effective synthesis of spectral information. Therefore, when this is combined with MMP as a feature vector during classification, they provide effective synthesis for both spectral-spatial information leading to improved accuracy during classification.

In summary, this chapter proposed a novel approach for effective classification of a heterogeneous urban landscape from very high resolution imagery. It was found in this chapter that MMP combined with either SVM/ML, provides effective synthesis for both spectral-spatial classification of a heterogeneous urban landscape. This is crucial for achieving significantly higher classification accuracy in a heterogeneous urban landscape.

CHAPTER 5

SYNTHESIS AND CONCLUSION

5.1 Introduction

In urban landscapes, classification of the heterogeneous land use and land cover (LULC) has remained a challenge. This is mainly attributed to improvement in sensor spatial and spectral resolutions, which has generated new demands for enhanced accuracies. Previous findings have indicated that increased accuracy in very high resolution imagery comes with increased classification challenges such as spatial contiguity, salt and pepper effects and over fitting that compromise classification accuracies (Weih and Riggan, 2010, Campagnolo and Cerdeira, 2006). Thus, due to its ability to analyse image spatial characteristics such as texture and context, object based image analysis (OBIA) techniques have been proposed to effectively deal with the increased volume of very high spatial resolution data. However, studies that have adopted OBIA based techniques have indicated that these techniques experience challenges such as over- and under- segmentation and non-robust statistical estimation that hamper optimum classification (Zingman et al., 2012a, Fauvel et al., 2008, Gong et al., 1991). Therefore, exploration of techniques that incorporate both spectral and spatial information is perceptually significant. Specifically, mathematical morphological techniques have been proposed and used in remote sensing to provide image analysis based on both spectral and spatial relationships using three level image analysis i.e. pixel, region and object based analysis.

Mathematical morphology (MM) provides various techniques used for image analysis. One such technique is the morphological profiles (MP) that involves reconstruction and extensions e.g. extended morphological profiles (EMP) and multi-morphological profiles (MMP). However, MP’s extension to MMP is based on the use of principal component analysis (PCA) technique, which may hamper the ability of MP’s extension to MMP in preserving geometrical characteristics such as shape and edges of image objects. Therefore, in the first analysis of the study, it evaluated the concatenation of MP’s referred to as concatenation of morphological profiles (CMP) against its extension to MMP in preserving structural characteristics as well as discrimination capabilities between the two techniques. Secondly, the study evaluated effectiveness of MMP’s ability to effectively enhance classification accuracies of support vector machine (SVM) and maximum likelihood (ML) in LULC classification of a heterogeneous urban landscape.

5.2 Challenges and opportunities of morphological profiles techniques in Classifying a heterogeneous urban LULC

Results in chapter 3 show the potential of MM techniques, i.e. CMP and MMP in classifying a heterogeneous urban land scape. Specifically, the study demonstrated the capabilities of CMP and MMP to effectively manage image spatial resolution. CMP struggles with managing high dimensional data such as the application in multispectral bands arising from its curse of data dimensionality. The extension MP/CMP to MMP effectively dealt with the issue of the curse of data dimensionality by use of PCA. However, evaluation of the classifier's overall accuracy based on preservation of shape, thematic, edge and positional similarity revealed that CMP effectively preserved geometrical features of image objects compared to MMP.

Chapter 3 also assessed the accuracy of the classifiers. The results revealed that both CMP and MMP classifications were similar for artificial objects such as buildings and roads. However, relative difference existed between the classifiers, with MMP achieving relatively higher classification accuracy compared to CMP. When testing both MMP and CMP classifiers using McNemar test of significance, it was revealed that the results for the two classifiers were not statistically significant. However, due to CMP's dimensionality reduction problem, MMP was used to test the classifier used in chapter 4.

Important findings regarding the significance of object structural characteristics preservation and dimensionality reduction in improving classification accuracy (as highlighted in chapter 3) are:

1. CMP and MMP can greatly improve LULC classification of a heterogeneous urban land scape, and effectively represent the structural information for discriminating spectrally similar classes.

2. The use of PCA in MMP to effectively manage the curse of data dimensionality from MPs may distort image structural objects, therefore, future work should explore other data dimensionality reduction techniques.

3. MMP provides effective synthesis of spectra-spatial information extracted from multicomponent base images, and effectively represent both structural and spectral information for discriminating similar spectral classes of a heterogeneous urban landscape.

These findings have proved the ability of both CMP and MMP in providing an effective framework for analysing very high spatial information from high resolution dataset in a heterogeneous urban landscape.

5.3 Improving urban LULC classification accuracy using MMP as a feature vector for SVM and ML classification techniques

In chapter 4, the study evaluated the efficacy of MMP used as a feature vector/base image in improving the LULC classification accuracy of pixel based SVM and ML classifiers. In this chapter, MMP was used as a feature vector for ML and SVM classification to perform object based classification. This was evaluated against ML and SVM classification without the use of MMP as a feature vector to perform a pixel based classification. The results showed that the use of MMP as a feature vector significantly improved the classification of a heterogeneous urban land cover.

The results in this study showed that the use of MMP as a feature vector for ML and SVM classification significantly improved the classification accuracies compared to non-use of MMP as a feature vector. This indicates the influence of MMP in exploiting image spatial characteristics of geospatial objects. However, there was no statistically significant difference between the overall classification accuracy of the ML and SVM classification method using MMP as a feature vector (p-values > 0.07) (table 4.2 and 4.3). Nevertheless, significant improvement in the classification results has proved that the use of MMP as a feature vector improves the classification of a heterogeneous urban landscape.

Important conclusions were drawn from this study are:

1. MMP combined with pixel based classifiers ML and SVM can greatly improve LULC classification of a heterogeneous urban land scape and effectively reduce or eliminate the mixed pixel problem associated with pixel based classifiers.

2. MMP can be used to increase classification performance by exploiting image spatial characteristics such as contextual spatial modelling, extraction based on structures of image objects and accounting for thematic characteristics in relation to co-existing structures.

3. The use of SVM and ML statistical classifiers provide robust statistical analysis during the classification, which is essential for effective synthesis of spectral information, useful for effectively dealing with non-robust statistical estimation associated MMP.

Results in this section indicated that MMP has the potential in improving classification accuracy of pixel based classifiers ML and SVM, hence improved accuracy for LULC classification accuracy of a heterogeneous urban landscape.

5.4 Conclusions and Recommendations

The aim of this study was to evaluate the efficacy of morphology in the classification of urban LULC. The results in this study showed that the use of MMP over CMP could be used to improve thematic accuracy and effectively deal with dimensionality problem related to CMP. Furthermore, results indicated that the use of MMP as a feature vector for ML and SVM classification significantly improved the classification results, compared to use of ML and SVM without MMP as a feature vector. However, there was no statistically significant difference between the overall classification accuracy of the ML and SVM classification using MMP as a feature vector (p-values > 0.07) (table 4.2 and 4.3). The use of MMP as a feature vector for the classification in the SVM classifier provided significantly better overall classification accuracy (77.6%) than ML (75.8%). However, the results were not statistically significant with (p-value> 0.05).

In summary, the following conclusive remarks were drawn from findings presented in chapter 3 and 4:

- The inherent curse of data dimensionality reduction of morphological profiles (CMP) has been identified as a major limitation in literature. Hence, use of MMP has proved to be effective in dealing with dimensionality associated with CMP. However, the use of PCA as a dimensionality reduction limit MMP’s capability to preserve image structural characteristics. Therefore, further research on the use of data dimensionality reduction techniques such as Independent component analysis (ICA) in constructing MMP is recommended.
- The use of MMP as a feature vector for SVM and ML classification provided and increased LULC distinction of objects with similar spectral signatures in a heterogeneous urban landscape. This is due to the capability to provide effective

framework for synthesis of spectral and spatial information of very high resolution dataset.

- The use of MMP as a feature vector for SVM and ML classification provided and increased LULC distinction of objects with similar spectral signatures in a heterogeneous urban landscape. This is due to the capability to provide an effective framework for synthesis of spectral and spatial information of very high resolution data set.
- Lastly, region growing methods should be used to select reference sampling units since manual selection are subjected to human error. This leads to inaccurate classification accuracies, especially when measuring geometrical characteristics based on STEP (Shape, Thematic, Edge and Positional accuracy).

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