Urban classification by pixel and object-based approaches for very high resolution imagery

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Abstract

Recently, there is a tremendous amount of high resolution imagery that wasn’t available years ago, mainly because of the advancement of the technology in capturing such images. Most of the very high resolution (VHR) imagery comes in three bands only the red, green and blue (RGB), whereas, the importance of using such imagery in remote sensing studies has been only considered lately, despite that, there are no enough studies examining the usefulness of these imagery in urban applications. This research proposes a method to investigate high resolution imagery to analyse an urban area using UAV imagery for land use and land cover classification. Remote sensing imagery comes in various characteristics and format from different sources, most commonly from satellite and airborne platforms. Recently, unmanned aerial vehicles (UAVs) have become a very good potential source to collect geographic data with new unique properties, most important asset is the VHR of spatiotemporal data structure. UAV systems are as a promising technology that will advance not only remote sensing but GIScience as well. UAVs imagery has been gaining popularity in the last decade for various remote sensing and GIS applications in general, and particularly in image analysis and classification. One of the concerns of UAV imagery is finding an optimal approach to classify UAV imagery which is usually hard to define, because many variables are involved in the process such as the properties of the image source and purpose of the classification. The main objective of this research is evaluating land use / land cover (LULC) classification for urban areas, whereas the data of the study area consists of VHR imagery of RGB bands collected by a basic, off-shelf and simple UAV. LULC classification was conducted by pixel and object-based approaches, where supervised algorithms were used for both approaches to classify the image. In pixel-based image analysis, three different algorithms were used to create a final classified map, where one algorithm was used in the object-based image analysis. The study also tested the effectiveness of object-based approach instead of pixel-based in order to minimize the difficulty in classifying mixed pixels in VHR imagery, while identifying all possible classes in the scene and maintain the high accuracy. Both approaches were applied to a UAV image with three spectral bands (red, green and blue), in addition to a DEM layer that was added later to the image as ancillary data. Previous studies of comparing pixel-based and object-based classification approaches claims that object-based had produced better results of classes for VHR imagery. Meanwhile several trade-offs are being made when selecting a classification approach that varies from different perspectives and factors such as time cost, trial and error, and subjectivity.

Classification based on pixels was approached in this study through supervised learning algorithms, where the classification process included all necessary steps such as selecting representative training samples and creating a spectral signature file. The process in object-based classification included segmenting the UAV’s imagery and creating class rules by using feature extraction. In addition, the incorporation of hue, saturation and intensity (IHS) colour domain and Principle Component Analysis (PCA) layers were tested to evaluate the ability of such method to produce better results of classes for simple UAVs imagery. These UAVs are usually equipped with only RGB colour sensors, where combining more derived colour bands such as IHS has been proven useful in prior studies for object-based image analysis (OBIA) of UAV’s imagery, however, incorporating the IHS domain and PCA layers in this research did not provide much better classes. For the pixel-based classification approach, it was found that Maximum Likelihood algorithm performs better for VHR of UAV imagery than the other two algorithms, the Minimum Distance and Mahalanobis Distance. The difference in the overall accuracy for all algorithms in the pixel-based approach was obvious, where the values for Maximum Likelihood, Minimum Distance and Mahalanobis Distance were respectively as 86%, 80% and 76%. The Average Precision (AP) measure was calculated to compare between the pixel and object-based approaches, the result was higher in the object-based approach when applied for the buildings class, the AP measure for object-based classification was 0.9621 and 0.9152 for pixel-based classification. The results revealed that pixel-based classification is still effective and can be applicable for UAV imagery, however, the object-based classification that was done by the Nearest Neighbour algorithm has produced more appealing classes with higher accuracy. Also, it was concluded that OBIA has more power for extracting geographic information and easier integration within the GIS, whereas the result of this research is estimated to be applicable for classifying UAV’s imagery used for LULC applications.

Keywords:
Ancillary data, land use / land cover classification, supervised algorithms, GIS, Remote sensing, OBIA
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List of Abbreviations

ANN: Artificial Neural Network
AP: Average Precision
DEM: Digital Elevation Model
DSM: Digital Surface Model
GIS: Geographic Information Systems
GISc: Geographic Information Science
GPS: Global Positioning System
GSD: Ground Sample Distance
IHS: Intensity, Hue, Saturation
ISODATA: Iterative Self-Organizing Data Technique Analysis
LBS: Location Based Services
LULC: Land Use and Land Cover
ML: Maximum Likelihood
NN: Nearest Neighbour
OBIA: Object-based Image Analysis
OSM: Open Street Map
PCA: Principal Components Analysis
PRC: Precision–Recall curve
RF: Random Forests
RGB: Red, Green, Blue
SOM: Self Organized Map
SVM: Support Vector Machine
UAV: Unmanned Aerial Vehicle
VGI: Volunteered Geographic Information
VHR: Very High Resolution
1. Introduction

Geographical data is ubiquitous and existed in many different forms, means and formats in the present century. This vast amount of different resolutions and high quality data is necessary to be transformed into useful information to acquire knowledge and understand the real world. Geographic information system (GIS) and remote sensing as technologies specialized in spatial science and modeling of our world have developed in two parallel directions. GIS started mainly on developing the ontology of vector data format while remote sensing focused on raster format type. Nevertheless, these two technologies combined in addition to the global positioning system (GPS) contribute to advancing the geographic information science (GISc). UAV systems is compatible and can be linked to these three components of GISc for its capability in providing spatiotemporal data in high resolution for geographical features, basically in raster format, in addition to digital elevation model, 3D, point cloud, terrain formats and others. Moreover, all UAVs are equipped with GPS devices that provide high resolution of geographic coordination for collected data which make data processing and modeling more accurate. UAV imagery as a source of high resolution spatiotemporal data, can provide new approaches for developing dynamic models of the real world, which helps in better analysis of the hidden and underlying structure of geographical processes for features and phenomena. In addition, this high spatial resolution imagery offers more classes to be identified than other forms of remote sensing imagery, for example vehicles can be a class for urban area studies and regional development. Also, specific features and objects can be counted such as birds and trees. VHR imagery acquired by UAV usually has few bands not like satellite imagery that may have hundreds of colour bands, the most common number of bands are the three main colours Red, Green and Blue (RGB). RGB imagery has some advantages and disadvantages like any other type of images. Most important advantages are the lower price comparing to other sources of sensors and in most cases, they are free, simple, available, and able to provide higher resolution imageries. The main disadvantage is RGB bands cannot be useful and adequate to study all geographical features such as in agricultural application, however, they approved their usefulness in different applications such as urban classification (Cleve et al. 2008).

Data classification is the essence of any data mining applications and main approach for knowledge discovery, which simply uncovers hidden relationships among data and provides meaningful representations of its behaviours, trends and patterns. Image classification as a type of data classification plays a major role in image analysis in remote sensing that include extracting features of interests, providing context, modeling or distinguishing different geographic features and objects. Image classification is basically a process of assigning picture elements (pixels) into a number of information categories based on their data file values (Addink et al. 2012). Algorithms are the keystone of data modeling which is involved in almost every step in the image classification process, includes image segmentation, feature extraction, selecting training areas, classification rule, and accuracy assessment. In addition, algorithms in general are always under continuous development where new algorithms are proposed every once in a while, for example, specific field of researches treats the algorithm as the core of the study itself. One of the most developed application that requires algorithms as core process are the machine learning types; mainly artificial neural network (ANN) algorithms e.g. self-organizing map (SOM), the main reason is their important role in the progress and advancement of the various major field for artificial intelligent. The various algorithms supposedly produce similar results for satellite imagery classification where major differences are the computational cost and the autonomous capabilities (Li et al. 2014).

There are mainly two approaches for image analysis and classification; pixel-based and object-based that can be performed by unsupervised or supervised algorithms (Blaschke et al. 2014). These two approaches are more common than others such as knowledge based and fuzzy classification. Various algorithms types are involved in establishing the final classification and in order to obtain the optimum desired classes of the study area. Several comparison studies have been conducted in the past aiming to identify the most appropriate pixel-based classification algorithm for satellite images, while most of these studies have shown a similarity in obtained classes from various algorithms (Li et al. 2014). Other studies aimed to compare the overall performance between pixel and object-based classification for satellite imagery, the results indicate that object-based analysis is a better method when dealing with imagery that have high, very high or ultra-high spatial resolution (Blaschke et al. 2014). The drawback of pixel-based approach when dealing with high resolution imagery is the algorithm treats each pixel as an independent entity and ignores the surrounded pixels, this technique works good in low resolution imagery, but in fine resolution, many pixels usually belong to one class and the spatial information of pixels is indispensable as the spectral statistics of these pixels. There are no definite indicators for what are the properties of high or low spatial resolution, but mostly very high resolution images offer a spatial resolution in the range of sub-meter. The essential step of any classification technique is the method of feature extraction which creates the signature basis for the classifier to work, whereas contexture information about the features is necessary alongside
the spectral information to obtain results with high accuracy for LULC applications (Yu et al. 2006). Segmentation is one of the most used techniques to embed contexture information in the classification process, through reconstructing the image into groups of pixels (homogeneous areas) that generates objects of different shape, colour and scale, in addition to other useful information from texture analysis.

Algorithms come in different types whereas in image classification they control more than one step, therefore, many are available for both pixel and object-based classification. Algorithms in Object-Based Image Analysis (OBIA) are attentive on the segmentation and feature extraction steps of the classifications. Two main segmentation types i.e. discontinuity and similarity, where on one hand, algorithms of mask processing and edge detection are more associated with discontinuity which deals with points, lines and edges. On the other hand, algorithms based on region and thresholding such as merging and splitting are more associated with similarity segmentation type. In case of feature selection algorithms, there are many types used in remote sensing applications, whereas one major domain that is very common and well developed is the principal component analysis. There are several issues that can interfere the performance of object-based classification especially during the segmentation and feature extraction steps, although on the other side for pixel-based classification; the main issue rises during the sampling of the training areas that should represent the classes correctly. Many pixel-based algorithms are based on the data values of the image pixels that usually represent the spectral information inherited in the image bands, most well-known and used algorithms are Maximum Likelihood (ML), Minimum Distance and Mahalanobis Distance algorithm. Nevertheless, no studies yet have been conducted to compare between theses famous algorithms or other available ones in pixel-based to identify the best approach for urban mapping or land cover classification of UAV’s imagery.

OBIA has been recognized as a unique paradigm for geospatial data especially for remote sensing imagery, one reason is the high ability for easy integration within GIS, consequently, the term sometime called Geographic Object-Based Image Analysis (GEOBIA) (Addink et al. 2012). OBIA is a systematic outline to create integrated geographic objects, the strategy to achieve that is by identifying geographic features through combining pixels with similar semantic information. These objects of features become available for modeling by using basic tools as spatial analysis in GIS, or a classification algorithm such as Nearest Neighbour (NN), Support Vector Machine (SVM), and Random Forests (RF). OBIA is a modern way for geographic modeling, which is mainly designed for high and VHR remote sensing imagery, where on the other hand, pixel-based methods were developed earlier since the start of using satellites to take photos and collect images of the earth (Blaschke 2010, Myint et al. 2011). Without a doubt, OBIA has become a common substitute for LULC classification of VHR imagery (Radoux and Bogaert 2014). OBIA has several advantages as a novel paradigm of data analysis for different applications and fields in remote sensing. The most unique aspect is the ability to be easily combined with GIS to deliver a complete raster and vector map of classified images i.e. land use layers that is ready for GIS modeling and analysis (Arvor et al. 2013). Nevertheless, the uncertainty and subjectivity of segmentation are widely discussed in object-based classification research as a limitation, despite the importance of segmentation in improving the overall accuracy in distinguishing homogeneous regions (Witharana and Civco 2014).

Data and image classification are widely used in scientific researches for many purposes, where in remote sensing, the image classification is considered a major part that can generate insights and reveals underlying information in the scene. Also, UAV imagery has high resolution spatiotemporal content whereas classifying this type of data is one of the most preferred area of study in GISc. This research for theses mentioned reasons will investigate image classification for UAV imagery, in addition to the fact of the current trend of GIS is shifted to the naive user rather than professionals. Although the results from the image classification can be valuable for many applications especially the ones that involves the public, where the community contribution can be highly noticed in the emergence of various developments in GISc in recent years. To name few, volunteered geographic information (VGI) and location based services (LBS) are two forms of GIS applications that are commonly used and recognized by average citizens. Image classification in its basic purpose intends to assign information classes for homogeneous features in the image. For naive users, it sounds like labelling objects in a digital image, this task can be achieved in a simple method in most image editing programs that is already available in operating systems or can be easily installed. Moreover, operating an UAV to acquire images does not require professional training or special certificate, and end users can simply operate an UAV and basically process the acquired images. In this context, UAV can be utilized for the future of spatial data analysis and modeling especially because of its familiarity to average people whereas the future of GIS is focused on the participation of naive users in unleashing the power of geographical data. In addition, UAV imagery can be part of big data and treated as most available online VHR multimedia data such as the geo-tagged pictures in flicker and social media website. Nonetheless, major components of this study consider simplicity and familiarity for naive users, which includes the classification steps and data inputs that were elected to be an image of only visible RGB bands despite their limitation.
An effective integration of information between remote sensing and GIS opens new opportunities for data analysis, modeling and visualization. This study will assess the ability of VHR with only RGB bands imagery in providing meaningful LULC classes and explore the capability of three different algorithms of pixel-based supervised classification along with object-based algorithm in producing LULC map. Also, the study will evaluate the results of incorporating different colour domains, and the possibility of integrating the results of classified UAV imagery into GIS environment. The integration is based on producing classified raster and vector data that is suitable for geographic modeling in GIS databases. Through conducting the classification, the study will assess the incorporation of different techniques used in improving the classification performance, such as transforming the three participated bands of RGB into IHS colour space. Using object-based approach to classify VHR imagery in remote sensing have been proved to provide more accurate classification than the pixel-based, therefore it was a successful approach for analysing UAV’s imagery of different applications (Laliberte and Rango 2008 and 2009). Object-based classification in this research will be approached through simple procedure and basic steps that includes applying the classifier algorithm after extracting the targeted features based on their spectral characteristics. The results from both classification approaches will be compared in term of capability for integration in GIS through flexibility in producing both raster and vector data model, in addition to comparing their overall accuracy.

1.1 The study design

The main part of this research is comparing the quality of pixel and object-based classification for RGB imagery that has VHR property. Different supervised classification algorithms will be investigated to produce LULC map for the UAV imagery. The general theme is naive user therefore the best candidate for the case study is off shelf UAV which mostly equipped with the visible colour sensors. The limitation of visible colours compares to hyperspectral bands, requires the consideration of using ancillary data or incorporating more layers by converting RGB colours to other colour domains or band ratio layers, most commonly are intensity, hue, and saturation (IHS) domain and Principle Component layers. Both incorporations techniques will be analysed to assess their effects on algorithms performance and the overall classification accuracy. Moreover, these techniques can be considered as an image enhancement approach through pre-processing steps that will be taken before conducting the image classification. Also, these two methods are normally used to solve one of the most well-known issue of classified images by pixel-based approach which is the misclassified pixels within the classes. This issue is mostly associated with high resolution imagery and also within imagery that has high coverage of shadow. However, the main reason of the appearing of misclassified pixels is the spectral heterogeneity that presents in the image pixels, particularly, in land cover classes. The use of ancillary data as an addition approach will be taken in order to improve the quality of the classification such data can be DEM layer, point cloud or GIS data.

The importance of producing accurate classification is desired in any image analysis and a prime goal in UAV imagery for all applications. One can imagine the misidentifying of objects in a battlefield what it can leads to, misclassification of LULC would cause a dramatic error in urban planning, or how much will be costly to misclassify the materials in a mining or a construction site. The accuracy can be measured for the classification by different statistical approaches where most common one is error matrix that will be used in this study, however, 98% accuracy was obtained by visual interpretation in previous studies when using high resolution imagery (Weeks et al. 2013). In some studies, for weed management application, the classification results were 100%, such results can-not be achieved for any other source of images rather than UAV platforms (Peña-Barragán et al. 2011). The study will evaluate the behaviour of three different algorithms of pixel-based supervised classification and one for object-based in term of overall accuracy. Also, it will verify the benefits of classifying VHR imagery of RGB through data analysis that is based on objects instead of pixels.

1.2 Motivation of the study

UAVs imagery and systems have been extensively applied in various study fields where no other technology can be utilized in the same manner (Fahlstrom and Gleason 2012). Some of the latest uses of UAVs are detection and tracking of humans, vehicles and animals, spraying insecticide and fertilizer for agricultural lands, counting and measuring of trees and birds, surveying of large construction sites, packages delivery, weapon launcher, hurricane tracking and observation, and much more. UAV is also unique for more other reasons where most important ones are the cost effectiveness of the whole system, reaching remote location to capture data without the risk of harming human or living species, and the capability to capture repeatedly images at low altitudes. Image analysis is an important field of research nowadays since big data is existed and ready for deriving useful knowledge, in addition, images are becoming available in vast quantities from various sources that includes cell phones and the
World Wide Web e.g. Facebook and Twitter. RGB colour images are widely accessible but they haven’t been studied very well for scientific usages especially in remote sensing applications, or to obtain information in geographic science context. The main reason can be the limitation of the three bands comparing to other source of sensors especially the satellite imagery that contain at least seven bands in most cases, this limitation is obvious in different kind of studies such as agricultural applications where the IR band provide information like no other. However, this is not the same for urban studies where most of the information can be acquired from the only three bands. Another limitation, VHR images of RGB are acquired in daylight therefore the shadow highly impacts the image thus any classification of such imagery.

The main focus of this research is analysing VHR imagery through different classification algorithms for both pixel and object-based approaches. The study will compare various supervised classification algorithms to identify which algorithm will produce the most accurate classes when processing a VHR image obtained from a UAV. Furthermore, it will emphasise a good approach to conduct such classification through examining several steps and highlight the impact of each step on the final result. Image analysis of UAVs imagery differs from image processing of other sources of imagery in remote sensing particularly in terms of the spatial resolution. Nevertheless, VHR imagery is challenging as it can be very hard to be classified accurately using conventional pixel-based methods since VHR pixels usually produce inconsistency in the classification. UAV technology is relatively new comparing to other remote sensing sources, therefore there are limited researches that deeply explore image classification from such resources, and compares the capabilities and limitations of different algorithms in performing the classification. However, few studies compared the available object and pixel-based classification algorithms to identify the best approach of the classification of UAV imagery. Most of these studies considered only one algorithm in pixel-based classification and one algorithm in object-based approach (Cleve et al. 2008, Whiteside et al. 2011, Whiteside and Ahmad 2005). This research investigates three most common algorithms for pixel-based classification, and evaluates the importance of the segmentation process in object-based approach to produce better results for the classification of UAV imagery.

In addition, despite RGB images are widely available, there are few researches that focus on processing such imagery while also analysing the different colour space that can be derived from the RGB bands, for instance, the IHS colour space. In IHS space, the intensity component is detached from the colour information, whereas the hue and saturation components relay on how humans perceive colour. This kind of transformation had improved the analysis approach of VHR of UAV imagery in object-based classification (Laliberte and Rango 2008). The study will verify the ability of the true colours in providing accurate classification results for UAVs imagery where these only bands can not provide meaningful classes for satellite imagery. Also, the study will assess the use of IHS transformation and other possible techniques such as ancillary data. Overall, the developed approach is focused on the capability of UAV imagery to be utilized as a source of data for GIS framework. Developing this research is useful to support the need to integrate remote sensing and GIS for naive users, and provide more understanding of classifying geographical data and modeling. The results of this research will be evaluated by conducting accuracy assessment for pixel-based classification, in addition to comparing the obtained results with the standard Precision–Recall curve (PRC), and Average Precision (AP) (Everingham et al. 2010) for both pixel and object-based approaches.

1.3 Research aims and objectives

Integrating remote sensing data into GIS framework is an advanced field of study that provides more reliable data analysis and powerful solutions for modern challenges, which tackle all types of geographical applications. The main objective of the study is to analyse VHR imagery acquired by normal sensor with only RGB colour bands using a UAV, and developing an effective approach for LULC classification of similar imagery. The classified image will be used directly for GIS modelling which will highlight one of many applications of geospatial technology in providing solutions for sustainable development in urban planning and creating smart cities. Achieving the objective will be done through finding what classification paradigm performs better for VHR imagery when only RGB bands are observed, the pixel or object based classification. Normal sensor in this context means the most common and simple cameras that provide images in RGB spectrum bands, as digital cameras for naive users.

Data modeling is a major element in GIS that converts data into information, whereas image processing especially image classification is used for the same aim in remote sensing. Image classification can be used to link remote sensing and GIS, basically through integrating classified remotely sensed data into geographic modeling. One common tool that is used for geographic modeling and works in both environments is spatial analysis, its fundamentals and functions are suitable to process images properly in disregard to the orientation of the study case either GIS or remote sensing. Producing an accurate classification results is one of the ultimate outcomes that is desired in any image analysis task in remote sensing, especially in applications that related to
geographic data modeling (Laliberte et al. 2010). Raster and Vector format are the main two types of data in GIS that are used to provide a true model of the real world, both data formats can be produced by image classification techniques. In this study, polygons as vector feature class for classified images will be produced, consequently other feature classes i.e. lines and points can be discussed for future work. Several aims are considered in order to achieve the objective of the study while effective approach includes simplicity, less time cost and acceptable accuracy. The specific aims are set as follows:

- Identify an applicable technique to classify VHR imagery of RGB bands acquired by UAVs
- Evaluate the effect of segmentation and ancillary data when conducting pixel and object based classification
- Verify the suitability of RGB imagery in providing LULC classes through producing vector tiles

The first aim will be achieved through image enhancement methods, integrating more derived colour bands, and manipulate the image properties, this aim will support the objective of the study by highlighting the best techniques that produces acceptably classified raster thematic image from VHR imagery for GIS modeling. The second aim will contribute in developing the approach by determining the most important elements that are needed to be included in the classification; such minor elements can be part of any pre-or post processing techniques. The ancillary data is usually needed to classify urban areas and produce better results, also segmentation as part of object-based classification has been valuable for VHR imagery. The third aim will verify if only RGB colour images can be used for urban applications, and will illustrate the importance and potential of UAVs in advancing GISc by evaluating the ability to provide the two main types of representing geographical features as raster and vector that is used for basic geographic data modeling. To serve the objectives of the study and as an example of integrating remote sensing with GIS, LULC classification is selected which can be useful for urban planning purposes as a common GIS application. In addition to achieving the overall objectives, the study will provide an overview of the implications of analysing VHR imageries of RGB bands.

1.4 Structure of the thesis

The thesis is composed of five chapters; introduction, literature review, materials and methodology, results and discussion, where the last chapter is conclusions and future work (Diagram 1.1, Thesis Structure). The introduction chapter will set the context of the study and provides a general brief about the emergence of VHR imagery acquired by UAVs through the two types of classification approaches that mainly used in remote sensing; pixel and object based classification, also it will highlight the general purpose of the study. In addition, the introduction consists of four subsections, the study design, motivation of the study, research aims and objectives, and the structure of the thesis. The second chapter, the literature review will focus on the development and various applications of UAVs in remote sensing and their advantages and limitations, also it includes a detail description for the steps taken in the classification process for both pixel and object-based techniques. The chapter of materials and methodology will describe the data source, type, processing, transformation, and the methods used to accomplish the study objectives. Results and discussion chapter will illustrate the results obtained from the case study and discuss possible limitations of the approach and implications of the results. The conclusions and future works chapter will summarize the whole thesis and suggests possible applications and future works.

Diagram 1.1: Thesis Structure.
2. Literature review

This chapter highlights the use of UAV’s in remote sensing which have increased in recent years in addition to introducing the importance of their applications in one hand. One the other hand, it describes the main components of any UAV’s platform and the unique capabilities in producing accurate data models. Furthermore, the chapter illustrates the advantages and disadvantages of using UAV’s that needs to be consider when using such platforms for remote sensing studies. Also, the chapter reviews the development of UAV’s from the beginning of its use to the current use in different fields of studies, and emphasis on recent applications of UAV’s in remote sensing and how to process UAV’s imagery. In addition, the chapter discuss image classification and the two paradigms of pixel and object-based classification approaches, in addition to an introduction about supervised and unsupervised techniques. Finally, the chapter describe land use and land cover classification and difficulties that may arise during the process of classification.

2.1 UAVs in remote sensing science

Van Blyenburgh (1999) states as a simple definition for UAV “UAVs are to be understood as uninhabited and reusable motorized aerial vehicles”. UAV’s platform is an integration of several systems that are always operated remotely from the ground surface, major systems include the photogrammetric and GPS systems, both are critical for remote sensing applications. Major components in the photogrammetric system are related to measurements and capturing capabilities, that includes the sensor types such as still, video, thermal infrared, LiDAR, optical, radar or a combination of two or more of these sensors. On the other hand, the integrated GPS system in all UAVs should be capable of tracking and registering the position of any sensor in a local or global coordination system. In general, UAV’s for remote sensing provides an advanced spatial and temporal resolution, spatial resolutions can reach a pixel size of few millimetres, whereas temporal resolution can be instantaneous.

UAV’s platforms can produce different imagery formats that meet recent challenges which requires instant actions and solutions, current challenges are mainly associated with real and big time data. Real time data for remote sensing studies is mainly provided by UAV. This cheap imagery can replace traditional sources such as aerial photography and satellites imagery, simply because the low cost and the higher resolutions. Such important topic is discussed in details by Kerle et al. (2008) through a study on real-time data acquisition from both airborne and UAVs sensors. UAV’s imagery in general produces precis data models which can be used for different applications in remote sensing, common applications includes the creation and production of point cloud data, digital surface and elevation modeling (DSM and DEM), infrared colour Ortho-photography, keyhole markup language (KML), 3d modeling, contour mapping, volumetric measurements, normalized difference vegetation index (NDVI) (Figure 2.1, A-H, Possible UAV’s applications from the U.S. Geological Survey website).

2.1.1 Advantages and limitations of UAVs

There are many key advantages of UAVs compared to other remote sensing data sources, especially to the most similar one manned aerial vehicles, unique advantage is the ability to fly in risky and dangerous conditions to any desired location any time, these locations include natural disaster areas, e.g. volcanic and earthquake. Also, UAVs are the only reliable option in situations of extreme weather conditions such as extensive clouds and fogs, such issue constrains traditional remote sensing platforms from acquiring clear and consistent images (Fahlstrom and Gleason 2012). As mentioned in previous sections, UAVs can quickly produce and transmit very high spatial and temporal resolution data, these data can be an image or video format with real time stamp. Moreover, financially UAV’s are more attractive since they are cheaper than any other source of remote sensing imagery as satellites or airborne. In addition, UAV images can be easily used for different data processing of high spatial resolution e.g. texture mapping, DEM and DSMs extraction, and 3D-modeling as shown in figure 2.1.

In general, UAV’s limitations are associated with the price which controls the quality, capacity, weight and dimension of the sensors, low price UAV’s mainly integrates basic systems which when used to collect data usually produces low image quality and decreases the flight durability. Also, the price is associated with the quality of major parts such as the navigation system and the engine, low price systems causes less accurate positioning of the sensors whereas weak engines limit the capability of the UAV to reach high altitude and cover large areas. Other limitations are detected for UAV’s that involved all types regardless of the price which includes the ability to avoid a sudden obstacle, such limitation is resolved in manned vehicles that usually are equipped with air traffic communication and collision avoidance systems (Colomina et al. 2008). One of the main reasons of this limitation is up to date there are no sufficient regulations for UAVs operation, these regulations should
discuss setting up a specific frequency for UAV’s systems since in the mean time they operate on the radio frequencies that are usually subject to interference by other systems.

Figure 2.1: A-H, Possible UAV’s applications from the U.S. Geological Survey website. (Note: (a) Point Cloud image. (b) Digital surface model. (c) Normalized Difference Vegetation Index (NDVI). (d) Infrared Colour Orthophotography. (e) Keyhole Markup Language. (f) 3D Modeling. (g) Contour Map. (h) Volumetric Measurements).
2.1.2 The development of UAVs in remote sensing

The distinctive properties and characteristics of UAVs have endorsed an increasing development in the technology of data collection in term of sensing devices, consequently data processing and analysis. The use of UAVs in collecting data just like remote sensing itself, was developed for military purposes which dated back to 1887, the first attempt was through using a kite holding a camera to observes and records the enemy movement in the Spanish-American war (Fahlstrom and Gleason 2012). Since that time UAVs becomes in high demand for both military and civilian applications, whereas in both cases they have been used in the last decade to cover various area of studies that includes security, law enforcement, survey, agricultural monitoring, and 3D mapping (Baker and Stuart 2009). Nowadays, vast amount of applications requires UAVs as a major component in their operation which demands continues development. Therefore, recent UAV’s researches aims to make the operation of such device as easy as it can be, while focusing in developments toward smaller platform size, precise and little positioning systems, higher resolution of multispectral sensors, lower price cost, and autonomous control. At the present time, UAV’s comes in many models and different capabilities and their prices range from hundreds of dollars to thousands depends on the quality and performance. Integrating high resolution images and real time data in remote sensing and GIS will create new functions for modeling, analysing and visualize spatial data that ultimately will support in better understanding of the dynamics of our world.

2.1.3 Applications of UAVs in remote sensing

There are numerous applications of using UAVs in remote sensing and other fields especially artificial intelligence, to name some common fields of studies in remote sensing: management of natural resources (Horcher and Visser 2004), crops mapping (Kise et al. 2005), forest fire monitoring (Zhou et al. 2005), vegetation monitoring (Sugiura et al. 2005), and for precision agriculture in general (Primicerio et al. 2012). Other applications are associated with more specific studies such as in documenting water flow and stress in crops (Berni et al. 2009, Masahiko 2007), the measurement of plant nutrition’s (Hunt et al. 2005), and for allocating of invasive plants and animal species (Hardin and Jackson 2005). For instance, Berni, et al. (2009) have shown that results obtained from a low-cost UAV for agricultural applications produced better or similar accuracies than aerial vehicles. As discussed earlier, some limitations encountered through the case study as the endurance was only 20 min, and the flight speed was 30 km/h which considers slow consequently the used UAV had minimized the total area that can possibly be covered in each flight trip.

Other researches were focused on urban studies such as traffic monitoring (Haarbrink and Koers 2006), vehicle and human detection (Breckon et al. 2009), inspection of large scale construction sites (Spatalas et al. 2006), and roads control (Egbert and Beard 2007). Many other fields of study are utilizing UAVs for advanced scientific research such as in archaeology mainly to map historic sites that is not existed any more (Bendea et al. 2007, Patias et al. 2007). A detailed overview about civilian applications of UAVs was giving by Niranjan, et al. (2007), which highlighted more applications like oil and gas pipeline construction and exploration, atmospheric sampling, earth movement and excavation, soil erosion supervision, precision agriculture, forest fire detection and other disaster management, water surfaces measurements, discolouring of vegetation and landscape mapping. All results that were achieved from these studies verifies that UAV’s systems can provide flexible and reliable data analysis for remote sensing applications, especially the ones that requires high spatial and temporal resolution data.

2.1.4 Processing UAV’s imagery

Conventional images from satellites in remote sensing usually require various steps of data processing in order to produce the preferred results. Image processing includes geometric and radiometric corrections, noise removal, image enhancement, and producing band ratio images to provide adequate analysis. The principal aspect of data processing includes image classification, which starts by choosing the appropriate remote sensed data and selecting suitable classification approach according to the study case needs. First step is image pre-processing that includes enhancement, after that comes selection of training samples that can represent the whole area, then extraction of desired features that support the chosen samples to be correct, then comes the most important step that affects the whole process which is the selection of most appropriate classification algorithm for the study area. The next step if needed is post-classification processing, and finally the accuracy assessment to evaluate how the results of the classification depict the real world (Lu and Weng 2007).

There are some steps that might not be needed depending on the image quality such as image pre-and post processing that includes image enhancement techniques, those steps are mainly used to assure better
interpretation and understanding of the features in the scene. In most cases these techniques are based on controlling the spectral range in the image by detecting the low – high frequencies in the image. Controlling the spectral range is usually done by manipulating the distribution of intensity values (0-255) of the image pixels represented in the digital values. One of the many approaches for that purpose is contrast stretching that mainly increase the spectral differences in the image, which leads to better detection of different objects and classes in the imagery. Another common pre-processing approach is detecting the frequencies by a spatial filter as high pass or low pass filters, which emphasize the kind of frequencies to be passed or surpassed in the image. This kind of filtering provides edge detecting, sharpening or smoothing for the image (Carlotto 1998), which can be utilized in the pixel segmentation for example.

Data collected from UAVs normally requires similar steps in pre-processing with a major extra task, the task lies in mosaicking hundreds of acquired images in order to produce one Orthomosaic image, which contains all needed information about the geographical features that will be used for analysis and modeling. All raw remote sensing imagery has varying amounts of geometric distortion this distortion can be systematic or non-systematic, where the prime reason of the distortion is representing the spherical shape of the earth into a flat image, in addition to the position and direction status of the sensor at the time and date of the acquisition of the imagery. In most UAVS imagery, the geometric distortion is resolved by the mosaicking process via the positioning system installed in the drones. The mentioned steps are the main and basic steps where some other steps can be included or excluded for the image classification according to the case study.

2.2 Image classification techniques

Classification of images is considered as one of the main purposes of remote sensing data, which provide solutions for analysing and modeling geographical features and phenomena. Object-based classification was first developed in the 1970s (De Kok et al. 1999), whereas at the same time pixel-based which also called spectral based was already in use for terrain mapping of multispectral images. The mechanism of all pixel-based algorithms is the same, it measures how much spectral reflectance is represented in each pixel in the image, and these measurements are dealt with to find meaningful numbers to establish the classification (Addink et al. 2012). In this respect, each pixel’s class is decided by the digital value in the image data, where the derived spectral statistics of all pixels at this point are used to classify the image through unsupervised or supervised classification algorithms. The significant step in image classification is collecting the different pixel values from the different participated bands in the image which produce meaningful information when combined together, however, in this research only three bands RGB in the image which make it harder to classify. Classification approach based on objects rather than pixels was evolved because of the advancement in technology; mainly the sensors capabilities to catch higher resolution than ever before with more details of earth surface, this approach focuses on imagery with highest quality and resolutions in remote sensing data. Since the beginning of using the new approach and being verified in different researches by several scientists, it becomes a study topic to compare between object and pixel-based classification techniques in several contexts, for example according to the quality of the results in regards to how accurate the classes or how long it takes to obtain the results itself (Oruc et al. 2004). Most of these comparison studies had found that object-based classification produced better results and more accurate classes when classifying VHR imagery than any algorithms of pixel-based (Yu et al. 2006). Also, some studies states that object-based classification has more advantages for applications related to detecting change in high resolution imagery, and OBIA has been successfully produced accurate results in such fields while processing UAVs imagery (Rango et al. 2008 and 2009).

2.2.1 Supervised and unsupervised methods

Image classification in remote sensing usually done by one of two main methods; supervised or unsupervised classification. For both methods of the classification techniques there are different algorithms types of processing the image, the algorithm responsibility is increasing the possibility to identify the classes correctly and raise the accuracy results. Unsupervised algorithms are recommended to use when no enough knowledge about the features or ground truth data are not available for the study area. The unsupervised classification is often used to provide general outlook of participated classes in the study area, where supervised one is used to produce specific classes for all features existed in the image. The prime difference between the two methods is fundamental, in unsupervised classification; first stage is identifying the spectral classes, which consequently will be the source to determine the information classes. The supervised classification is totally the opposite procedure where information classes are identified first by training areas to produce the spectral classes.
Various techniques are used to create more accurate classification results for LULC applications when processing remote sensing data (Hulchinson 1982). One important and critical task in supervised classification is obtaining an acceptable number of training areas, whereas the training areas are usually collected from the field, from high spatial and temporal resolution of aerial photographs, and/or satellite images. Not only the number of the training areas that matters but also the collection methods of training areas, such methods can be done by collecting single pixels to represent the class or group of pixels, other approaches are also possible, in all cases the method has a large effect on the classification results (Chen and Stow 2002).

2.2.2 Pixel-based image classification

In pixel-based unsupervised classification, the image pixels are aggregated according to their spectral information in order to create groups of similar pixels in properties that entitled clusters. In this case, the main tasks for the analyst are to determine how many clusters needed to be generated, and which image layers to be used as basis for clustering, and based on this information, the image classification software creates the clusters which usually represents different spectral classes. There are different algorithms for unsupervised image clustering that are available for remote sensing imagery, where most common ones are K-means and Iterative Self-Organizing Data Technique Analysis (ISODATA) algorithms. The analyst then assigns each cluster with the appropriate information class that represents, whereas in most cases in unsupervised classification, multiple clusters represent single class. In general, there are two steps to conduct unsupervised image classification, generates the clusters and assigns the classes. In supervised classification, the analyst starts by selecting representative training regions or areas of interest for each information class in the image, where the image classification software accordingly uses these training areas to assign the spectral classes in the imagery. Pixel-based supervised classification calculates the statistical properties of the pixels to define the training areas (Addink et al. 2012). The image classification software then assigns each class according to what it possibly represents in the training areas. There are much more supervised algorithms than unsupervised ones where most common supervised classification algorithm is Maximum Likelihood classifier. In general, three basic steps are involved to conduct a supervised classification, selecting of training areas, generating a signature file, and image classifying.

2.2.3 Object-based image classification

In general, four main steps are engaged to conduct object-based analysis, perform the segmentation, selecting training areas, extracting features and classification. The core of object-based classification is segmenting the image into groups of well-defined and similar pixels (homogeneous areas) that creates objects of different characters; this processing tool is called segmentation. Objects are mainly classified according to the geometrical and topological properties of the geographical features which basically include their shape and length, also adjacency is considered in most cases. Several parameters can control the segmentation process that includes the colour of the pixels, the scale of the image, and the general or specific form of the objects (Forghani et al. 2007). These segmented groups which represents different features or classes are usually more expressive than pixels alone, main reason is the ability to include more than only spectral information to identify a class, such information for the segmented pixels can be more related to their texture, the context they fall in, or their geometrical properties (Pal and Mather 2003). Segmentation gathers similar things in one group and a specific algorithm is needed to setup the behaviour of segmentation, one of the most common ones that used for classifying imagery in object-based approach is the Nearest Neighbour (NN) algorithm, which similar in mechanism to the supervised classification technique.

After the segmentation, the analyst identifies training areas for each class which consequently detects specific statistics, the OBIA software then classifies the pixels based on their similarity to the training areas and the predefined statistics. The colour parameter is important in the segmentation because it supports the balance between the homogeneity of the segmented objects colour with the homogeneity of these objects shape. As the scale is always an important factor in GIS especially when analysing geographic features, the scale parameter in segmentation is determined in all study cases by the analyst, which is primly influenced by the heterogeneity or homogeneity of the image pixel and controls the relative size of the image segments (Baatz et al. 2004). Also, the form parameter controls and balances the smoothness of the borders for each segment with its compactness. Since these parameters are very important and controls the results of the segmentation and subsequently the classes, it is useful to weight the contribution of each parameter to the overall segmentation process which is a basic use in OBIA. The parameters weighting establishes the homogeneity for the pixels, also image layers and other parameters can be weighted in OBIA such as the form and smoothness parameter that usually weighted from 0 to
1. Because various parameters are involved and almost each one has different constituents, thus parameters in OBIA have no units.

2.2.4 Land Use \ Land Cover classification

Land Use \ Land Cover classification (LULC) is an evolving study in geographic researches that was developed along with the advancement in producing high spatial resolution imageries. The traditional satellite imageries have not been able to provide accurate information about urban areas because of the coarse resolution that neglects a lot of urban features e.g. individual houses cannot be identified, also the conventional pixel-based paradigm considers only the spectral information and ignores other important factors in urban environments such as the shape. Using pixel-based for urban mapping has major limitation since many land cover shares the same spectral information e.g. the cement material can be found in streets, rooftops, parking and other covers, also many different land covers have similar spectral properties and same material such as asphalt can be used for parking lots and for rooftops, wooden rooftops and trees, dark objects and water. For these reasons, aerial photographs have been the major source for urban planning and management studies, and object-based approach was emerged to conduct LULC classification (Myint et al. 2011). Recently UAV’s for the many advantages over aerial photography has been widely used for urban studies. Using VHR imagery for land cover identification definitely is much better than coarse resolution imagery but it carries some challenges; mainly new objects and features can be seen in VHR imagery that could be considered a land cover such as swimming pools, playing courts, sidewalk and more.
3. Materials and methodology

This chapter presents the data sources used in the research and introduce all methods that was taken to accomplish the study. The data used in this research is basically a UAV image with the standard three colour bands of RGB that was downloaded from the internet, in addition to a DEM layer and point cloud image for the same area. The following sections describe how the image classification for geospatial application of LULC mapping was undertaken through the research starting by data analysis and selecting the appropriate training areas until finishing the accuracy assessment for each algorithm. This chapter describe the major two types of unsupervised and supervised classification and their differences, where this research is using supervised technique, also it emphasizes on the two approaches along their algorithms which were used for this research as pixel and object-based approach. The last section describes the accuracy assessment procedure that was conduct while ensuring fair representation to the study area, and allowing to compare between all algorithms in the pixel-based approach and select the most accurate one to compare it with object based algorithm. The chapter describe in details all steps for each approach, also highlights scientific background and mechanism for each algorithm used in the research.

3.1 Data

The UAV image for this research was chosen to be heterogeneous and representative for LULC classification of urban areas. The dataset was downloaded from a website for specialized company in UAVs data management called drone mapper, https://dronemapper.com/sample_data, which also has specialized software DroneMapper for processing UAV imagery, phenomenology investigations and analysis. The image was acquired by Pteryx UAV that was processed at a ground sample distance (GSD) of 6.7 cm per pixel. The camera which was used is Canon Powershot S90, 10 megapixels at an altitude of 200m where the image covers an area of 1.15 km², and composed of 20,356 x 22,642 pixels in three bands of RGB. The study area is located in Wroclaw, Poland, where VOLVO factory is one of the major landmarks of the city and it can be seen clearly in the image. The image was processed and mosaicicked in DroneMapper software to produce all available sample data i.e. DEM, DSM, point cloud and Orthomosaic image (figure 3.1). This sample image is representative and suitable to use in this research to study UAVs imagery in general and LULC classification of UAV imagery, because it has the normal and common characteristic of any UAV imagery in term of spatial resolution < 10cm, and the spectral resolution is limited to the three visible bands, which make this sample image a good reference for UAV’s imagery classification. However, advanced UAVs provides higher spectral resolution that includes IR and other useful bands similar to any satellite sensors, LIDAR or other types. For the purpose of LULC classification of urban areas, this sample image is representative and contains most standard classes that can clearly be identified in any urban environment by suing a satellite imagery, which include buildings, greenery, bare area, and water. VHR imagery usually provides more land cover classes such as the roads, individual buildings, asphalt, parking lots, rooftops, trees, grass and others. In addition, the rooftops of the buildings in the image have different materials such as wooden, metal and concrete which makes it a good sample for buildings classification. In this study, the buildings class will be examined as a vector component to be integrated into GIS.
3.2 Image classification

The production of LULC map is a common application of remote sensing; these maps can include different classes that vary according to the objective of the map, and to the study scale which can be local, global or any other scale (Forghani et al. 2007). The oldest and consequently the most widely used approach for classifying imageries in remote sensing is pixel-based, which classify each image’s pixel as an independent component in the scene according to its spectral information, regardless of its spatial context. The main issue usually when generating classified maps by pixel-based approach is the absence of detailed and accurate spatial context, in addition to the confusion in classes that may happen because of the similarity of spectral responses from the main geographic features in urban locations. It is often the case where two or more different features are recognized as one class, or these classes overlapped and produced a mixed class, both cases will eventually reduce the accuracy in the final map, these issues were the driving force to develop the object-based classification. In this study, both approaches of pixel-based (spectral based) and object-based for image classification were conducted for VHR imagery of RGB bands in order to compare the effectiveness and applicability of each approach in producing accurate LULC classes and provide better urban mapping and interpretation. This research deliberate on three most common algorithms in pixel-based approach since these algorithms usually produce the best classified images in various applications, on the other hand, only one algorithm in object-based approach was considered because the segmentation process is the key factor that affects the algorithm performance, also the Nearest Neighbour algorithm is the most common one that is used frequently in similar researches for comparison purposes (Cleve et al. 2008, Whiteside et al. 2011).

The research undergoes several methods in order to be able to achieve its objectives. Several tests were conducted, in addition to many trials and error attempts to reach appropriate values based on visual interpretation. The image was enhanced at the beginning through testing different layer combination and incorporating IHS and PCA layers in order to select the desired image for classification. After selecting the final image, pixel-based image classification started by selecting area of interests to be used as a signature file for the algorithms, then the three pixel-based algorithms ran to assign the classes. The object-based image classification started with segmentation, feature extraction and then assigning the right parameters to run the NN algorithm. The accuracy of pixel-based classes is assessed by error matrix where AP measure is used to compare between the results of pixel-based algorithm with the results from object-based in relation to the building class.

3.3 Pixel-based classification

In general, the procedure to conduct image classification for remote sensing imagery has several tasks in order to complete. The full procedure is summarized in the figure 3.2 which includes all main steps before, during and
after processing the image, all mentioned steps have been taken through this study. For example, step 1 is defining and designing the whole classification approach with outline for the procedure, and step 2, the geographical stratification, that includes image pre-processing; radiometric and geometric correction, and image enhancement. The Orthomosaic image used in this research is a VHR imagery that already geometrically corrected from the source, however geometric and radiometric correction is needed for most remote sensing imagery, but recently the images shared over the internet or the phones are already geo-referenced or geo-tagged. The Orthomosaic image is geometrically corrected and projected for WGS 84 coordination system and has a skip factor of 999 for X and Y while this factor was recalculated to 1 in ERDAS IMAGINE2014. Changing the skip factor in the original image from 999 to 1 cell did not affect or change the overall look of the classified image because of the high number of pixels in the image which was over 460 million. However, changing the skip factor in satellite imageries usually has an impact on the image especially when number of pixels is low. The software ERDAS IMAGINE2014 was used in this study for pixel-based classification including all steps. Image enhancement was performed by histogram stretch to decrease the effect of the illumination and brightness in the image. Contrast stretch by histogram equalization which was used in this research is one of the simplest techniques that proven to be effective for all kind of imageries, also the histogram equalization tool is available in most basic image processing programs, this enhancement works by distributing the digital values from 0 – 255 for all pixels where each pixel will have a value from that range.

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Figure 3.2: Image classification steps.

Several major classes in the Orthomosaic image were identified at first trial; greenery, bare area, buildings, concrete, water and others. The greenery area class includes grass and trees. The concrete class includes asphalt and vehicle parking areas. The buildings class includes all buildings that made of any material. Bare area and water classes did not include any potential subclasses. However, some issues usually appear when conducting pixel-based approach for image classification in remote sensing, most common are the size and scale of the training samples (Ma et al. 2015). It is very important that the number of classes that will be created for the study area to be enough and satisfactory for describing the different land covers in the image, also the selected training areas must offer a representative depiction of each class. For example, a basic requirement when using ML classifier is to have the total number of pixels collected in each training sample in the satellite imagery for any class to be at least 10–30 times of the sum of all classes identified in the image (Ma et al. 2015). However, despite how many algorithms are used in classifying images in remote sensing, no standard number was proposed as an optimal number of training samples (Li et al. 2014). Nonetheless, what already well known and has been verified in many studies is the size of the training samples has a substantial influence on the results and its accuracy measure, particularly when using pixel-based approach (Foody 2009).

Through selecting the training areas for each potential class in a pre-test that was done to evaluate the performance of pixel-based approach, it was clear that shadow presented in the image will largely affects all classes and therefore the results. Just like any other source of remote sensing imagery e.g. Landsat, the shadow causes misclassification in most classes and specifically with water features. In addition, other classification criteria were evaluated such as the size of the training samples, and their ability to represent all features and create a good class e.g. selecting samples where shadow was considered as part of the class and in another try selecting samples without taking any shadowed pixels in the training sample for any class. Also, shadow was tested to be a class by itself in order to be omitted later. To ensure the selection of the best and more representative training samples with lowest overlap rate, a separability analysis was done before all classification process which will eventually help to obtain more accurate results. This analysis shows the total number of pixels that have similar statistical measures in each band layer. After the first test was finished, it was clear that having different sizes of
the training samples changes significantly the results of the classification by visual comparison. Also, including or excluding the shadow as part of a class did not considerably affect the results, moreover, creating a shadow class was not possible. It is important to mention that scale was highly noted to be a main parameter to be carefully adjusted in the classification process of VHR imagery, basically because different objects can be identified or disappeared at a different scale. In addition, ERDAS IMAGINE offers different parameters to be included in the supervised classification beside the algorithm itself such as fuzzy classification, adding non-parametric rules, and using distance files. For the pixel-based classification approach in this research, none of these parameters were adjusted for any used algorithm to assure a fair comparison for the performance of each algorithm by itself.

The first results of classifying the Orthomosaic image had pointed out the need of using a specific technique that would assist in producing more accurate classification result and solving the main issue in the image which will be caused by the shadow. Most common techniques in such cases are doing an intensive pre- or post processing or incorporating ancillary data as suggested in previous researches and it is well known procedure in remote sensing studies. The classified image (figure 3.3) shows the blue pixels that represent the water class are distributed everywhere in the image, and areas with shadow were difficult to be correctly identified and assigned to a specified class, this consequently affects all classes since the shadow is existed in the whole image. In general, misclassified pixels within classes are disturbing the major objects e.g. the big buildings in the centre in the scene. Greenery areas were identified easily and correctly in many locations in the image whereas sub class as trees and grass can be identified, as well as the bare areas were differentiable. The concrete class was misclassified with buildings in most parts as well as with bare areas in other locations. As was suggested from the beginning according to previous researches where converting the RGB colour space to IHS space for UAV imagery has contributed positively in feature extraction thus the classification, therefore it was considered to be investigated in this case study. Other techniques were examined that consider the Principal Components Analysis (PCA), PCA is a method of data compression which eliminates redundant data through compacting all image bands into fewer number of bands usually less than three. Both techniques did not significantly contribute to identify correctly a meaningful training sites mainly because of the shadow needs different approaches to remove, or because only three bands are existed which make PCA approach not very effective, however, its usefulness is well known in hyper and multi spectral images, the results of both classified images are included in appendix A.

Finally, a DEM layer (figure 3.4) was downloaded from the same source of the original image was selected to be incorporated to the image layers by layer stack function in ERDAS IMAGINE2014. Using the DEM layer as ancillary data has been used and verified in previous studies to be able to enhance the process of feature extraction in different applications of remote sensing especially for agricultural and urban studies (Duro et al. 2012, Whiteside 2011). Hereafter, the DEM layer was stacked as a fourth layer to the Orthomosaic image (figure 3.4) to complete the classification in this research. Incorporation of the DEM layer will offer the possibility to enhance the quality of the signature file, because the features were extracted based on more than spectral information and data values of only three layers. This incorporation at least will support the distinguishing between similar spectral information of two classes such as buildings and concrete, basically because buildings have an elevation higher than other features or classes, and another example is water areas in the DEM layer have lower values than other classes. However, adding a DEM layer might not be helpful in separating the misclassified water classes with shadow in different study areas or applications, for example in a scenario where water bodies are existed in a hill, it will be confused with other objects that has high value of spectral reflectance. The initial test of classifying the four layers’ image showed the possibility to produce better results in term of the visual look of the classes and the accuracy by considering this approach. Eight classes were created as information classes; water, trees, grass, bare area, buildings, concrete, asphalt, and vehicles, though vehicles are not a land use or land cover class but they were considered in the study for been existed in different areas in the image.
3.3.1 Maximum Likelihood algorithm

ERDAS IMAGINE as a specialized remote sensing software is oriented towards pixel analysis, and offers several supervised algorithms for image classification. The most common and powerful algorithms are available in the software including the three algorithms used in this research. The only thing needed for the classifier to work is the signature file that was created from the four layers Orthomosaic image through the training areas. The three
visible bands RGB are basically enough for naive user to distinguish between different LULC types that include major classes i.e. greenery area, water, and bare area at small scale. Besides buildings class can be also easily recognized at any scale, therefore the results of any image classifier it is expected to have at least correctly identified these major areas of each class. Adding the DEM layer to the RGB image contributed to enhance the features signature through distinguishing the digital values that became considerably different than digital values of only the three layers.

ML algorithm calculates the probability for each pixel to belong to a certain class from all eight classes; buildings, trees, grass, bare area, water, concrete, asphalt and vehicles. Basically, to initiate the ML algorithm which is similar to the work of many other algorithms in pixel-based classification, it needs to calculate the spectral statistics for each pixel in the training sample of a given class, while at the same time creates a classification signature. The signature consists of the spectral information of the three RGB bands that represents the different land covers in the training areas, in this research; also, the mean value for the DEM layer was included in the signature file. The signature file was saved at this point to be used in comparing the other two algorithms. One of the disadvantages of ML algorithm are the basic assumption that data values of all pixels in the image follows a normal distribution, and the assumption of only statistical parameters of the training areas can be representative enough to distinguish all classes (Lillesand et al. 2008). The same LULC categories that were defined in ML classifier will be used with the other algorithms and the object-based approach.

3.3.2 Distance algorithms

ERDAS IMAGINE software offers algorithms that are based on the distance between pixels, the Minimum Distance (also called spectral distance) and the Mahalanobis Distance are the most common types. Minimum Distance algorithm works by measuring the spectral Euclidean distance between any candidate pixel and other pre-classified pixels, by calculating the mean value for each class and the data value of the pixel, based on that the algorithm assigns the class that has the closest mean for each candidate pixel (Leica 1999). The advantages of this types of algorithms are the low computational time cost that made this algorithm as one of the fastest classifiers, also this algorithm does not yield any unclassified pixels in the results. As a disadvantage, the algorithm does not consider class variability. For example, bare area as a land cover class is usually mixed up of pixels with a high variance, may tend to be further from the mean of the signature. Using this algorithm, outlier pixels in bare area most likely will be falsely classified. In contrast, pixels in water class usually has low variance that tends to be over classified in most cases, to be over classified it means generating wrong or mixed classes when classifying more pixels than what are actually belong to a specific class, the reason for that to happen is all pixels that fits in a certain class are usually closer to their spectral mean in comparison to the distance of the pixels to their means in the rest of classes. The same signature file that was developed from the training areas for ML algorithm was used for the Minimum Distance algorithm to classify the four layers’ image in ERDAS IMAGINE2014 with default parameters settings.

Mahalanobis Distance algorithm is similar in mechanism to the Minimum Distance algorithm with an exception, considering the class variability by measuring the variance and covariance when calculating the Euclidean spectral distance between the mean of the class and data value of the candidate pixels. Because of the covariance matrix the algorithm assumes that pixels that are highly varied should create also highly varied classes. As an example, in this research for a case study in LULC classification, correctly classified pixels in any class where the pixels vary significantly i.e. bare areas, pixels are much far away from the mean than those of a water class for instance, which is usually not a highly varied class (Leica 1999). Mahalanobis Distance algorithm was applied to the Orthomosaic image in ERDAS IMAGINE2014 without any modification on the default settings. Similar to ML classifier, the Mahalanobis Distance algorithm undertakes the normal distribution in considerations, while in this algorithm it is in connection to the histogram of the image bands, also Mahalanobis Distance consider to be slower than other algorithms. The same signature file and LULC classes used for the previous two algorithms were also used for Mahalanobis Distance algorithm.

3.4 Object-based classification

eCognition software 9.0 was used to run the object-based classification, the software has been considered as the most powerful program for OBIA, and it’s the leader in developing the approach in general. A necessary prerequisite for image processing based on objects is the segmentation process, where many different parameters and algorithms are discussed in literature and available in the software for this task. Segmentation in object-based classification is the most important and main step that determine the accuracy results, nevertheless, the multiresolution segmentation algorithm is very common and has been applied in many studies and produced

17
accurate and appropriate classes in VHR imagery (Ma et al. 2015). This algorithm can be complex and user-dependent, mainly because the parameters of scale, shape, and compactness plays a major role in controlling the behaviour of the algorithm are manipulated by the analyst. The multiresolution algorithm usually involves trial and error, especially when used for the first time, in order to assign optimal values for involved parameters in the segmentation, which is based most likely on the experience of the person who conducts the analysis (Laliberte and Rango 2009). The scale parameter is one of the most important factor in object-based classification approach that sets the acceptable size of the image objects, thus it controls all subsequent steps in the classification process (Hussain et al. 2013). Blaschke et al. (2014) claims that semantically significant regions are existed at different scales, which requires trial and error in adjusting the scale parameter during the segmentation step in order to identify all needed objects for the classification. Trial and error approach is not desirable in scientific research because it allows for subjectivity, for that reason, several methods have been established to determine the optimal value for the scale parameter (Johnson and Xie 2011), yet, none of them has succeeded in determining a value to be adequate for all kinds of imagery.

One of the unique advantages of OBIA is the ability to include hundreds of different variables in the feature extraction process that ultimately support better classification (Duro et al. 2012). As in this research, by using eCognition software for the object-based classification approach for the VHR UAV imagery, the total number of features that can be extracted for each object can reach more than 200 features when classifying the image at 1:1 scale, while it is known that the available features for extraction increases when the scale becomes finer. Using high number of features does not always benefit the classification process because it usually takes a lot of time to analyse, and sometimes complicates the structure of any algorithm, which might cause uncertainty or Hughes phenomenon (Pal and Foody 2010). Nevertheless, features extraction is a vital step to produce more efficient image classification that reflects spatial, spectral and contexture information. The two main reasons of feature extraction in object-based classification are the understanding of the underlying processes that control the data, and finding discriminative and meaningful data features for the classification. For this study, spectral features were mainly selected that can be simple for naive user, and adequate for the comparison with the pixel-based, therefore features selection was mainly based on the mean value of all four layers of the segmented pixels in the Orthomosaic image.

All layers were weighted in this research before running the multiresolution segmentation, while the DEM layer is more important than other bands therefore number 2 was assigned for this layer, and 1 for all other three layers. Several scale values were examined to select the optimal value, 50, 100, 150, 500 based on literatures and visual interpretation of the results (Myint et al. 2011). Scale of 100 was finally used and 0.5 for both compactness and shape parameters to segment the Orthomosaic image as can be seen in both figures 1.3 and 1.4 in appendix B, figure B1 and B2. Feature selection step was performed after the segmentation was done, at the same time a class hierarchy was created for all participated classes of buildings, bare area, water, trees, grass, concrete, asphalt and vehicles. The training samples were selected for all classes randomly where NN algorithm was applied to initiate the classification.

The final classified image by using eCognition software can be simply exported to different raster and vector formats, in addition, the software permits saving only the objects or and the classification results. The obtained objects in the classified image are the link to integrate remote sensing applications with GIS modeling. The classified Orthomosaic image was exported to shape vector format as polygons, while also lines and points types can be exported from the software. In ArcMap10.1, the classified image was overlaid a basemap of Open Street Map (OSM), buildings on OSM coloured in brown polygons and parking areas labelled by blue P letter in the middle of a polygon at scale of 1:15000 (figure 3.5). OSM is a crowdsource project to create a free editable map of the world and is highly recognized in GIS and remote sensing software’s. Both polygons in the classified image are represented as buildings class and concrete class, whereas major buildings and all four parking areas in the OSM map was 100% correctly classified. More useful measurements can be produced in the classified image such as the total area coverage of a class or the buildings perimeter, which highlights more potential use for LULC classification of UAVs imagery.
3.5 Accuracy assessment

After finishing the classification, it is important to know how accurate the results to the real world are, therefore the accuracy assessment is usually done which works as a general approach for comparing the results of classified images to true geographical data. Usually, true data are obtained by samples collected from the field, however, in most cases the ground truth data is very hard or impossible to collect for each pixel, therefore acceptable number of reference pixels is usually used for the comparison. The reference pixels are selected randomly to cover the whole study area while these pixels represent points on the classified image (Congalton and Green 2009). ERDAS IMAGINE2014 provides the accuracy assessment in form of CellArray matrix, which basically generates a comparison matrix for the value of classified pixels with the corresponding value in the used reference of the same pixel. The accuracy report obtained from the CellArray is based on error matrix to calculate the percentages of overall classification accuracy; it also contains the producer’s and user’s accuracy for each class. The error matrix simply compares the reference pixels to the classified pixels in a \( c \times c \) matrix, where \( c \) is the number of classes (Leica 1999).

Reference pixels are the major part to run the accuracy assessment and determine the performance of the chosen classification approach and algorithms, where location, size and quantity are some important aspects of reference pixels that has to be considered when selecting the reference samples. In case of satellite imagery, there are several researches focused on determining the optimal number of reference pixels, however, to agree on a specific number is not possible, some reasons are each image and case study have different properties such as the actual coverage area and image resolution, and also the purpose of the classification. In most cases, reference pixels are identified by the same analyst who biases the comparison in the accuracy assessment, as this is the case of this research, whereas selecting randomly points is reported to decrease or eliminate the bias (Congalton and Green 2009). In general, accuracy assessment approaches have source of errors where many factors are involved in the process, this aspect has attracted many researches in remote sensing. However, error matrix is a widely-used approach for pixel-based classification, which was done for this research by assigning total of 50 random reference points for all eight classes to create the accuracy assessment report. The accuracy results will indicate which algorithm is more applicable for LULC classification of UAV imagery among all the three pixel-based algorithms used in this research.

PRC and AP assessment was adopted in this research as an approach for accuracy, these assessments quantitatively measured the performance of classifying the buildings in both pixel and object-based algorithms. The results of these assessments were used to generally compare pixel and object-based algorithms in this research. MATLAB software was used to obtain the PRC and AP, to generate the curve; Precision axis represents the total number of true positives objects and Recall axis represents the number of positive objects that were identified correctly in the classification. AP is a value from 0 to 1 that represents the average value of Precision
over Recall, where higher AP value indicates better performance. The Precision and Recall can be calculated by the following equations

\[
\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}
\]

\[
\text{Recall} = \frac{\text{TP}}{\text{NP}}
\]

Where TP is true positives, FP is false positives, and NP is the number of total positives.

Table 3.1: Precision and Recall parameters.

<table>
<thead>
<tr>
<th>Factor</th>
<th>ML algorithm (Pixel-based)</th>
<th>NN algorithm (Object-based)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total positive</td>
<td>81</td>
<td>81</td>
</tr>
<tr>
<td>True positive</td>
<td>64</td>
<td>73</td>
</tr>
<tr>
<td>False positive</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>False negative</td>
<td>17</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 3.1 contains the values for each factor that are needed to calculate the precision and recall, false negative are buildings that were identified as concrete or other classes, false positive are other classes that were identified as buildings in the classification. Counting the building in the pixel-based classified image is challenging, all buildings contains number of misclassified pixels, for this reason a threshold was set in order to consider a building as a true or false positive. In this research, the smallest total number of correctly identified pixels for a building was 50,000 pixels, therefore, any total areas of pixels larger than 50,000 pixels that was misidentified as building is counted as false positive. OSM basemap was used in this step to verify the buildings location and size.
4. Results and discussion

The results and discussion chapter highlights the classification results for both pixel and object-based approach where eight classes have been easily and clearly identified in the study area. This chapter presents the LULC maps resulted from each algorithm, and describe each class with its accuracy in comparison to other classes. In addition, it highlights the accuracy measures for each algorithm in pixel-based approach in term of the producer and user accuracy for each class and the overall accuracy for the algorithm. The discussion section deliberates on all results in details with reference to both accuracy assessments, the standard error matrix and the AP measures, also it presents the comparison results of both assessment methods to indicate the best performing one. The end of this chapter assesses the ability of the results to be integrated in GIS environment, and the ability of the three-band image to represent the real world, and the capability of such studies to be considered in applications of urban sustainable development.

4.1 Results

Adding the DEM layer was necessary in order to provide more visually appealing classes and minimize the noise occurred by misclassified pixels within classes, also it allowed more applicable comparison approach that serves the aims of this research. Moreover, class separability analysis confirmed that the incorporation of DEM layer allows a more accurate basis for extracting representative and correct training samples with less overlapped pixels. The shadow impacted the classification of UAV imagery in both approaches, and was the major reason for the misclassification of most pixels. Image classification using the three most common pixel-based classifiers led to three error matrices, which allows for comparison and identifying the most applicable algorithm for LULC mapping for UAV’s imagery. Evaluating IHS colour space was done by classifying IHS colour space image and classifying a 6 layers’ image that contains the two-colour space of RGB and IHS. Transforming the image to IHS domain from RGB did not noticeably produce more accurate classes in the pixel-based classification comparing to the results from classifying only RGB bands. The classification results by ML algorithm for the four layers’ image; DEM and IHS layers can been seen in appendix A, figure A1. The failure of this approach can be stated only for this case study where shadow was classified as water, yet its usefulness can be seen in the building and concert classes where almost the whole building was identified completely correct, and the concert looks more illustrative, however, the usefulness of this technique for object-based approach has been reported in previous studies (Laliberte and Rango 2008). Also in appendix A, figure A2, the classification results by ML algorithm for the four layers’ image; DEM and PCA layers can been seen. Both classified images have a very high percentage of misclassified pixels especially with the water class, and high overlapped pixels between concrete and bare area classes.

For the classification, eight classes were identified in the study area; water, trees, grass, bare area, buildings, concrete, asphalt, and vehicles. The eight classes were chosen based on the percentage of the land use participation in the image and the visual interpretation. The separability analysis was done when selecting the training samples of these LULC classes; it was clear from the results the significant overlapping between the classes in all image layers. For example, comparing the buildings class with all other classes shows the overlapping is very low in the mean of DEM layer except for greenery class i.e. trees. Buildings class significantly overlaps with concrete class because they share similar spectral statistics in most of the RGB bands. Also, the classification results from the pixel-based approach shows water class and bare areas are overlapped despite they are spectrally very heterogeneous and totally different in nature as land cover classes. In this study area, some building rooftops are constructed from natural materials such as wooden, these materials cause substantial confusion in spectral detection, thus classification results. Figure 4.1 shows the overlapping mean values for each layer when comparing the buildings and greenery classes. In addition, a motivating finding was noticed from the figure 4.1 that mean value of blue layer has the lowest overlap measure, this indicates blue band can be a good candidate for distinguishing between buildings and greenery for LULC classification of VHR UAV imagery.
Figure 4.1: Separability analysis for the four layers' image.
(Note: (a) represents the mean red layer with overlap 54%. (b) green layer with overlap 60%. (c) DEM layer with overlap 67% (d) blue layer overlap 14%).

Figure 4.2a shows the results of the classification by ML algorithm in the pixel-based approach, the recoding process took place after the classification to assign a specific colour for each class. It is clear in the image that water class is still misclassified in some locations in the image especially with bare area dominated by shadow. The two areas of water in the image are correctly identified, big buildings, trees and grass are mostly correct, and the boundaries of bare area and concrete classes are distinguishable. Asphalt class is mixed with concrete class in many parts in the image, because they have similar spectral information. For the classified image by Minimum Distance (figure 4.2b), the major difference is within the bare area that covers more areas than ML algorithm. In addition, the results from Minimum Distance algorithm show a high amount of misclassification of asphalt, vehicles and concrete classes. Figure 4.2c shows the classified image by Mahalanobis Distance algorithm; which looks acceptable in providing good overview of all participated classes, the general look is similar to ML results. The bare area located within the railway in the right area in the image was misidentified as red colours that represent the vehicles class in the results from ML and Mahalanobis Distance algorithms. This results highlights the potential of Mahalanobis Distance algorithm to produce accurate results for VHR imagery and can be included in future comparison studies between pixel and object-based approaches, whereas in most previous cases studies only ML algorithm is used to compare with object-based classifiers. Figure 4.2d shows the results from the Nearest Neighbour algorithm in object-based classification. By basic visual comparison, object-based classified image looks more appealing and accurate than all pixel-based results, in addition to very low noise of misclassified pixels. The water class is correctly identified and its border is well determined. The bare area is more realistic and looks very accurate and similar to the original Orthomosaic image. The concrete class does not mix with buildings class in most areas and is very well distinguishable, even the asphalt class can be seen clearly in the classified map. The result obtained from object-based classification was confirmed to be highly dependable on the type of segmentation.
Figure 4.2: LULC maps resulted by all tested classification algorithms.
(Note: Each panel show the classified map by a specific algorithm where (a) Maximum Likelihood algorithm, (b) Minimum Distance algorithm, (c) Mahalanobis Distance algorithm and (d) Nearest Neighbour algorithm).

4.2 Discussion

Accuracy assessment methods based on selecting random reference points are commonly known to be more reliable than using homogenous group of pixels of LULC types, this assumption may be wrong when assessing the results of object-based image classification (Foody 2009). The main reason is that single pixels are merged with the surroundings by segmentation, thus using single pixels or points makes the accuracy of object-based classification to be less evaluated. One of the challenges in this research was deciding on the total number of classes and determining the accuracy assessment procedure to compare between the results from the two approaches. The main types of land cover classification were included such as water, bare area, trees, grass, buildings, where three more classes were identified: vehicles, concrete and asphalt in this UAV imagery, these extra classes usually cannot be clearly seen in satellite imageries. Since UAV applications in remote sensing is a new trend comparing to satellite imageries so some limitation may arise due the absence of standards, for this research, it occurred when selecting the appropriate number of classes, nevertheless, number of classes normally does not influence how to measure the accuracy of the classification. Also, the total number of training areas for each class was hard to detect as another challenge in addition to selecting the best method to compare the results. Both measures of accuracy used in this research are commonly used to assess quality and performance of pixel and object- based algorithms (Everingham et al. 2010), whereas PRC measure depends on quantities and objects thus the buildings were selected for comparison since they are a major element in many urban applications.

The overall classification accuracy of ML algorithm in this research was 86% with kappa coefficient equals to 0.826 as shown in the error matrix in table 4.1 that includes the users and producers’ accuracy for each class. For the Minimum Distance algorithm results, the overall classification accuracy was 80% and kappa
coefficient 0.7411, the error matrix for all classes can be seen in table 4.2. For the Mahalanobis Distance algorithm, the overall accuracy of the classification was 76% and kappa coefficient 0.7037, the error matrix for the algorithm can be seen in table 4.3. The users and producers’ accuracy are commonly used approach to measure the accuracy of each class alone in pixel-based classification, and therefore generates an overall accuracy report. Finally, the AP measure for object-based classification was 0.9621 and for pixel-based classification was 0.9152; both PR curves can be seen in figure 4.3.

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Producers Accuracy</th>
<th>Users Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings class</td>
<td>10</td>
<td>12</td>
<td>10</td>
<td>100.00%</td>
<td>83.33%</td>
</tr>
<tr>
<td>Trees class</td>
<td>6</td>
<td>5</td>
<td>5</td>
<td>83.33%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Grass class</td>
<td>15</td>
<td>14</td>
<td>14</td>
<td>93.33%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Concrete class</td>
<td>11</td>
<td>10</td>
<td>8</td>
<td>72.73%</td>
<td>80.00%</td>
</tr>
<tr>
<td>Water class</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Asphalt class</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>33.33%</td>
<td>33.33%</td>
</tr>
<tr>
<td>Bare Area class</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Vehicles class</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>100.00%</td>
<td>50.00%</td>
</tr>
<tr>
<td>Totals</td>
<td>50</td>
<td>50</td>
<td>43</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Classification Accuracy = 86.00%, Overall Kappa Statistics = 0.8260

The producer’s accuracy works by calculating the probability that a certain class in the real world is correctly classified in the image, while on the other hand the user’s accuracy measures the probability that a classified pixel in a certain LULC class is in reality corresponds to this class (Congalton and Green 2009). In this research for example, building class in all algorithms results was 100% for producer’s accuracy, where user’s accuracy was 83.33%, 88.89% and 79.95 for ML, Minimum Distance and Mahalanobis Distance algorithms respectively. The difference in accuracy results between the two algorithms ML and Mahalanobis Distance verifies the bias that might occurred in the accuracy assessment approach where the two classified images looks similar by visual comparison. One reason is the reference points were located in different areas for the assessment i.e. many reference points where located in border of two classes when assessing the Mahalanobis Distance classified image, so it was hard to identify the right class which probably decreased the overall accuracy measure.

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Producers Accuracy</th>
<th>Users Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings class</td>
<td>8</td>
<td>9</td>
<td>8</td>
<td>100.00%</td>
<td>88.89%</td>
</tr>
<tr>
<td>Trees class</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Grass class</td>
<td>18</td>
<td>13</td>
<td>13</td>
<td>72.22%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Concrete class</td>
<td>15</td>
<td>16</td>
<td>13</td>
<td>86.67%</td>
<td>81.25%</td>
</tr>
<tr>
<td>Water class</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>100.00%</td>
<td>66.67%</td>
</tr>
<tr>
<td>Asphalt class</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>66.67%</td>
<td>66.67%</td>
</tr>
<tr>
<td>Bare Area class</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>33.33%</td>
<td>33.33%</td>
</tr>
<tr>
<td>Vehicles class</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>100.00%</td>
<td>50.00%</td>
</tr>
<tr>
<td>Totals</td>
<td>50</td>
<td>50</td>
<td>40</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Classification Accuracy = 80.00%, Overall Kappa Statistics = 0.7411
Table 4.3: Error matrix table for Mahalanobis Distance algorithm.

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Producers Accuracy</th>
<th>Users Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings class</td>
<td>15</td>
<td>19</td>
<td>15</td>
<td>100.00%</td>
<td>79.95%</td>
</tr>
<tr>
<td>Trees class</td>
<td>7</td>
<td>8</td>
<td>7</td>
<td>100.00%</td>
<td>87.50%</td>
</tr>
<tr>
<td>Grass class</td>
<td>10</td>
<td>7</td>
<td>7</td>
<td>70.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Concrete class</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>50.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Water class</td>
<td>4</td>
<td>7</td>
<td>3</td>
<td>75.00%</td>
<td>42.86%</td>
</tr>
<tr>
<td>Asphalt class</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>40.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Bare Area class</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>----</td>
<td>----</td>
</tr>
<tr>
<td>Vehicles class</td>
<td>4</td>
<td>6</td>
<td>3</td>
<td>75.00%</td>
<td>50.00%</td>
</tr>
<tr>
<td>Totals</td>
<td>50</td>
<td>50</td>
<td>38</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Classification Accuracy = 76.00%, Overall Kappa Statistics = 0.7037

Figure 4.3: The standard Precision–Recall curve, left: ML algorithm, right: NN algorithm.

From the results of the classified maps, it can be noticed that pixel-based approach can be successful when classifying VHR imagery for land covers despite that some classes are homogeneous (i.e. grass class). Object-based approach was able to provide more accurate results of LULC classification of VHR UAV imagery by incorporating the segmentation process as a major step for feature extraction, where many variables can be included to enrich the selection of meaningful training samples. The object-based approach used in this research produced results with accuracy higher than the pixel-based classification in the way of identifying correct classes. The results propose that OBIA has great potential for extracting land covers and land use information from UAV imagery, for the most part, with the increasing applications of VHR imagery and the good quality of information content it carries. By visual interpretation between the results of each classification algorithm it is easy to spot the differences, where pixel-based classifications misclassified a lot of pixels, mostly in land covers that are spectrally heterogeneous, such as concrete and buildings class. Object-based classification was able to solve some of these problems associated with pixel-based approach in classifying LULC types and their heterogeneity.

In this study OBIA has found to be able to provide several advantages over the pixel-based image analysis. The main advantage is segmenting the image into objects is similar to how humans recognize the surrounding space, also integrating useful properties such as shape, texture and context can produce data that can be easily modelled in GIS (Hay and Gastilla 2006). It was also found that scale parameter is very important for both techniques, whereas adaptation of more quantitative and qualitative approaches for selecting optimal values of all parameters will possibly reduce trial-and-error. The use of multi sensor data or ancillary data such as available GIS layers can be suggested for similar future work. It is worth to mention; naive users may favour the general appearance of object-based classification images as compared to pixel-based classification images even if accuracy assessments result for pixel-based are shown to be better. The aims of this research were accomplished when ML algorithm was identified as more applicable for classifying VHR imagery of RGB bands when using
the pixel-based approach than other common algorithms. Another aim was assessing the segmentation process; the study reveals that segmentation has high effects on classifying UAV imagery and contributes in producing more accurate results. Finally, the results verify the ability of UAVs in providing high quality raster and vector format data for geographical modeling and analysis. However, object-based performed better, yet, many possible classes that can be clearly seen in the image were not easy to identify such as cars and windows.

The results of this study verify the capability of both pixel and object based classification techniques in analysing VHR of RGB colour and provide acceptable classes. Also, the method of assessing the results are not similar for both techniques which may cause slight disturbance, however, the same method of accuracy assessment was used in many previous researches (Everingham et al. 2010). It was noticed that considering more classes had helped in providing better overall classes’ identification for the primary classes despite the vehicles couldn’t be identified easily and correctly in such VHR image of RGB, hence, a specific algorithm is needed for such class. In addition, adding the DEM didn’t resolve the problem completely in both approaches and other techniques might be useful such as adding more rule-based values, and contexture information in object-based classification. By visual interpretation, three classes were correctly identified in all parts of the image i.e. trees, buildings and grass, other classes were not completely classified correctly especially the vehicles and asphalt. It is worth to mention, one of the drawback of the object approach is the time needed to process the segmentation especially when reducing the segmentation scale, although having small segmentation scale assists in producing better object segments.
5. Conclusions and future work

This study tries to identify the best algorithm in pixel-based approach to classify a UAV imagery and at the same time compares between the pixel and object-based approach for UAV image classification. This chapter presents what can be concluded from the results and research methodology, also it emphasis on the ability to integrate the results of the classification from both approaches to be used directly in GIS for any geospatial projects. The section future work describes the limitation and future recommendations to conduct similar studies in the same field of applications. There are several possible adjustments can be taken in consideration and this subject can be studied more for a wide range of deployments in urban application such as city planning.

5.1 Conclusions

Classification algorithms can-not be described as right or wrong, but rather they do a better or worse job in classifying pixels for UAV’s imagery. By comparing the results of accuracy for the three pixel-based algorithms that participated in this research, ML algorithm produced the highest accuracy measure for classifying UAVs imagery. In general, classified maps produced by ML algorithm in pixel-based and NN algorithm in object-based approaches has a similar description of LULC classes within the study area. The object-based classifications in comparison to pixel-based classification had presented more continuous depiction of LULC classes, however, further processing in pixel-based approach may also provide similar continuous demonstrations of the classes. Features extraction is highly needed in GIS studies which make the analysis and modelling faster for example for digitizing, this method is usually done through object based approach, despite the high demand of such technique in extracting urban features, water bodies or geographical objects; the approach is mature and needs more advancement in different aspects mainly the accuracy and standards of procedures.

There is a need to evaluate the performance of the available algorithms for image classification, and their applicability of producing accurate classes to various kinds of remote sensing applications. This need can be achieved only if standard sets of representative images are developed along a predefined classification model and satisfactory yet descriptive training samples. This research illustrates one of these efforts towards classifying VHR UAV imagery that became very popular in last years to acquire remote sensing and geographical data. Nevertheless, more image datasets containing high quality testing samples should be analysed for different types of UAVs imagery over distinctive environments in the real world to support objective assessment, and verify which algorithm is more appropriate for a particular application of image classification. One aspect that has not been evaluated deeply in this research is the extraction of non-spectral features whose effectiveness for UAV imagery has been demonstrated in previous studies.

It was recognized from the results of this research that pixel-based image analysis is limited for VHR UAV imagery because of several reasons. Mainly pixel-based image analysis neglects important spatial elements such as texture, context, and shape, and also it lacks the power of aggregating high number of pixels into less and meaningful objects, both reasons can potentially affect the classification accuracy (Hay and Castilla 2006). Not like the pixel-based image analysis, many features can be evaluated for the classification process in OBIA since it is based on homogeneous objects generated by image segmentation. Objects information such as the layers mean values, brightness, variance, standard deviation, etc. can be computed; in addition, the contextual properties of the objects are available to include which can be ultimately differentiate LULC classes that usually have similar spectral value. These additional types of information give OBIA the possibility to create LULC map with higher accuracies than what possibly can be made by pixel-based approach. OBIA is more efficient for urban planning applications where the classes are more accurate particularly the buildings. The study presented the effectiveness of object-based approach in reducing the difficulty of classifying mixed pixels in VHR imagery of RGB, in addition to identifying all possible classes in the scene while preserving the high accuracy.

5.2 Future works

This research focused on VHR UAV imagery that has a high spatial resolution of RGB bands for less than 10 centimetres. In summary, the results of this research contribute to the understanding of the applications of UAV imagery classification, and also to the integration of remote sensing with GIS, where both fields of study will continue to be evolving and provides answers to many geographical questions. Also, it was recognized UAV imagery can be the potential link between remote sensing and GIS especially by using OBIA which easily provide both raster and vector data format. This research evaluated polygon type in vector data formats where lines and points types can be suggested for future work for example streets in a UAV imagery to be exported as lines. Another possible idea for future works are using GIS data as ancillary data for the source image, conduct the AP
measure to all classes, and taking an urban planning specific application as an example and outline for the research such as solar energy production from building rooftops, or smart cities designing in 3D by using UAV imagery as basemaps. The image enhancement technique such as edge detection can be investigated further to be utilized to improve the segmentation process. It is important to declare that this study has some limitations since object-based approach is different from pixel-based when assessing the accuracy for classified images and further assessments are required.
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Appendix A: Classification results for images incorporated IHS and PCA layers

Appendix A illustrates the results of two techniques that were used to enhance the image to obtain better classification results. The most common methods are incorporating IHS and PCA layers to the original image, as can be seen in figure 1-1 adding the IHS layers did not provide better result where misclassified pixels are distributed throughout the whole image in addition to that water class is miss represented in many parts of the image especially in the upper left. Figure 1-2 that show the incorporation of PCA layers have the same issues as in incorporating IHS layers which clearly did not improve the classification results.

Figure A1: Classification results for four layers’ image, DEM and IHS colours.
Figure A2: Classification results for four layers’ image, DEM and three PCA layers.
Appendix B: Segmentation results by multiresolution algorithm

Appendix B shows the segmentation result for the study area by using the multiresolution algorithm which is very popular algorithm in segmenting UAV imagery. The segmentation parameters that control the segmentation are scale, shape and compactness. After trying different values for the parameters and reference to some previous studies the values of 100, 0.5 and 0.5 were assigned respectively to the parameters. Scale is the most important parameter that determine the size of the objects which consequently control the accuracy of produced classes in object-based approach. In the zoom in figure 1-4, it can be noticed that all objects fall within one class and there are no or very few objects that are misplaced and falls within two or more classes.

![Segmentation result, scale 100, shape 0.5, compactness 0.5.](image1.png)

![Zoom in for the segmentation result.](image2.png)