UNIVERSITI PUTRA MALAYSIA

OBJECT-BASED IMAGERY ANALYSIS FOR AUTOMATIC URBAN TREE SPECIES DETECTION USING HIGH RESOLUTION SATELLITE IMAGE

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By

RAZIEH SHOJANOORI

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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Abstract of the thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman : Assoc. Prof. Helmi Zulhaidi bin Mohd Shafri, PhD
Faculty : Engineering

Sustainable management and monitoring the urban forest is an important activity in an urbanized world and subsequently operational approaches requires information about the status to determine the best strategic. In spite of availability of some traditional methods which imposes difficulties for tree species identification in larger urban areas, there is a demand for a fast, sensitive, that is expected to facilitating improvement of monitoring involve remote sensing technologies and image analysis techniques for urban forest inventory, urban tree species detection and ecology management. The main goal of this research is to build generic rule from World View-2 satellite imagery in conjunction with spectral, spatial, color and textural information, which is extracted from available training data for tree species detection. After segmentation, the most important step was feature selection, which is used for dimensionality reduction and discrimination between different attributes. The attribute evaluator method, which performed in this study, was CfsSubsetEval. Result of attribute selection indicates that 26 attributes were extracted from 56 attributes of the WorldView-2 image. In this research, most of satisfactory results achieved from the generic model and proves it can be easily performed to different WorldView-2 images from different areas and provided the high accuracy through algorithms for tree species detection namely, *Mesua Ferrea*, *Samanea Saman*, and *Casuarina Sumatrana* without using any training data. This study also explores the use and comparison of object-based classification, and two common pixel-based classification methods namely, maximum likelihood and support vector machines based on WorldView-2 satellite imagery to evaluate the potential of the object-based in compare to pixel-based to detect urban tree species. The method of maximum likelihood classification and support vector machines leads to the lowest classification accuracy since these algorithms extract only the spectral information of each pixel and consequently fail to utilize spatial, color and textural information.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

ANALISIS IMEJ BERASASKAN OBJEK UNTUK PENGESANAN SPESIS POKOK A BANDAR SECARA AUTOMATIK MENGGUNAKAN IMEJ SATELIT RESOLUSI TINGGI

Oleh

RAZIEH SHOJANOORI

Mei 2016

Pengerusi : Professor Madya Helmi Zulhaidi Mohd Shafri, PhD
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Pengurusan mampan dan pemantauan hutan bandar adalah satu aktiviti yang penting di kawasan perbandaran yang memerlukan maklumat mengenai status untuk menentukan strategik terbaik. Walaupun terdapat beberapa kaedah tradisional yang menyatakan kesukaran untuk mengenal pasti spesies pokok di kawasan bandar yang lebih besar, terdapat permintaan terhadap teknik yang cepat dan sensitif, yang dijangka akan memudahkan peningkatan pemantauan melibatkan teknologi penderiaan jauh dan teknik analisis imej untuk inventori hutan bandar, pengesanan spesies pokok bandar dan pengurusan ekologi. Matlamat utama kajian ini adalah untuk membina peraturan generik daripada imej satelit Worldview-2 yang menggabungkan informasi spektrum, ruang, warna dan tekstur yang diekstrak daripada data latihan yang disediakan untuk mengesan spesies pokok. Selepas proses segmentasi, langkah yang paling penting ialah pemilihan sifat yang digunakan untuk mengurangkan dimensi dan mendiskriminasi sifat-sifat khusus yang berbeza. Kaedah penilaian sifat penilai yang diaplikasi dalam kajian ini adalah CfsSubsetEval. Keputusan pemilihan sifat khusus menunjukkan bahawa 26 sifat telah dipilih daripada 56 sifat yang terdapat pada imej WorldView-2. Dalam kajian ini, sebahagian besar daripada hasil yang memuaskan dicapai daripada model generik. Ini secara langsung membuktikan bahawa teknik ini boleh dilakukan dengan mudah pada imej WorldView-2 yang berbeza dari kawasan yang berbeza dan mampu memberi ketepatan yang tinggi melalui penggunaan algoritma untuk mengesan spesies pokok *Mersua Ferrea, Samanea Saman* dan *Casuarina Sumatrana* tanpa menggunakan apa-apa data latihan. Kajian ini juga meneroka penggunaan dan orbandingan klasifikasi berdasarkan objek, dan dua teknik klasifikasi berasaskan piksel yang biasa digunakan iaitu "maximum likelihood" dan "support vector machine" berdasarkan imej satelit WorldView-2 untuk menilai potensi pengesanan pokok bandar melalui teknik klasifikasi berbeza. Kaedah klasifikasi menggunakan "maximum likelihood" dan "support vector machine" menghasilkan keputusan ketepatan klasifikasi yang paling rendah disebabkan algoritma ini hanya mengekstrak maklumat spektrum sahaja dari setiap piksel dan seterusnya gagal untuk menggunakan maklumat ruang, warna dan tekstur.

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I certify that a Thesis Examination Committee has met on 27 May 2016 to conduct the final examination of Razieh Shojanoori on her thesis entitled "Object-Based Imagery Analysis for Automatic Urban Tree Species Detection using High Resolution Satellite Image" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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This thesis submitted to the Senate of Universiti Putra Malaysia has been accepted as fulfilment of requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee are as follows:

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This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
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LIST OF ABBREVIATIONS

AF	Attribute Filters
AGFLVQ	Adaptive Gaussian Fuzzy Learning Vector Quantization
ANN	Artificial neural network
CHM	Canopy height model
C.Sumatrana	*Casuarina Sumatrana*
DBH	Diameter at breast height
DEM	Digital elevation model
DSM	Digital surface model
DT	Decision tree
FLAASH	Fast line-of-sight atmospheric analysis of spectral hypercubes
GFLVQ	Gaussian fuzzy learning vector quantization
GIS	Geographic information system
GLCM	Grey level co-occurrence matrices
HSR	High spatial resolution
KL	Kuala Lumpur
Landsat ETM+	Landsat enhanced thematic mapper plus
Landsat TM	Landsat thematic mapper
MCH	Mean canopy height
MD	Minimum distance
M.Ferrea	*Mesua Ferrea*
MODIS	Moderate resolution imaging spectroradiometer
MIVIS	Multispectral infrared visible imaging spectrometer
MLC/MLH/ML	Maximum likelihood classification
MS	Multispectral
NDVI	Normalized difference vegetation index
NIR	Near infrared
NLP	National landscape policy
OB	Object-based
OBIA	Object-based images analysis
Pan	Panchromatic
PCC	Percent canopy cover
QUAC	Quick atmospheric correction
RBF	Radial basis function
ROI	Region of interest
RS	Remote sensing
SVM	Support vector machine
SAR	Synthetic aperture radar
SID	Spectral information divergence
SAM	Spectral angle mapper
S.Saman	*Samanea Saman*
UPM	Universiti Putra Malaysia
VHR	Very high resolution
WV-2	WorldView-2

CHAPTER 1

INTRODUCTION

1.1 Background

Nowadays the world's population in urban areas is more than rural areas. The latest statistics of world's population has demonstrated that 54 precents of the world's population lives in urban areas, and this population is going to be 66 precents by 2050 (The United Nations, 2014). Urban area is commonly defined as spaces with artificial surfaces and dense population, and the vegetation that covers an urban area is considered an urban forest. Urban forests may include any type of vegetation in a metropolitan area; types of vegetation include trees, shrubs, and woody plants on the roadside or plants on a larger scale, such as a forest park.

Urban forests not only result in social and economic advantages, such as recreational spaces and tourism attraction, but also provide several benefits to the ecosystem. The most important effect of urban forests in the ecosystem include the following: protection of biodiversity, avoidance of soil erosion, carbon storage, nutrient cycling, improvement of air and water quality, slowing wind and reducing water volume caused by storms, moderate local climate, energy waste minimization by creating shades to buildings, and decreasing heat in an island (Akamphon & Akamphonb, 2014; Conine et al., 2004; Gobster & Westphal, 2004; Huang et al., 2007; Ma & Ju, 2011; Shahidan et al., 2010; Xiao & McPherson, 2005).

As urban forests are vital in ecology, their management, which is called urban forestry, must include strategic and appropriate urban design and planning (Huang et al., 2007; Iovan et al., 2008; Kong & Nakagoshi, 2005). Nevertheless, rapid urbanization, which poses a threat to the safety of an ecosystem (Hepinstall-Cymerman et al., 2013), has compelled scholars to focus on urban green spaces. Human society seems to have realized that living without nature is difficult and unsafe (Kong & Nakagoshi, 2005; Li et al., 2010).

With progressing urbanization, managing urban forests has become a significant concern. The growth of residential and commercial areas can negatively affect vegetation and ecology. Hence, one of the issues in urban forestry is determining the state and quantity of urban vegetation and buildings and controlling their growth and deterioration (Gillespie et al., 2012; Iovan et al., 2008; Kong & Nakagoshi, 2005). Sufficient knowledge on urban forests, such as tree location, size, and species, is essential for effective urban forestry (Ardila et al., 2012).

For instance accurate and reliable information on different tree species is crucial to urban vegetation studies. This information assists urban planners and researchers in urban planning and disaster management (Gong et al., 2013; Hao et al., 2011; Iovan et al., 2008).

Urban spaces are complex areas; hence, accessibility to all trees by field survey is extremely difficult and time-consuming. In this method, the entire city or some parts of an area are randomly selected for sampling (Nowak et al., 2008). At present, remote sensing can overcome these limitations. It can be used to obtain highly accurate information by monitoring and managing urban areas and vegetation(Ardila et al., 2012).

Given the spectral similarity between different tree species, hyperspectral data can discriminate urban tree species appropriately because of characteristics such as narrow-band, multi-channel, and inclusion of continuous spectrum information. However, these data have several drawbacks, including limited coverage, high volume, and high cost(Shafri et al., 2012). Studies conducted with high-resolution satellite imageries, such as IKONOS and QuickBird, also extract tree species effectively (Hájek, 2006; Ke & Quackenbush, 2007; Mora et al., 2010; Puissant et al., 2014; Sugumaran et al., 2003; Voss & Sugumaran, 2008).

Nonetheless, tree detection and information extraction from urban areas are difficult when traditional pixel-based image classification methods are used. This classification lowers classification accuracy due to the high-grade spectral variability within land cover classes that are affected by sun angle, gaps in tree canopies, and shadows (Johnson & Xie, 2013; Yu et al., 2006).

To overcome the aforementioned limitations, object-based image analysis (OBIA) approaches can be utilized to improve classification accuracy (Li et al., 2010; Lobo, 1997; Puissant et al., 2014; Shouse, 2013). Several studies have been conducted to detect tree species; however, the lack of rule sets for conducting this detection process in urban areas remains a major setback.

In tropical areas such as Malaysia, common urban management issues involve controlling the wind, cooling the environment, and increasing energy savings. Thus, the present study attempts to develop new generic rule sets to extract the tree species, which are among the most popular species of urban trees and can increase energy efficiency and limit the damage to properties by windbreak. Moreover, WorldView-2 (WV-2) imagery is used because of the potential of new bands with high spatial resolution to detect vegetation (Immitzer et al., 2012; Latif et al., 2012; Marshall et al., 2012; Nouri et al., 2014; Pu & Landry, 2012; Rapinel et al., 2014).

1.2 Problem Statement

In tropical countries such as Malaysia, the urban development leads to deforestation and disappearing of urban trees. The estimated global deforestation rate is about 7.3 milion hectares annually. If the current rate of deforestation continues, up to 28,000 species are expected to become vanish by next quarter, and it will take less than 100 years to destroy all the forests on the earth.

Rapid urbanization, which poses a threat to forests and the safety of an ecosystem (Hepinstall-Cymerman et al., 2013), has compelled scholars to focus on urban green spaces. With progressing urbanization, managing urban forests has become a significant concern. Insufficient knowledge on urban forests, such as tree location, size, and species, will be destroyed the urban forestry.

Since urban spaces are complex areas; accessibility to all trees by field survey is extremely difficult and time-consuming. Although remote sensing technique is the best method to overcome the time and coverage limitations, some data such as hyperspectral data has the important limitations such as cost, time and coverage. Hence the purpose of this research is to develop a new generic rule set to detect urban tree species based on the remote sensing economical data using statistical approach.

1.3 Scope of the Study

This study focuses on detection of three tropical urban tree species. For this purpose the characteristics of the trees are limited to the colour, texture, spatial and spectral information, so the ages of the trees will not be considered in the analysis. Moreover the minimum size of the trees will be 1.5 m^2.

The study will not cover the counting of trees and will only focus on the detection of tree species. Lastly the study area is limited to the urban area, and the locations are situated in Malaysia.

1.4 Research Objectives

The general objective of this thesis is to develop a new generic rule set to detect urban tree species from Very High Resolution Satellite (VHR) imagery such as WorldView-2. The specific objectives of this study include:

- To evaluate the performance of pixel-based and object-based image analysis (OBIA) methods for detection and discrimination of urban tree species.
- To develop a new generic rule set to discriminate urban tree species based on an OBIA by utilizing spectral, spatial, color and texture information.
- To validate the transferability of the new generic rule sets in other study areas.

1.5 Structure of thesis

The thesis is made up of five chapters, each corresponding to the objectives and contributing towards an advance understanding of the remotely sensed precursors. This first chapter introduces the thematic context of the study, the research problem, the motivation to pursue the research, and the research objectives.

The second chapter reviews literature related to the proposed topic. Aside the literature of the importance of urban forest, the previous efforts on approaches and techniques for urban tree species detection and discrimination by remote sensing are explained (including different imagery and classification techniques).

The third chapter explains an improved framework for urban tree species detection. In first part of this chapter the image pre-processing on WV-2 imagery is considered; secondly the pixel-based classification (Maximum Likelihood and Support Vector Machine) and object-based (OB) classification are explained. Finally the procedure to develop a new generic model to discriminate urban tree species is discussed.

In the fourth chapter of this thesis, the analysis results, which are done on the remotely sensed imagery, are collected. The first part is the spectral-based classification results, and the main part of this chapter is the result of the new generic model which is based on OB classification.

Finally, chapter five focuses on the summary, conclusions, contribution of this study and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to review other researches that are related to urban forest especially urban tree species detection by field measurement and remote sensing techniques. In this chapter firstly the definition of urban fore stand the benefits of them are discussed. Secondly remote sensing technique is explained briefly, afterward the application of remote sensing techniques and imagery in order to urban tree detection and discrimination by different classification methods (pixel-based and object-based) are evaluated. Finally the last part of this chapter focuses on the summary of the literature review and the gap of this study.

2.2 Urban Forest

Urban area commonly implies spaces with artificial surfaces and dense population, and the vegetation that covers the urban area is considered the urban forest. Urban forests may include any type of vegetation in a metropolitan area, such as trees, shrubs, and woody plants on the roadside, or comprise plants on a larger scale, such as a forest park.

The urban forest not only results in social and economic advantages, such as recreational spaces and tourism attraction, but also has several ecosystem benefits. The most important ecosystem benefit is on the urban atmosphere which is divided to four main issues: 1) Influence on microclimate and temperature decreasing: By changing wind speeds, making shadow on surfaces and finally transpiring water. 2) Remove the air pollution. 3) Release the volatile carbon-based compounds by trees. 4) Avoid of wasting energy in buildings: by making a shade for building, to reduce heating and cooling energy of building.

The other effect of urban forest is on the urban hydrology. Urban trees can help to the water quality problems by reducing the storm water overflow volume, and decreasing flooding destruction caused by roots' water absorption and avoidance of soil erosion. After urban atmosphere and hydrology problems, the sound pollution is the other difficulties in the urban area. The leaves and stems of urban trees and shrubs can reduce the noise by scattering the sound primarily, so the tree and shrubs planting in urban area leads to decrease sound pollution (Nowak et al., 2008).

In conclusion the most important advantages of urban forest can be defined as follows: The protection of biodiversity, avoidance of soil erosion, carbon storage, nutrient cycling, improvement of air and water quality, slowing wind and storm water, moderate local climate, shading homes, and decreased island heat effects(Akamphon & Akamphonb, 2014; Conine et al., 2004; Gobster & Westphal, 2004; Huang et al., 2007; Ma & Ju, 2011; Shahidan et al., 2010; Xiao & McPherson, 2005). Figure 2.1 shows some advantages of urban trees on ecosystem.

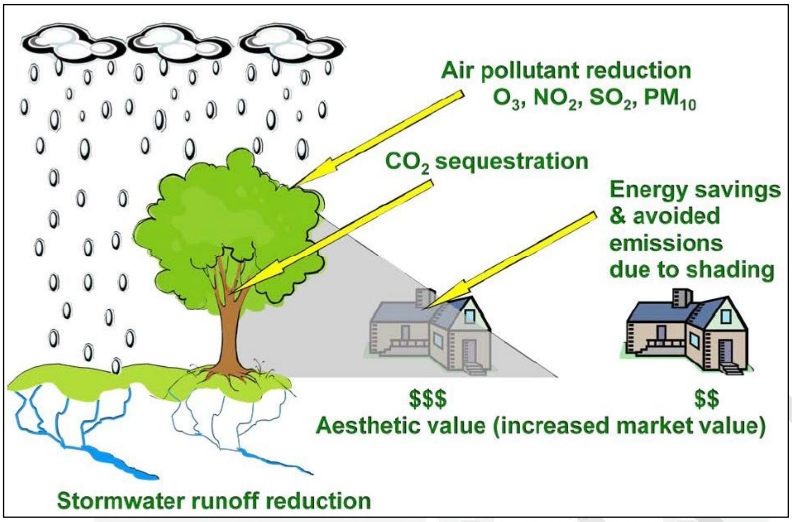

Figure 2.1: Ecosystem services provided by urban trees (Phillips et al. 2011)

Since urban forest is vital in ecology, and thus, its management, which is called urban forestry, must strategize appropriate urban design and planning (Huang et al., 2007; Iovan et al., 2008; Kong & Nakagoshi, 2005). However, rapid urbanization, which poses a certain threat to the safety of ecology (Hepinstall-Cymerman et al., 2013), has pushed people to pay more attention to urban green spaces. Human society seems to have realized that living without nature is rough and unsafe (Kong & Nakagoshi, 2005; Li et al., 2010).

As urbanization increases, managing urban forest has become significant. The growth of residential and commercial areas can negatively affect the vegetation and ecology. Hence, one of the issues in urban forestry is finding the state and quantity of urban vegetation and buildings and controlling their growth and deterioration (Gillespie et al., 2012; Iovan et al., 2008; Kong & Nakagoshi, 2005). Sufficient knowledge on urban forest, such as tree location, size, and species, is essential for effective urban forestry (Ardila et al., 2012).

Manual field measurement is the earliest method for studying urban forest (Francis, 1987). In this method the entire city or some parts of the urban area are selected randomly for sampling (Nowak et al., 2008). On the other hand urban space is a complex area. Thus, accessibility to all trees and vegetation by field surveying is difficult, time consuming, and inaccurate. Knowledge on remote sensing overcomes these limitations and allows gaining highly accurate information by monitoring and controlling urban areas and vegetation (Ardila et al., 2012).

2.3 Remote Sensing

Remote sensing is a technique to observe the earth surface or the atmosphere from out of space using satellites (space borne) or from the air using aircrafts (airborne). In other words remote sensing refers to obtaining information about objects or areas at the

Earth's surface without being in direct contact with the object or area. Remote sensing uses a part or several parts of the electromagnetic spectrum. It records the electromagnetic energy reflected or emitted by the earth's surface (Aggarwal, 2004).

Remote sensing imagery has many applications in mapping land-use and cover, soils mapping, agriculture, forestry, urban planning, archaeological investigations, military observation, and geomorphological surveying.

2.3.1 Application of Remote Sensing in Urban Forest

To obtain vegetation cover map scientists developed traditional tools into new remote-sensing systems (Huang et al., 2007; Iovan et al., 2008). For this purpose, different satellite images, passive optical systems, and active sensors have been utilized.

Moderate resolution imaging spectroradiometer (MODIS) is one of the medium-resolution imageries in monitoring urban forest with about 250-500 meters spatial resolution. MODIS and Landsat imagery are multi-temporal remote-sensing tools, and thus, their most important characteristic is the ability to gain the seasonal and annual information of different types of vegetation covers and land covers (Peijun et al., 2010; Qu et al., 2014; Zheng & Qiu, 2012). Vegetation covers have been shown to have different patterns in the time series in various conditions, such as humidity, because of their potential to combine various information or species compositions (Zheng & Qiu, 2012). However, MODIS and Landsat have temporal limitations (16 days of repeat cycles)(Shouse et al., 2013). Moderate-resolution imageries often have mixed pixels because of low spatial resolution (approximately 30 m), and thus, they cannot be defined as a specific pure class (Peijun et al., 2010) and can detect only land-use types at the city level (Huang et al., 2007; Zheng & Qiu, 2012).

Other medium-resolution satellite systems for studying urban forest have provided Landsat systems, which can provide a means to monitor urban forests rapidly (Huang et al., 2007; Zhang et al., 2007). The visual interpretation of Landsat TM shows that bands 2 and 4 provide sufficient information on land-cover types, and this image with a false color composite of band 4-5-3 (R-G-B) has better differentiations of vegetation types, especially when an adaptive enhancement technique is used (Cai et al., 2010; Ismail & Jusoff, 2004; Jusoff & Hassan, 1996). However, when the study area is bound with a compact plantation because of spectral similarity, small urban and clearance areas are difficult to separate from species trees and mixed agriculture crops (Ismail & Jusoff, 2004). Huang (2007) demonstrated that the Landsat ETM+ imagery of spread urban trees is less coarse than other medium-resolution imageries.

High-resolution satellites have been launched to overcome the limitation of moderate-resolution imageries, such as low spatial resolution. Hence, high-resolution imageries, such as QuickBird (Ardila et al., 2012; Hashiba et al., 2004; Tooke et al., 2009), IKONOS (Greenberg et al., 2009; Ma & Ju, 2011; Pu & Landry, 2012), SPOT (Kong & Nakagoshi, 2005), RapidEye (Tigges et al., 2013), FormoSat-2 (Sun, Lin, & Ou, 2007), WorldView-1, and WorldView-2 (Immitzer et al., 2012; Latif et al., 2012; Nouri et al., 2014; Rapinel et al., 2014), have become popular in detecting and monitoring urban forest.

QuickBird and IKONOS images had been common high resolution satellite imagery in urban forest studies, which both have panchromatic and four-multispectral bands (i.e., red, green, blue, and near infrared) with high spatial resolution (HSR) (Pan: 0.6 – MS: 2.44 m). By contrast, red and near-infrared bands are sensitive to vegetation and contain approximately 90% of the vegetation information, and thus, these imageries can detect vegetation (Li et al., 2010; Puissant et al., 2014). Nonetheless, more bands may be required for extracting vegetation and trees from different land-cover types because of the complex environment in urban areas (Ouma & Tateishi, 2008). The resolution of the multispectral image is 2.4 m. Thus, the objects, which are smaller than 6 m will have mixed pixels, and the spectral characteristic of these pixels will be characteristic of mixed objects, such as roads and trees. Researchers have used different techniques to avoid this error. For instance, Hong et al. (2009) applied the grey level co-occurrence matrices (GLCM) mask and hierarchical classification to improve the accuracy, but they remain insufficient for high-accuracy extraction in urban areas. Consequently, some high-resolution imagery, such as IKONOS and QuickBird, are insufficient to detect urban vegetation as the species because of the number of spectral bands.

The World-View 2 satellite was launched in 2009 to improve high-resolution satellites. This high-resolution imagery has eight spectral bands, which involve bands sensitive to vegetation. It has four old bands, namely, blue, green, red and near infrared, and four new bands, namely, coastal (to detect chlorophyll content), yellow (to detect yellowness), red-edge (to detect plant diseases and vegetation species), and near infrared 2 (to study biomass). Immitzer et al. (2012) demonstrated that the World-View 2 imagery, especially the four new bands (Pu, 2009), can likely detect urban forest. However, some misclassifications have been seen in the classification of tree species because of spectral overlaps, the complex structure of the area, and the small tree crown, which leads to mixed pixels. The Airborne Hyperspectral is the best sensor to overcome spectral limitations. Ghiyamat and Shafri (2010) demonstrated that hyperspectral imagery provides adequate data to distinguish homogenous and heterogeneous forest biodiversity, but urban areas have different environment characteristics and should be evaluated separately.

The hyperspectral data have characteristics such as narrow-band, multi-channel, continuous spectrum information, which can help detect urban vegetation (Hao et al., 2011). Several studies on urban forest have been conducted with hyperspectral data (Adeline et al., 2013; Cho et al., 2012; Forzieri et al., 2013; Hao et al., 2011; Wania & Weber, 2007; Zhang & Qiu, 2012). Most researchers have demonstrated the effectiveness of hyperspectral data to detect vegetation and even tree species accurately. However, certain limitations, such as limited coverage and high volume and cost (Shafri et al., 2012), have pushed researchers to resort to high-resolution satellite imageries.

With the technology advancement in remote sensing, active sensors are also used to detect urban forests. The most traditional satellites can detect tree species well, but they can only delineate urban features and tree crowns in 2D by reflected solar radiation. By contrast, active sensors, such as synthetic aperture radar (SAR) and light detection and ranging (LiDAR), can extract the shape of the tree crown and urban features in 3D even in the shadows and at night (Maksymiuk et al., 2014; Yao & Wei, 2013; Zhou, 2013). Therefore, active sensors have improved the monitoring of urban forest.

Although the benefits of RADAR sensors such as SAR to detect forests are observed (Perko et al., 2010), related studies are mostly limited to forest classification and tree roots evaluation, and the studies in urban forest is rare and new. Maksymiuk et al. (2014) in order to detect urban trees utilized SAR data; finally only single urban trees by Morphological Attribute Filters (AF) were detected. Accordingly, further studies should be done to evaluate the potential of SAR data to detect urban trees in large-scale and to discriminate different tree species. Versus RADAR data, the application of LiDAR data in urban forest is well known and adopted.

Sung (2012) applied LiDAR data to assess the mean canopy height (MCH) and percent canopy cover (PCC) of an urban forest. According to the land development ordinance, the landowner should get a permit to remove the trees larger than 41cm in diameter at breast height (DBH) and Sung (2012) utilized LiDAR data to gain the canopy height model (CHM) by calculating the difference between digital elevation model (DEM) and digital surface model (DSM) (only on tree canopy), and the cells that had value less than 1m were not included in analysis. Although the results demonstrated that LiDAR data are highly applicable and recommended to detect the tree structure and to evaluate the tree canopy heights, the mentioned method (subtracting DEM from DSM) is not applicable in urban area, because sometimes the highest surfaces can be the man-made materials such as buildings roofs, and when the uppermost surfaces is not tree canopy, the difference between DSM and DEM will not be functional for CHM.

Many studies on aspects of urban forest through LiDAR data have been conducted, such as studies on tree crown shape and structure (Oshio et al., 2012, 2013; Sung, 2012), tree detection and urban vegetation mapping (Höfle et al., 2012; MacFaden et al., 2012; Yao & Wei, 2013; Zhou, 2013), tree position and plant density (Forzieri et al., 2009), and individual tree species detection (Vaughn et al., 2012; Zhang & Qiu, 2012). Zhang and Qiu (2012) used the simple confusion of LiDAR data with hyperspectral imagery to discriminate more than 10 tree species. They utilized LiDAR data only to detect tree crown, so the accuracy of tree species was directly related to the resolution of imagery. In other study, Nicholas et al. (2012) applied discrete Fourier transform on LiDAR data to discriminate five individual tree species. However in other researches the discrete point of LiDAR data is mentioned that is better than airborne waveform LiDAR data in order to tree classification (Heinzel & Koch, 2011; Hollaus et al., 2009; Reitberger et al., 2008), the Nicholas et al. research which was the first investigation to compare the accuracy of tree species by using discrete point of LiDAR data and waveform LiDAR data, shows that the overall accuracy by waveform information increase the overall accuracy about 6.2 percent (overall accuracy by discrete point data was about 79.2 percent, and by using waveform LiDAR data was reached to 85.4 percent). Although airborne remote-sensing data, such as LiDAR data, have many advantages as mentioned above, but they have some limitations for urban land-cover classification, which are the processing and interpolating of point clouds into raster layers that are time consuming and vulnerable to misclassification (Zhou, 2013). Appendix A shows the satellite and airborne sensors for urban forest studies.

In conclusion although the best data to detect urban forest and discriminate urban tree species is Hyperspectral data, it is not recommended for urban forest researches due to its limitation such as limited coverage, high volume and cost, thus the other satellite imagery should be replaced. The moderate-resolution imagery because of the low spatial resolution, which leads to mix pixels, is not suitable for urban forest detection. In contrast the high-resolution imagery has presented the potential of this imagery to detect urban forest. However they were not sufficient to distinguish urban tree species till the higher resolution imagery such as World View-2 were launched. The result of urban tree species classification by traditional and new bands of World View-2 imagery has demonstrated the effectiveness of World View-2 to discriminate urban tree species, though they have some misclassification due to the spectral similarity. In order to overcome this limitation the extra information like spatial information, texture, colour should be utilized. The last data, which is almost used as an ancillary data, is LiDAR data. Although this data can extract urban features even in the shadows and night, the processing and interpolating of point clouds into raster layers leads to time wasting and some misclassification. Finally the review has shown that World View-2 imagery is the best data to detect urban forest if the cost, time, and accuracy be considered as the research factors.

2.3.2 Urban Tree Detection by Different Classification Methods

Tree detection by remote-sensing images is the recognition and classification of trees that lead to urban tree canopy and green space mapping (Johnson & Xie, 2013; Lang et al., 2007). The mapping is conducted by urban forestry monitoring methods, which can be classified into three groups, namely, visual interpretation and pixel- and object-based methods (Li et al., 2013).

High-resolution data can be valuable in extracting land cover information, but tree extraction and information collection are difficult in urban areas when traditional pixel-based image classification methods are used. Traditional methods involve supervised and unsupervised classifications. Although unsupervised classification techniques, such as ISODATA and K-mean, are used for thematic mapping (Langley et al., 2001; Sung, 2012; Xie et al., 2008), these methods are rarely used for urban tree detection. Supervised classification methods, such as maximum likelihood classification (MLC), are often used to perform urban land cover mapping (including vegetation cover mapping) because of easy operation and good result (Ardila et al., 2011; Forzieri et al., 2013; Peijun et al., 2010; Shen et al., 2010). The basis of MLC is a statistic classification of all pixels in each band to a specific class even when the threshold is defined. By contrast, MLC might cause certain misclassifications in urban areas. For instance, some parts of the grass area are often classified as trees. Thus, filters, such as intra-class uniformity, inter-class contrast, and smoothness of boundaries between classes, can be utilized to increase the contrast of features and consequently higher classification accuracy (Ouma & Tateishi, 2008). Minimum distance (MD) is another supervised classification for studies on urban forest, and some researchers believe that this method classifies better than other methods (Kamaruzaman Jusoff, 2009; Latif et al., 2012). However, Shen et al. (2010) utilized three classification algorithms (i.e., ML, MD, and DT) for urban forest mapping, and the comparison of these algorithms showed that MD leads to the least classification accuracy and that decision tree (DT) has the highest accuracy among the three algorithms. The principle of DT classification is opposite to that of MLC, by which the separation of the complicated decision to several easier decisions is vital to reach the required classification (Ouma & Tateishi, 2008).

Vapnik (1996) developed a new method called support vector machine (SVM). This method shows the ability to classify urban areas because of their needs to overcome limited training data and low sensitivity to the sample size (Mountrakis et al., 2011; Van der Linden et al., 2007). Therefore, some studies on urban forest to detect vegetation are done through the SVM algorithm (Iovan et al., 2008; Iovan et al., 2014; Lafarge et al., 2005; Tigges et al., 2013).

These pixel-based classification algorithms may lead to low classification accuracy because of the high grade of the spectral variability within land cover classes affected by the sun angle, gaps in tree canopy, and shadows (Johnson & Xie, 2013; Yu et al., 2006). The pixel is the cause of within-class spectral variability in high-resolution images; a pixel is only a small part of a classification object (Huang et al., 2007). Thus, the object-based classification is recommended to overcome this classification limitation.

When compared with the visual interpretation and pixel-based method, object-based approaches can improve the classification accuracy. The object-based method can combine color, shape, spatial information, and contextual analysis for vegetation change detection(Li et al., 2010). The basis of object-oriented methods is image segmentation, which is the split of the image to spatially continuous and homogeneous regions and leads to reduce local spectral variation (Lobo, 1997). Li et al. (2010) combined the segmentation and fuzzy multi-threshold classification to classify urban land cover, where accuracy can reach up to 93.72%. Fuzzy logic and intelligence techniques, such as the artificial neural network (ANN), or integrated ones, such as the Adaptive Gaussian Fuzzy Learning Vector Quantization (AGFLVQ) can become other classification algorithms for urban forest detection and tree species identification (Höfle et al., 2012; Zhang & Qiu, 2012). These classification methods not only detect urban forest but also distinguish urban tree species, and this ability is explained in the subsequent section.

Briefly by comparing several methods for urban tree detection, the object-based classification has shown the best classification result. However the pixel based methods such as ML and SVM have easy operation and good result for tree mapping, they are not adequate for urban area specially for distinguishing urban tree species (which is explained in next section), because the base of this classification is pixel, thus due to the spectral variability in urban area it cannot be applicable to reach to high classification accuracy. Lastly to overcome the limitation of pixel-based classification, not only the spectral information should be used, but also the more information about objects such as spatial information, texture and color should be utilized, hence the object-based classification is the best technique for urban tree detection.

2.3.2.1 Urban Tree Species Detection

Information on tree species is important for urban planning, disaster management, and ecological safety. Accurate, reliable, and expressive measurements of the types of urban vegetation help urban planners and researchers reach their targets (Gong et al., 2013; Hao et al., 2011; Iovan et al., 2008). The concept of the classification of tree species was introduced in the forestry field when satellite and aerial imagery were used to monitor forests (Gougeon, 1995). Numerous studies on the detection of tree species in forests are available (Immitzer et al., 2012), but research on urban areas remains scarce.

The limitation of methods for different satellites or airborne sensors is one of the challenges in studies on urban tree species. For instance, classical methods, such as MLC, can be applied on multispectral imageries. However, these methods are often failed to be applied to hyperspectral data because of small training samples. Hence, other techniques, such as SAM (Forzieri et al., 2013; Wania & Weber, 2007), linear spectral unmixing, and spectroscopic library matching, are utilized for the classification of urban tree species through hyperspectral data (Zhang & Qiu, 2012). However, Forzieri et al. (2013) applied ML, Spectral angle mapper (SAM), and spectral information divergence (SID) on airborne hyperspectral data (i.e., multispectral infrared visible imaging spectrometer (MIVIS)) to detect 10 urban tree species (i.e., herbaceous, heatland, arundo donax, poplar, oak, pine, cypressus, spruce, willow, and olive) and ML had the highest accuracy of up to 92.57%. The reason for the high accuracy may be the availability of LiDAR data because other researchers used them as the ancillary or main data to improve the accuracy of the classification of urban tree species (Höfle et al., 2012; Tigges et al., 2013; Tooke et al., 2009; Voss & Sugumaran, 2008; Zhang & Qiu, 2012).

Zhang and Qiu (2012) utilized LiDAR data for the classification of urban forest species based on tree crown (i.e., crown-based species classification), as such data can address the limitation of the tree crown-shaded side, small tree crowns (might be seen as one object), and the boundary of tree crowns, which leads to mixed pixels. The authors developed a method based on hyperspectral data by combining the fundamental aspect of the neural network and fuzzy logic. The AGFLVQ algorithm is the method utilized to distinguish 20 urban tree species, and the result demonstrates classification accuracy (approximately 68.8%) higher than that of other hyperspectral methods, such as SAM (approximately 39.95%). The classification accuracy is less than the accuracy shown in the study of Forzieri et al. in 2013, although the difference can be caused by the number and types of tree species (Forzieri et al. (2013): 10 Species, Zhang and Qiu (2012): 20 Species). For instance, when the evergreen and deciduous trees are considered, the Gaussian Fuzzy Learning Vector Quantization (GFLVQ) method is unsuitable because the determination of at least two spectra should be used for deciduous trees. However, the basis of the GFLVQ algorithm is that all species have the same spectral signatures; one spectral signature is enough for evergreen species. Therefore, GFLVQ has a limitation, and ancillary data, such as LiDAR data, may solve this problem (Zhang & Qiu, 2012).

The multispectral data can apply different classification methods. Hence, most studies on urban forest species were conducted via multispectral imageries because of other limitations of hyperspectral data (e.g., high volume, expensive, and time consuming). Appendix B shows the summary of the detection of urban forest species through remote sensing and different classification methods.

The review has demonstrated that the most study areas are in non-tropical areas, which have a lot of evergreen and deciduous species, and discriminate between evergreen and deciduous species by spectral signatures in spring or autumn is easier than to discriminate tree species in tropical area. Tree species have different spectral characteristics. Therefore, spectral signatures are useful in distinguishing tree species. Despite this fact, pixel-based classifications, such as ML, and MD on the multispectral imagery without any ancillary data, such as LiDAR, have shown low accuracy (Ismail and Jusoff 2004: ML approximately 61%). By contrast, the complexity of the environment leads to high spectral similarity between vegetation in urban areas. Furthermore, urban areas have numerous pollutants that can change atmospheric conditions and affect spectral reflectance (Iovan et al., 2014). As a result, spectral signatures in multispectral imagery are insufficient to distinguish urban tree species, and thus, other characteristics of tree species, such as spatial information, texture, and color, should be utilized to improve the classification of urban tree species.

The object-based classification is recommended to overcome the above-mentioned limitation. Shouse et al. (2013) compared two classification methods (i.e., pixel-based and object-based classification) in two types of multispectral imageries (i.e., Aerial and LandSat TM5) to detect the species called bush honeysuckle (i.e., *Lonicera maackii*). The results show that the object-based approach has higher accuracy than the pixel-based approach. Moreover, HSR imagery has demonstrated high accuracy (Aerial (HSR): 94.2% / Landsat (MSR): 74.6%).

Texture information is one of the effective kinds of information that can be used to distinguish tree species. Iovan et al. (2008 and 2014) used HSR data and SVM to distinguish urban tree species (Platanus, Sophora, Tilia, Celtis, Pinus, and Cupressus). Spectral information was inappropriate to be used independently, and thus, texture information, which involves information about the spatial and physical arrangement of objects, was utilized (Mather & Tso, 2009). The results demonstrated that both methods of texture measures (i.e., first- and second-order GLCM) could detect urban tree species and separate deciduous trees from coniferous ones.

LiDAR data are optimal for gaining the information on texture or other information, such as height. LiDAR data were used in many studies on urban forest species (Forzieri et al., 2013; Höfle et al., 2012; Tigges et al., 2013; Tooke et al., 2009; Voss & Sugumaran, 2008; Zhang & Qiu, 2012). When information increases, the classification or segmentation needs a robust technique. Hofle et al. (2012) showed that intelligence algorithms, such as the ANN, is a suitable for LiDAR information analysis. He applied two methods according to the object based-approach (ANN and Decision Tree (DT)) for the detection of six tree species, namely, *Fagus sylvatica, Acer platanoides*, *Platanus acerifolia*, *Tilia cordata, platyphyllos*, and *Aesculus hippocastanum*. The result shows that ANN with 95% overall accuracy has higher accuracy than DT with 72% overall accuracy. The spatial, texture, shape, or height information from LiDAR data can be utilized to detect tree species. Zhu et al. (2012) showed that the spectral characteristics from LiDAR data are applicable to distinguish the real leaf from the fake one. In spite of these results, trees often have approximately the same height and shape; and the high density of tree species may lead to the misclassification of tree species or that small trees may be overlooked (Iovan et al., 2008; Latif et al., 2012).

The challenges of high-resolution imageries for the detection of urban tree species were highlighted as soon as the new HSR imagery called World View-2 was launched. Pu and Landry (2012) attempted to the segmentation and two methods (i.e., LDA and regression trees) to detect seven tree species (i.e., Sand live oak, Laural oak, Live oak, Pine, Palm, Camphor, and Magnolia) and demonstrated that four new bands of WorldView-2 imagery can improve the accuracy by about 16% to 18% (in comparison with the IKONOS imagery).

The review has shown that due to the complexity of urban area and spectral similarity between tree species, the high resolution imagery by pixel-based method is not sufficient to discriminate urban tree species, and the ancillary data such as DEM, spatial information, texture, and color is needed. Although the LiDAR data as the ancillary data has shown the high classification accuracy, it cannot be reached to high classification accuracy separately. So to gain high classification accuracy, two images (HSR and LiDAR) are required, that is not cost effective. In contrast the object-based method in order to utilize the urban tree species information was utilized to distinguish species. For this purpose different high-resolution satellite imagery were used, and the World View-2 in compare to other high-resolution satellite imagery has shown the highest accuracy. Accordingly, in order to urban tree species detection, the object-based technique should be improved and applied on the World View-2 imagery or new high-resolution imagery such as World View-3.

2.3.3 Feature Selection and Compute Attribute Coefficients

Very briefly, the Feature Selection is a process by which it automatically searches for the best subset of attributes in the dataset that will correctly discriminate the classes from the training data set. It is conceivable that feature selection raises the accuracy since it may eliminate noise and over fitting and may reduce the number of insignificant dimensions as well as training time.

In WEKA software different attribute evaluators are allocated for attribute selection. There is two type of attribute subset evaluators, the first one is Scheme-dependent evaluators which including WrapperSubsetEval and ClassifierSubsetEval, and the second type is Scheme-independent that including CfsSubsetEval and ConsistencySubsetEval. Based on the study by Li et al. (2004) it is difficult to select the best feature selection method. It does not seem to exist a clear winner. By the way Wrapper method and CfsSubsetEval are the common attribute evaluators, and the comparison between them shows that CfsSubsetEval is almost as good as Wrapper, but is much faster (Witten, 2014).

CfsSubsetEval evaluates the value of a subset attributes by considering predictive value of each attribute, along with the degree of inter-redundancy. This method is good when attributes is highly correlated with the class attribute while they have low inter-correlation to each other (Hall & Holmes, 2003)

Finding the functional technique to best discriminate between different classes in order to gain attribute coefficients is challenging tasks in image processing. Recently, a number of powerful kernel-based learning classifiers such as Fisher discriminate analysis (Mika et al., 2001) have been provided successful results in various fields at the machine learning community.

Fisher's analysis is usually used for pattern classification problems (Bandos et al., 2009; Du & Chang, 2001; Wentz et al., 2009), feature extraction and dimensionality reduction (Liao et al., 2011; Mohan et al., 2007).

2.4 Importance of Urban Trees in Malaysia National Landscape Policy

The National Landscape Policy (NLP) is a guide to turn the National landscape development, comprise of strategic policies and action plans as the means for the National Development Policy. The vision of this policy is transforming Malaysia into the Beautiful Garden Nation by year 2020, and the policy statement is to create a functional and sustainable landscape based on Malaysia's natural environment in realising the Beautiful Nation vision.

Some of the National landscape policy action plans are as follows:

- Impose at least 30% of urban development areas as green areas (Strategy 2.1.1).
- Create a green network by planting shade trees in urban areas, roadside, riverside, parks and public areas (Strategy 2.1.5).
- Systematically and efficiently plan, implement, and manage green infrastructure to address the issues of global warming and climate change (Strategy 3.1).
- Encourage manageable and sustainable landscape development programs in order to achieve beautiful garden nation (Strategy 3.2).

According to the mentioned strategies and other NLP action plans, urban green spaces are a main issue in Malaysia development by year 2020. Thus controlling, managing and protecting urban trees are an important matter for urban planners.

2.4.1 Advantages of Some Tropical Urban Trees

The study by Grimme and Laar (2005) has demonstrated that Malaysia and other tropical countries are highly exposed to radiation that would affect the energy and temperature on the overall climate for the whole year. In figure 2.2 monthly global radiations in Kuala Lumpur and Cologne, Germany is compared.

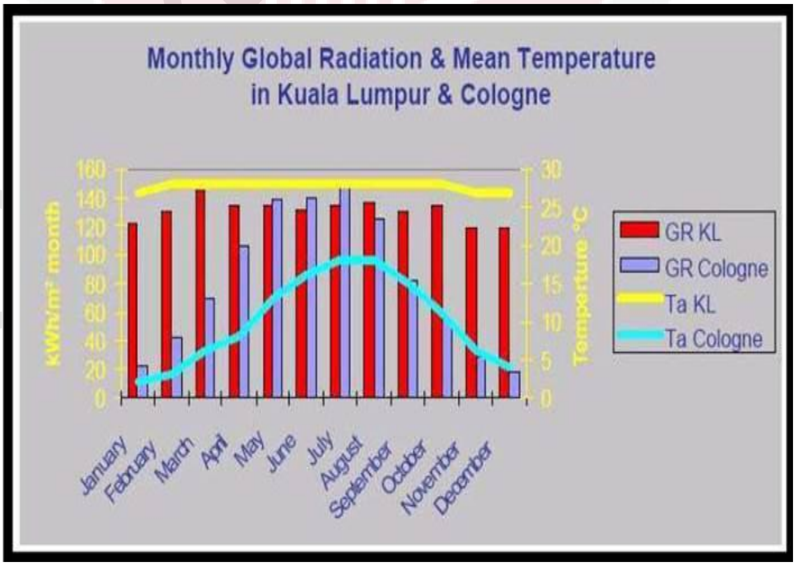

Figure 2.2: Monthly global radiation and mean temperature in Kuala Lumpur and Cologne (Grimme and Laar 2002)

Thus in tropical areas, common issues involve cooling the environment, increasing energy savings and controlling the wind. *Mesua Ferrea* (*M.Ferrea*), *Samanea Saman* (*S.Saman*), and *Casuarina Sumatrana* (*C.Sumatrana*) are among the most popular species of urban trees in tropical areas such as Malaysia. These trees can increase energy efficiency and limit the damage to properties by windbreak. Specifically, the *M.Ferrea* species (figure 2.3) can lower thermal radiation by approximately 92.55% through reflection and absorption (Shahidan et al. 2010).

Among the six common tropical tree species, *S.Saman* has saved the most energy for the past 40 years (Akamphon & Akamphon, 2014). Figure 2.4 shows the comparing energy saving of Rain Tree, Mango, Jackfruit, Mahogany, White cheesewood and Indian cork tree. The *C.Sumatrana* species is among the most typhoon- and tsunami-resistant trees (Chonglu et al., 2010); thus, it is the best method of wind breaking to protect properties in urban areas. In figure 2.5 the effect of a windbreak on wind speed has shown. Therefore, the aforementioned tree species are important to the urban environment in tropical areas.

Figure 2.3: Mesua Ferrea tree.

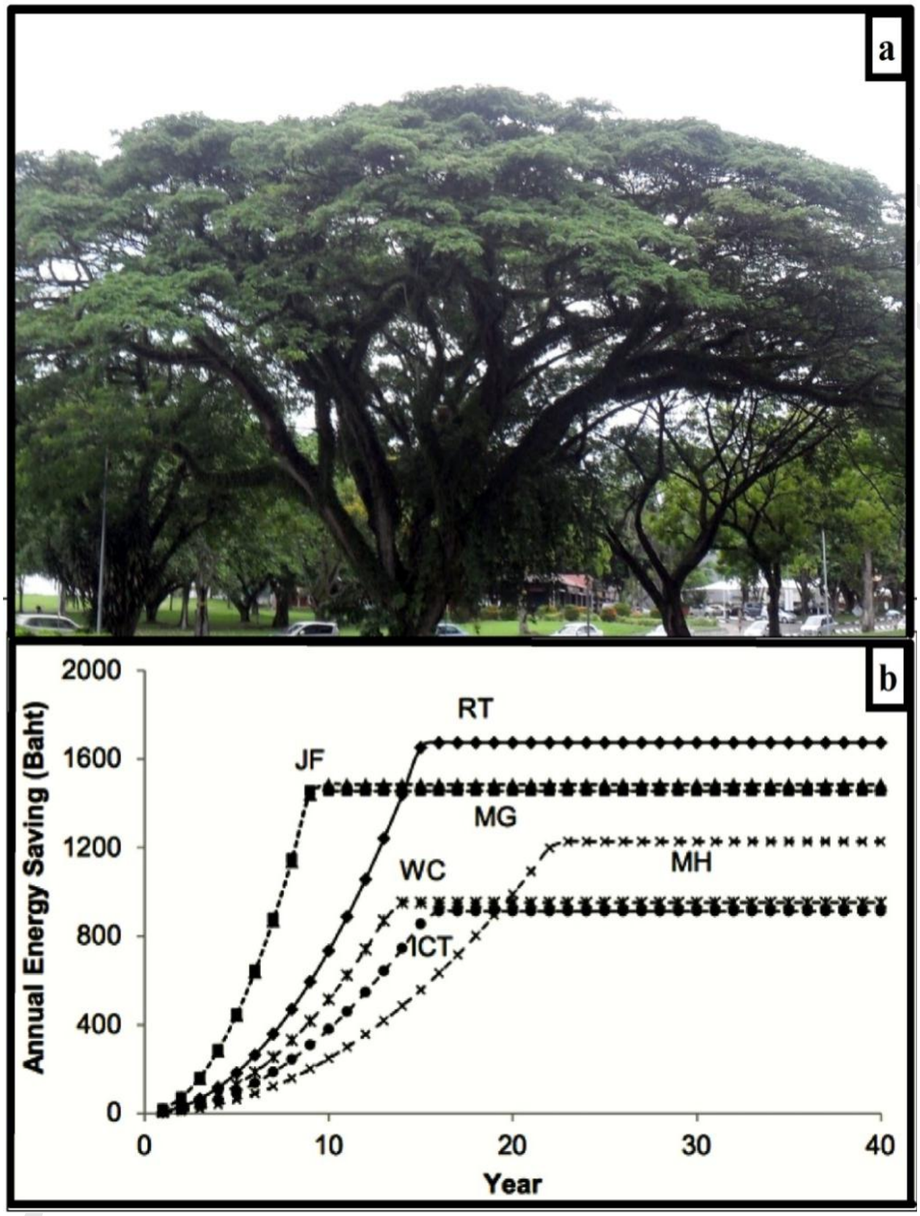

Figure 2.4: Rain Tree (a), Simulated 40-years annual cooling energy savings for the building shaded by 6 famous tropical urban tree species (RT: Rain Tree, MG: Mango, JF: Jackfruit, MH: Mahogany, WC: White cheesewood, ICT: Indian cork tree) (b) (Akamphon & Akamphonb, 2014)

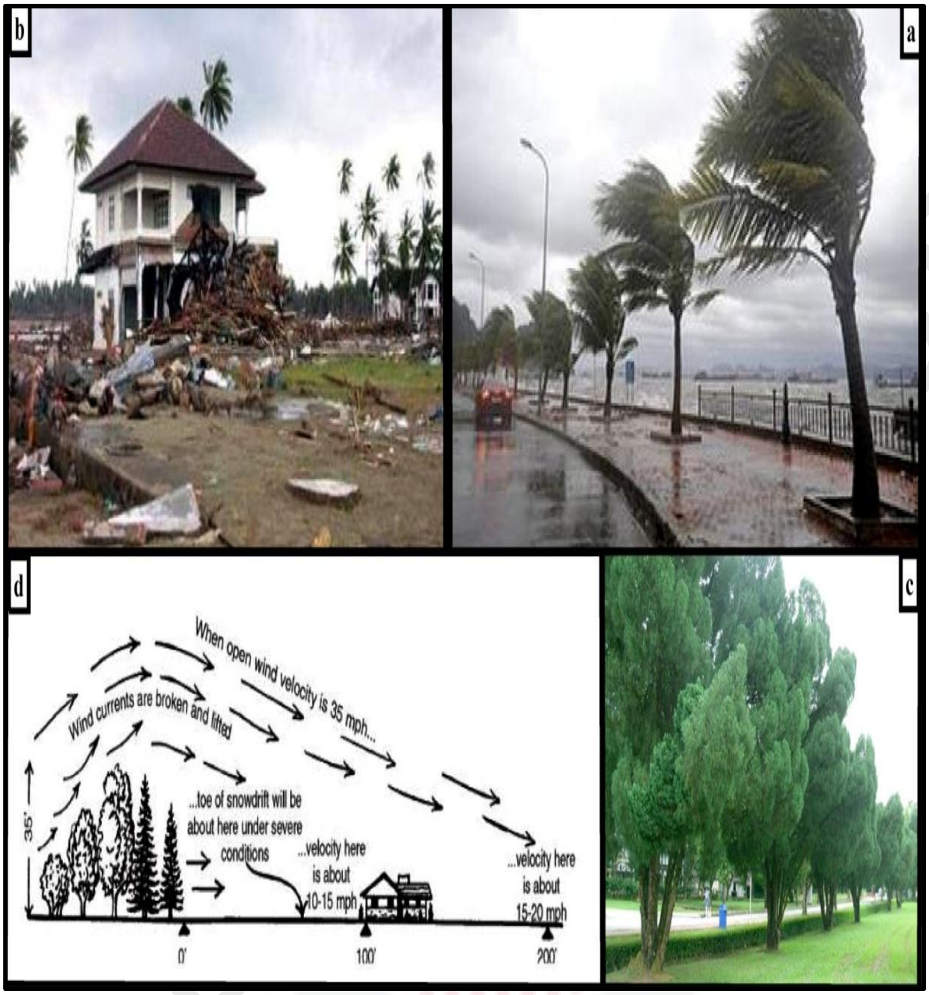

Figure 2.5: An example of property damages by typhoon and tsunami (a, b), Casuarina Sumatrana tree (c), the effects of a windbreak on wind speed (d) (Kuhns 1998).

2.5 Summary of Literature

This chapter presented the status of urban forest monitoring through remote sensing. First, different remote sensing sensors in order to urban vegetation mapping were evaluated. Second, various classification methods to extract urban forest and distinguish urban tree species were mentioned. Third, the importance of urban green areas in Malaysia and the benefits of some tropical urban trees were explained. This chapter has considered the most significant problems and mentioned the solution based on the remote sensing methods through related researches.

Remote-sensing imageries can detect urban forests, but different sensors have their own limitations. For instance, hyperspectral data are the best sensor for extracting and distinguishing urban forest by spectral information, but the high volume data, availability, and cost are the limitations. The other data, which can detect urban features even in shadow and night, is LiDAR data, but it leads to misclassification and time wasting caused by converting point clouds into raster layers. Thus other high-resolution imageries such as World View-2 were utilised.

By contrast, urban areas are complex environment, and the limitation of spectral information for multispectral imageries, especially for distinguishing tree species, has propelled researchers to utilize other urban vegetation information in the classification, such as spatial information, texture, and color. Hence, the object-based approach is more applicable than traditional pixel-based classifications, such as MLC and MD, because of the formers potential to combine various information.

Finally remote-sensing techniques have been proven to be able to detect and monitor urban forests. Moreover, studies on remote sensing have been gaining interests. Nonetheless, the work in this field remains limited especially in tropical areas. Since collecting the ground truth data is difficult task due to the limitation of accessibility to all urban areas (such as the road sides, highways, private properties, etc.), so the automatic approach means the approach which does not need the ground truth data to detect urban tree species is recommended. In conclusion, further studies on remote sensing in urban forests are suggested to develop a high-accuracy algorithm to distinguish urban tree species automatically (without using training data), which could have transferability for other study areas.

CHAPTER 3

MATERIALS AND METHODS

3.1 Introduction

The main stages of this study are summarized in Figure 3.1, and the details of them are shown in Figure 3.2. The work is started with identifying remote sensing data and urban tree species, which are World View-2 (WV-2) imagery and three effective tree species in tropical area respectively. Then in order to detect the urban tree species, spectral-based classification (SVM and ML) and object-based classification is done on the WV-2 image. Finally the object-based approach was utilized to develop new generic rule-sets to detect urban tree species automatically.

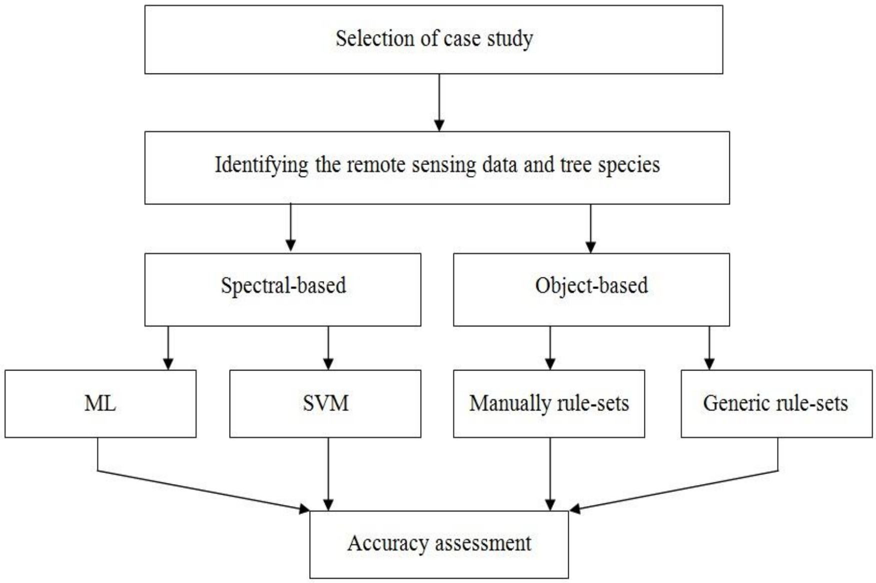

Figure 3.1: Research outline

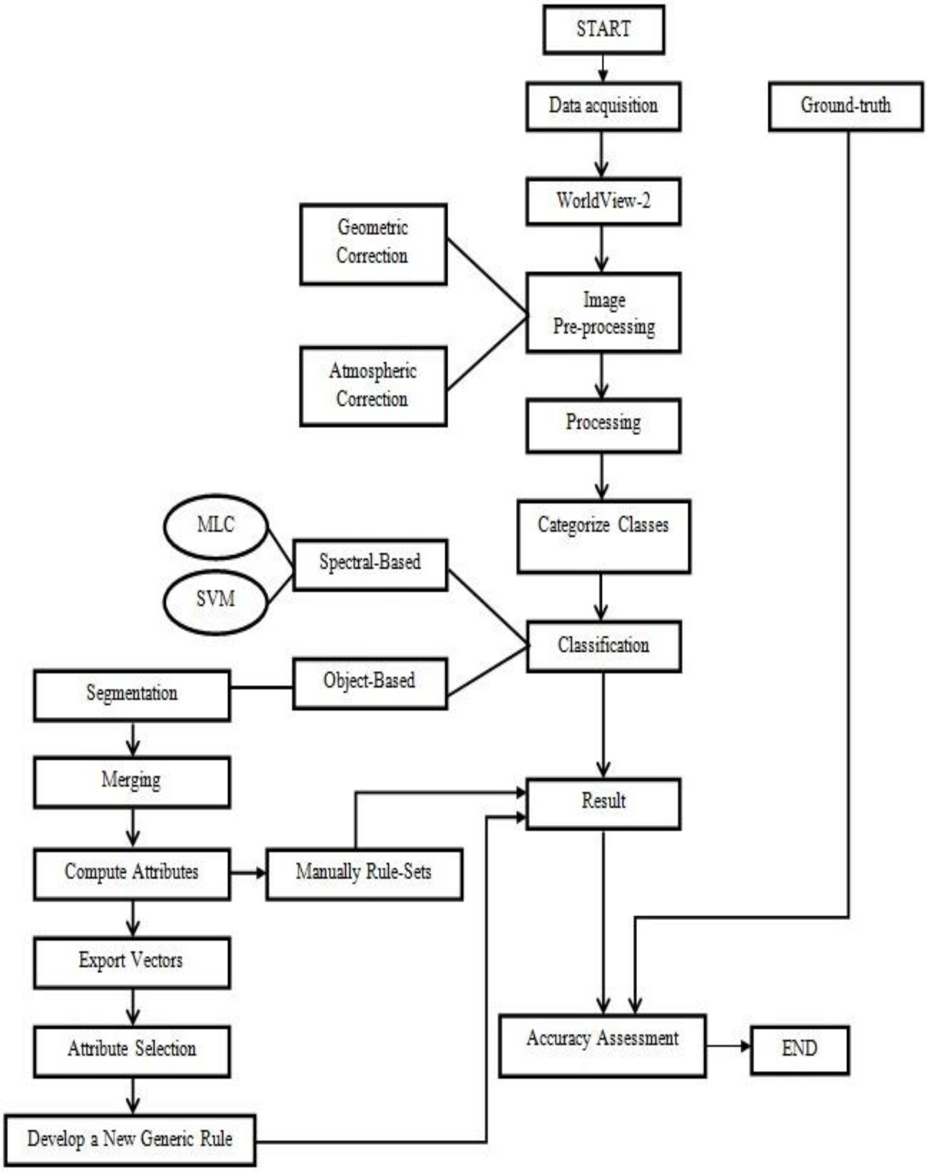

Figure 3.2: Work flowchart of this study.

3.2 Data Acquisition

World View-2 satellite imagery is the remote sensing data that is used in this study. WV-2 satellite imagery was acquired in March 2009. Unlike other commercial satellites, the WV-2 satellite displays high spatial resolution (0.5 m for the panchromatic band and 2 m for multispectral bands) with eight spectral bands and four new bands. Standard bands are blue (0.45–0.51 µm), green (0.51–0.58 µm), and red (0.63–0.69 µm). The near-infrared 1 band is in the range of 0.77–0.90 µm. The four new bands are coastal (0.40–0.45 µm), yellow (0.59–0.63 µm), red edge (0.71–0.75 µm), and near- infrared 2 (NIR2) (0.86–1.04 µm). The potentially high spatial and spectral resolution of WV-2 imagery facilitates the classification and discrimination of different types of urban tree species.

3.2.1 Study Area

Based on the Chapter 2, urban area commonly implies spaces with artificial surfaces and dense population, and the vegetation that covers the urban area is considered the urban forest. The urban area which was considered in this study is part of the Universiti Putra Malaysia (UPM) campus, which is located in Serdang, Selangor, Malaysia (Lat. 03° N, Long. 101° E) and the validation area is part of Kuala Lumpur (Lat. 03.13° N, Long. 101.69° E), Malaysia and Serdang (Lat. 02.99° N, Long. 101.70° E), Selangor, Malasyia. These study areas were covered with buildings, roads, different tree species, grass and water. Figure 3.3 shows all study areas, which are located in Kuala Lumpur and Serdang.

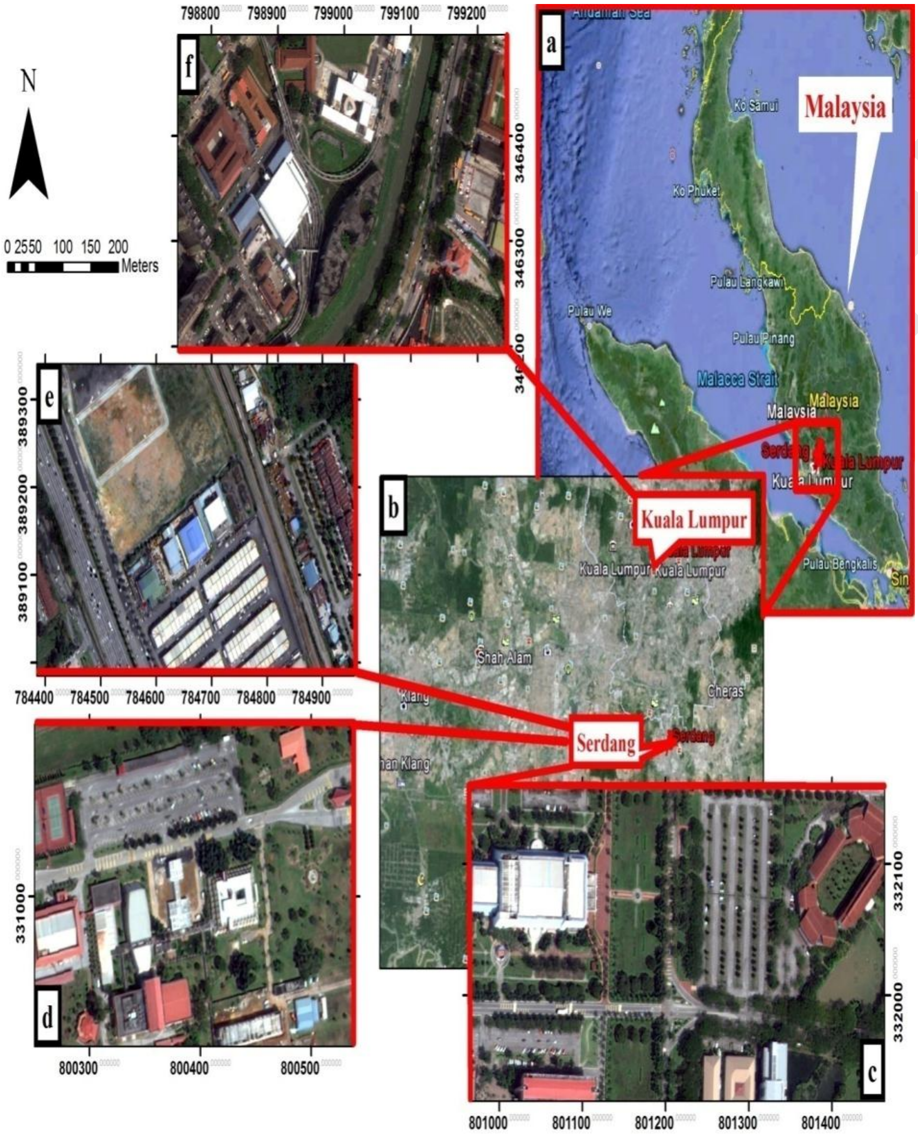

Figure 3.3: Map of Malaysia (a), location of study area and validation area (Serdang and Kuala Lumprur) in Malaysia map (b), Study area which is part of UPM campus, Serdang (c), validation area for Casuarina Sumatrana, Mardi, Serdang (d), validation area for Mesua Ferrea, Jalan Sungai Besi, Serdang (e), validation area for Samanea Saman, Jalan Syed Putra, Kuala Lumpur (f).

3.2.2 Pre-processing

The WV-2 imagery same as the other remote sensing data is required to employ different pre-processing techniques to be prepared for the classification. In this study the WV-2 image was subject to atmospheric and geometric corrections before processing and classifications.

3.2.2.1 Atmospheric Correction

The satellite imagery resolution is substantially ruined by existence of the atmosphere. Various atmospheric effects cause absorption and scattering of solar radiation by atmospheric aerosols and molecules. Usually the remote sensing applications need to remove the atmospheric effects to recover the essential spectral reflectance of the surface materials. In order to remove the atmospheric effects, the atmospheric correction should be done (Bernstein et al, 2012).

Quick atmospheric correction (QUAC) is one of the atmospheric correction methods that need only specification of sensor band locations and radiometric calibration. Since the QUAC does not utilize first principles radiation transport, it is faster than physics-based methods such as fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) (Bernstein et al., 2012).

Finally QUAC is the fast atmospheric correction method, which can convert radiance to reflectance. For this purpose in this study the QUAC extension in ENVI 4.7 software was used.

3.2.2.2 Geometric Correction

Remote sensing data such as aircraft or satellite imagery usually geometrically distorted caused by the acquisition system and the movements of the platform (Baboo & Devi, 2011). Thus in order to remove geometric distortion, a geometric correction should be done on the imagery when the image will be compared to other images or other maps. In this research the WV-2 dataset was geometrically corrected in the Universal Transverse Mercator projection zone at zone 47N and with a WGS 84 datum.

3.3 Processing

3.3.1 Categorize Classes in Study Area

The main classes of this research are urban tree species. The study area contains different species of trees. This study considered three species (*M.Ferrea*, *S.Saman*, and *C.Sumatrana*) that significantly benefit the urban environment and temperature, thus resulting in high energy savings (Akamphon & Akamphon, 2014; Shahidan et al., 2010). Since urban area is a complex area, thus aside the urban tree species, six more classes are considered for the land cover classifications which are as follows: other trees, grass, water, man-made, road and shadow.

3.3.2 Spectral-Based Classification

In order to compare the spectral-based and object-based classification accuracy, two common spectral-based classifications were utilized on WV-2 image. The spectral-based classifications were done on the UPM campus image.

3.3.2.1 Maximum Likelihood Classification (MLC)

MLC is one of the most popular supervised classification method used with remote sensing image data (Al-Ahmadi & Hames, 2009). ML is a parametric classifier that can classify unknown pixels based on the probability threshold. Thus, each pixel is allocated to the class with the maximum probability.

3.3.2.2 Support Vector Machine Classification (SVM)

SVM is another supervised classifier that separates classes based on the decision surface, which is called an optimal hyperplane. This method shows the ability to classify urban areas because of their needs to overcome limited training data and low sensitivity to the sample size (Mountrakis et al., 2011; Van der Linden et al., 2007). The Figure 3.4 shows the base of the SVM classifier.

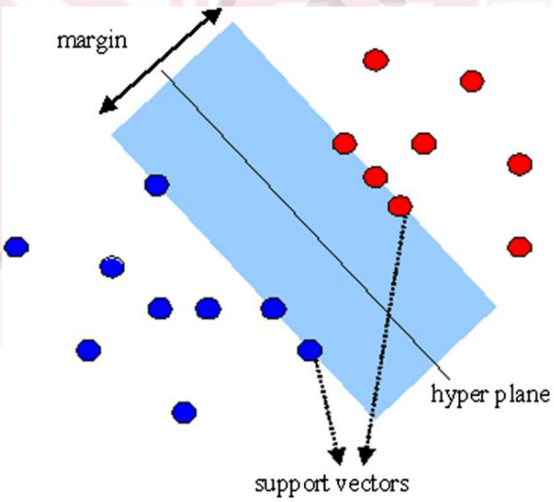

Figure 3.4: The theory of SVM (Yang et al. 2013)

In the SVM classification different parameters such as Kernel type should be considered. There is four Kernel type in SVM parameters that are: Linear, Polynomial, Radial Basis Function and Sigmoid. Based on the literature (Cao et al., 2008) RBF Kernel shows better classification result, thus in this study RBF Kernel was used. The mathematical equation of RBF Kernel is:

$$K(x_i x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right), \qquad \gamma > 0 \tag{1}$$

The output of the Kernel is dependent on the Euclidean distance of x_j from x_i (one of these will be the support vector and the other will be the testing data point). In this equation γ is the gamma term in the Kernel function. The (γ) value and penalty parameter (C) are the most important parameters in the RBF Kernel type. Cross-validation using the grid-search method is a common method to determine the optimal parameters of the RBF Kernel (C and γ) through SVM classification.

3.3.3 Object-Based Image Analysis (OBIA)

In the previous section ML and SVM classifications were explained. These mentioned methods only utilize spectral information of the images, but another technique which is called Object-Based Image Analysis (OBIA) employs spectral and spatial information simultaneously (Zhou et al., 2009). This method can increase the amount of information regarding the object in the classification, such as color, texture, and compactness. OBIA can also reduce the number of units to be classified (Youjing & Hengtong, 2007).

Based on the literature, the object-based classification shows higher accuracy than pixel-based classification. The pixel-based classification algorithms may lead to low classification accuracy because of the high grade of the spectral variability within land cover classes affected by the sun angle, gaps in tree canopy, and shadows (Flanders et al., 2003; Johnson & Xie, 2013; Yu et al., 2006). Thus, in this study in order to develop new generic rules to detect urban tree species, the object-based image analysis was used.

For this purpose, firstly the OB classification was done manually and creating the rule was based on some characteristic of tree species, in order to evaluate the potential of OB classification compare to pixel-based classification to detect urban tree species. Secondly the OB classification was done automatically based on the generic rule-sets, which were developed through the research.

3.3.4 Manual Object-Based Classification (Based on Trial and Error)

This OB classification was done manually and the rule-sets were developed based on trial/error and the characteristic of each tree species. The foundation of object-based classification was segmentation and merging.

3.3.4.1 Segmentation and Merging

The OBIA method is based on image segmentation techniques that divide the image into spatially continuous and homogeneous regions (Flanders et al., 2003) and limit local spectral variation (Li et al., 2010; Lobo, 1997). This technique can combine the information on colour, shape, and space with contextual analysis to detect vegetation. The algorithm in image segmentation is based on homogeneity descriptions, and object borders are extracted on such basis (Li et al., 2010). Small segments can merge into larger segments.

In this study, the feature extraction module in Envi Ex software is used for image segmentation, merging, computing attributes and export vector layer (figure 3.5). In Envi Ex software, the segmentation is based on Edge segment algorithm, and the merging method is based on Full Lambda Schedule. The edge segmentation method draws lines along the strongest intensity gradients and full Lambda schedule algorithm combines adjacent segments with similar spectral attributes (Feature Extraction tutorial).

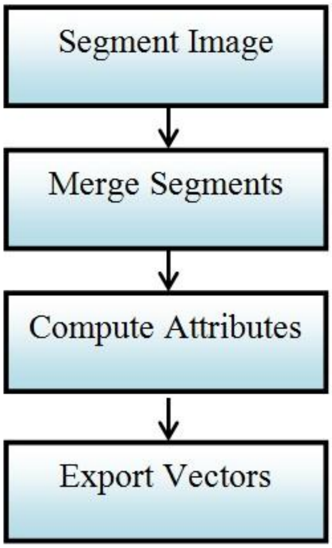

Figure 3.5: Feature extraction steps.

Since some urban trees by VHR imagery are considered as small objects, thus in order to develop a generic rule for detecting *M.Ferrea, S.Saman*, and *C.Sumatrana*, the segment scale should be small value to detect all urban trees even the small one. The segment scale in manually OB classification is considered 20 for the *M.Ferrea*, *S.Saman*, and *C.Sumatrana* species. The merging level is 85 for *M.Ferrea* and *S.Saman*, whereas that for *C.Sumatrana* is 65. In this research the value of segmentation and merging are determined based on trial and error. For this purpose through the scale bar, different range of segment scales and merging levels were applied and compared, consequently the best scales were selected for segmentation and merging level.

3.3.4.2 Attribute Computation

As mentioned previously, the benefit of an object-based method is its maximization of the advantages of spatial, spectral, texture and color attributes. In this study, information on the new bands of WV-2 imagery and on characteristics of the *M.Ferrea*, *S.Saman*, and *C.Sumatrana* species was considered for attribute selection. These characteristics include compactness, solidness, and texture.

3.3.4.3 Rule-Based Classification

Rule-based classification is based on the rules that have been defined by object attributes. This method is an advanced feature extraction technique that detects targets in detail through data mining and fuzzy logic. Rule set development is based on the varying knowledge of analysts regarding the spatial, spectral, and textural characteristics of each feature. Therefore, several tree characteristics are defined as rules in this study, including high values of normalized difference vegetation index (NDVI), texture, solidness, compactness, and different band values. Rule-based classification is often superior to supervised classification in feature extraction (ENVI Feature Extraction Tutorial). The process of constructing rule sets for *M.Ferrea*, *S.Saman*, and *C.Sumatrana* species is explained in the following subsections.

- Detection Of *Mesua Ferrea* Species

The NDVI band ratio was utilized to extract trees from impervious surfaces. Given that NIR2 is insignificantly affected by atmospheric influence, the band ratios of bands 5 and 8 were selected for NDVI calculation. Second, Tx_mean and Tx_range were utilized to separate trees and grass because trees have a higher texture value than grass does. Given that each tree species has its own special characteristics, their significant objective difference in terms of shape, compactness, and color can discriminate them. The leaves of the *M.Ferrea* species are highly compact, and the tree is approximately round. Thus, spatial attributes such as compactness, roundness, and solidity were considered. Moreover, three new bands of WV-2 were applied as the spectral attributes. These bands have the advantages of feature classification (band 4: yellow), high reflectivity of a portion of vegetation response (band 6: red edge), and broad vegetation analysis (band 8: NIR2).

- Detection Of *Samanea Saman* Species

Aside from the attributes used in the *M.Ferrea* rule set, two other spatial attributes were utilized to detect the *S.Saman* species. This attributes are called rectangular-fit (rec-fit) and majaxislen. Given that the shape of *S.Saman* species is almost four-sided, the leaves display a wide coverage despite the presence of *M.Ferrea*. Thus, the rec-fit and majaxislen attributes can distinguish the *S.Saman* species from other trees.

- Detection Of *Casuarina Sumatrana* Species

To extract the *C.Sumatrana* species, the spectral attributes used in the rule sets for this tree are bands 1 (coastal), 5 (red), and 8 (NIR2). The shape and compactness of this tree effectively assist in its detection; therefore, the spatial attributes that are related to these factors are utilized in the rule set. These attributes include roundness, compactness, area, form-factor, and rec-fit. Given that *C.Sumatrana* species are often planted in Malaysia using the coppice technique, the high compactness darkens color and the texture value increases. Therefore, the other attributes considered in the rule set are Tx_mean, Tx_entropy, hue, saturation, and band ratio.

3.3.4.4 Accuracy Assessment

Accuracy was assessed by comparing the classification map with a reference map. The confusion matrix was used as the statistical technique in this study to evaluate accuracy. A large amount of ground truth data was obtained for this assessment through in situ observation. A confusion matrix is a contingency matrix that is generally utilized to estimate the overall or specific accuracy of different classifications. The outputs of the confusion matrix in order to evaluate the classification accuracy involved some parameters such as user accuracy, producer accuracy, overall accuracy and kappa coefficient.

- User accuracy: Also known as Reliability. It is the fraction of correctly classified pixels with regard to all pixels classified as this class in the classified image. For each class in the classified image, the number of correctly classified pixels is divided by the total number of pixels, which were classified as this class.

- Producer accuracy: It is the fraction of correctly classified pixels with regard to all pixels of that ground truth class. For each class of ground truth pixels, the number of correctly classified pixels is divided by the total number of ground truth or test pixels of that class.

- The overall accuracy: It is calculated as the total number of correctly classified pixels divided by the total number of test pixels.

- Kappa coefficient: Measures the agreement between classification and ground truth pixels. A kappa value of 1 represents perfect agreement while a value of 0 represents no agreement.

3.3.5 Automatic Object-Based Classification (Based on Generic Rule-Sets)

In this section the OB classification was done based on the generic model which was developed through this research in order to predict urban tree species by using WV-2 imagery. The process of developing the generic rule is explained in the following sections.

3.3.5.1 Segmentation and Merging

Segmentation and merging is the fundamental of OB classification. The definition of segmentation and merging was discussed in section 3.3.4.1. In order to develop a generic rule for detecting *M.Ferrea*, *S.Saman*, and *C.Sumatrana*, the segment scale should be small value to detect all urban trees even the small one. Therefore segment scale in this study was considered 20, and the merging level was 65.

3.3.5.2 Attribute Computation

Attribute computation was explained in section 3.3.4.2. However in this section in order to develop a generic model to discriminate urban tree species, aside the utilizing of spectral, spatial and texture information, the band ratio of the WV-2 bands, which are effective to detect urban trees, were computed in this study.

WV-2 image has new bands that would help to vegetation analysis. Thus for band ratio, not only the band ratio of tradition bands (Red and NIR 1) was computed, but also the band ratio of new bands (Red Edge and NIR 2) was considered.

After computation of all attributes, in order to use the information of the segments attributes, the segments should be exported to a vector layer to use in other software. In this research ArcGIS software was utilized.

3.3.5.3 Categorize Segments and Define Training data

After segmentation and attribute computation, the segments which were exported to vector layer was open by ArcGIS software. In order to see the segments and their computed attributes, the attribute table of the mentioned vector layer in ArcGIS software should be utilized. In this attribute table each row demonstrate each segment with its computed attributes, and each field or column shows all values of one attribute.

To create training data set to develop generic rule sets, at first the classes based on the ground truth data should be categorized. For this purpose in the attribute table one field was added, and then some segments from each land cover class were selected and defined as its own category. For instance in this study 9 classes were determined (*M.Ferrea*, *S.Saman*, *C.Sumatrana*, other trees, grass, water, road, man-made and shadow), and in the field in front of each segment the name of category was written. Finally some of them were selected as training data set, and were exported as a “dbf” format file. Dbf format files can open in excel software.

3.3.5.4 Attribute Selection

In section 3.3.5.2 all attributes of segments were computed. Now in this section the attributes, which were more significant to discriminate the 9 classes were selected. For this purpose in this study the WEKA software was used.

WEKA is a collection of machine learning algorithms and data pre-processing tools written in Java and distributed under the terms of the General Public License (GNL). In WEKA software different attribute evaluators are allocated for attribute selection. There were two types of attribute subset evaluators, the first one is Scheme-dependent evaluators which including WrapperSubsetEval and ClassifierSubsetEval, and the second type was Scheme-independent that including CfsSubsetEval and ConsistencySubsetEval. Wrapper method and CfsSubsetEval are the common attribute evaluators, and the comparison between them shows that CfsSubsetEval was almost as good as Wrapper, but was much faster (Witten, 2014). Thus in this research the CfsSubsetEval was used as an attribute evaluator for attribute selection.

CfsSubsetEval evaluated the value of a subset attributes by considering predictive value of each attribute, along with the degree of inter-redundancy. This method is good when attributes are highly correlated with the class attribute while they have low inter-correlation to each other. Figure 3.6 shows the components of Cfs, and equation (2) demonstrates the fundamental of this method:

$$Merit_S = \frac{k r_{cf}}{\sqrt{k+(k+1) r_{ff}}} \quad (2)$$

In equation 2, $Merit_S$ is the heuristic "merit" of a feature subset S containing k features, r_{cf} is the mean feature-class correlation ($f \in s$), and r_{ff} is the average feature-feature inter correlation.

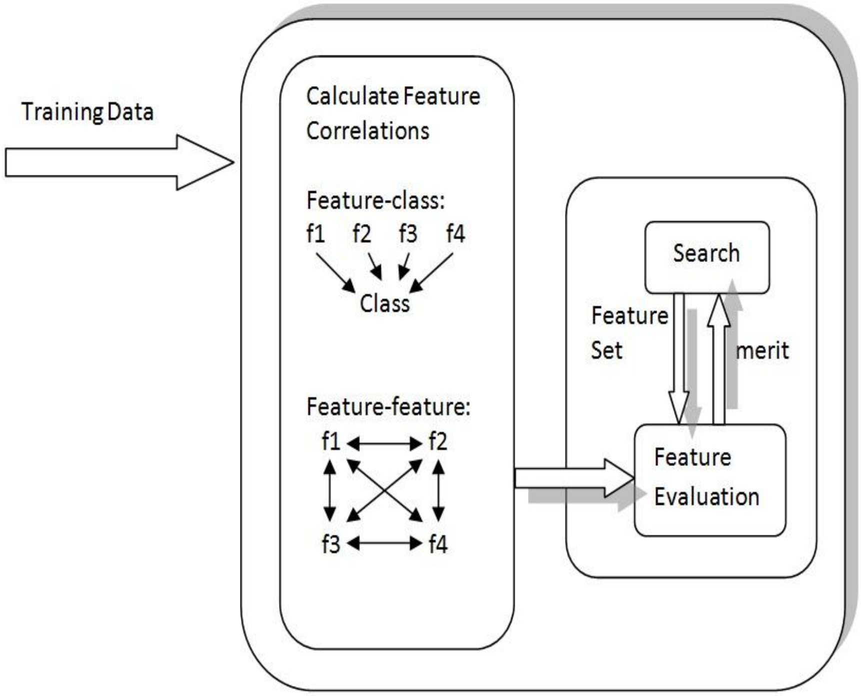

Figure 3.6: Components of Cfs (Pradhan and Bamnote 2015).

3.3.5.5 Compute Coefficients of Selected Attributes

In this section the selected attributes by WEKA were analysed through SPSS software to assigns a weight to the particular attributes. For this purpose fisher's method as a predictor was used to provide the best discrimination between the groups. The Fisher linear discriminate analysis is one type of the principal components analysis (PCA), which is the most famous example of dimensionality reduction (Welling, 2005). The Fisher's linear discriminate is given by the vector w which maximizes:

$$J(w) = \frac{w^T S_B w}{w^T S_W w} \qquad (3)$$

Where S_B is the "between classes scatter matrix" and S_W is the "within classes scatter matrix".

The fisher's analysis output include unstandardized coefficient allows the creation of rule sets based on coefficient. The mean discriminate scores for each particular class belong to the centroid, in other words group means are centroids. Basically, based on the number of classes and functions, there are centroids which are shown in the fisher's analysis output. Differences in location of centroids show dimensions along which groups differ. Thus it would be possible to visualize how the two functions discriminate between groups by plotting the individual scores for the two discriminant functions.

With using fisher discriminate function all variables in the final model for each class, were multiplied by the coefficients. The coefficients are the correlations between the variables in the model and the discriminant functions. The discriminant function coefficients represent the unique influence of each variable to the discriminant function.

3.3.5.6 Develop a New Generic Rule Sets

In order to develop a new generic rule sets a correlation between attributes and their coefficients were defined to allocate each segment to its correct class. For this purpose the Cartesian distance was used.

Cartesian distance is the ordinary distance between two points. The distance between two points expressed in Cartesian coordinates, so the distance AB where $A \text{ is } (x_1, y_1, z_1) \text{ and } B \text{ is } (x_2, y_2, z_2)$ is given by:

$$d(AB) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \qquad (4)$$

(Clapham & Nicholson, 2009)

Figure 3.7 is the summary of the process to develop a generic rule sets and the software which were used for this purpose.

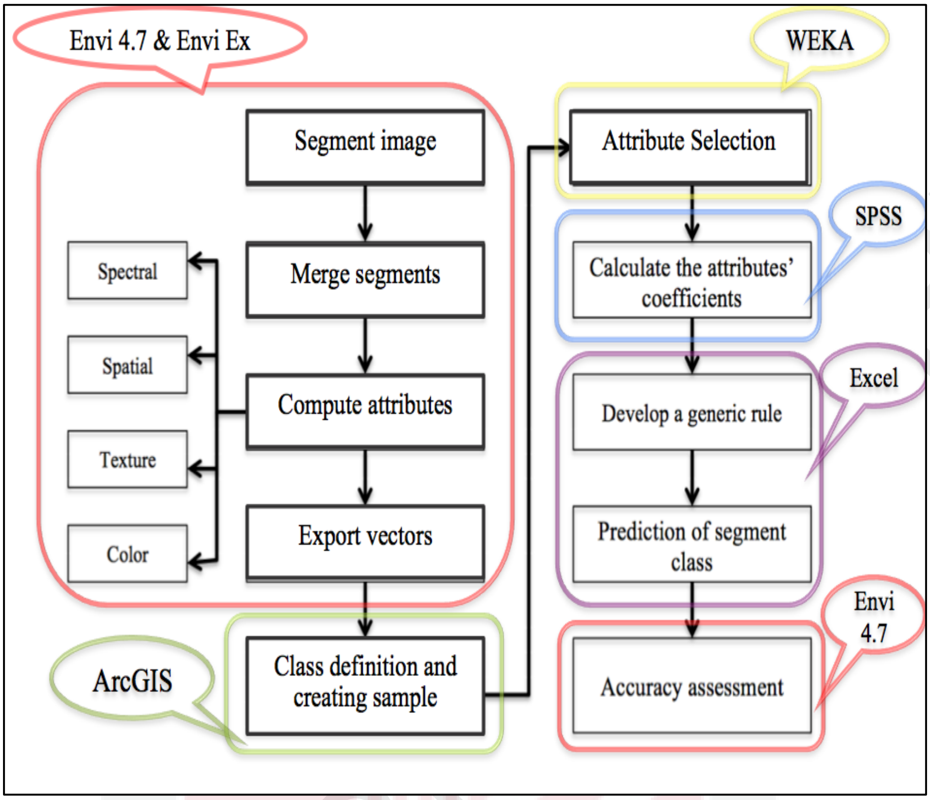

Figure 3.7: Workflow of developing a new generic rule sets.

3.3.5.7 Transferability

In order to check the transferability of the generic rule sets, the new rule sets were applied on different areas. Since the tree species were not in the same area, so for each tree species the separate area and image was used. For *S.Saman*, the rule sets were validated on part of the Kuala Lumpur and for *M.Ferrea* and *C.Sumatrana* the area in Serdang was used.

3.3.5.8 Accuracy Assessment

The accuracy assessment for OB classification automatically was same as the OB classification manually. Thus the confusion matrix was used as the statistical technique in this study to evaluate accuracy. A large amount of ground truth data was obtained for this assessment through in situ observation.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter the results of spectral-based classification (MLC, SVM) and object-based classification (manually and generic rule-sets) in order to detect different tree species are discussed. Moreover through the OB classification, the result of the attribute selection is shown.

4.2 Data Collection

In order to do spectral-based classifications on the WV-2 image, data collection was done to create a ground-truth image. For this purpose the ground-truth image of the study area, which was some parts of UPM, campus was provided by field surveying. 9 classes were defined in the study area, 3 of them are urban tree species (*M.Ferrea, S.Saman and C.Sumatrana*), and the remained classes were other trees, grass, water, road, building and shadow. Figure 4.1 shows the ground-truth image of the study area. Moreover table 4.1 demonstrates the number of region of interest (ROI) pixels for training and testing.

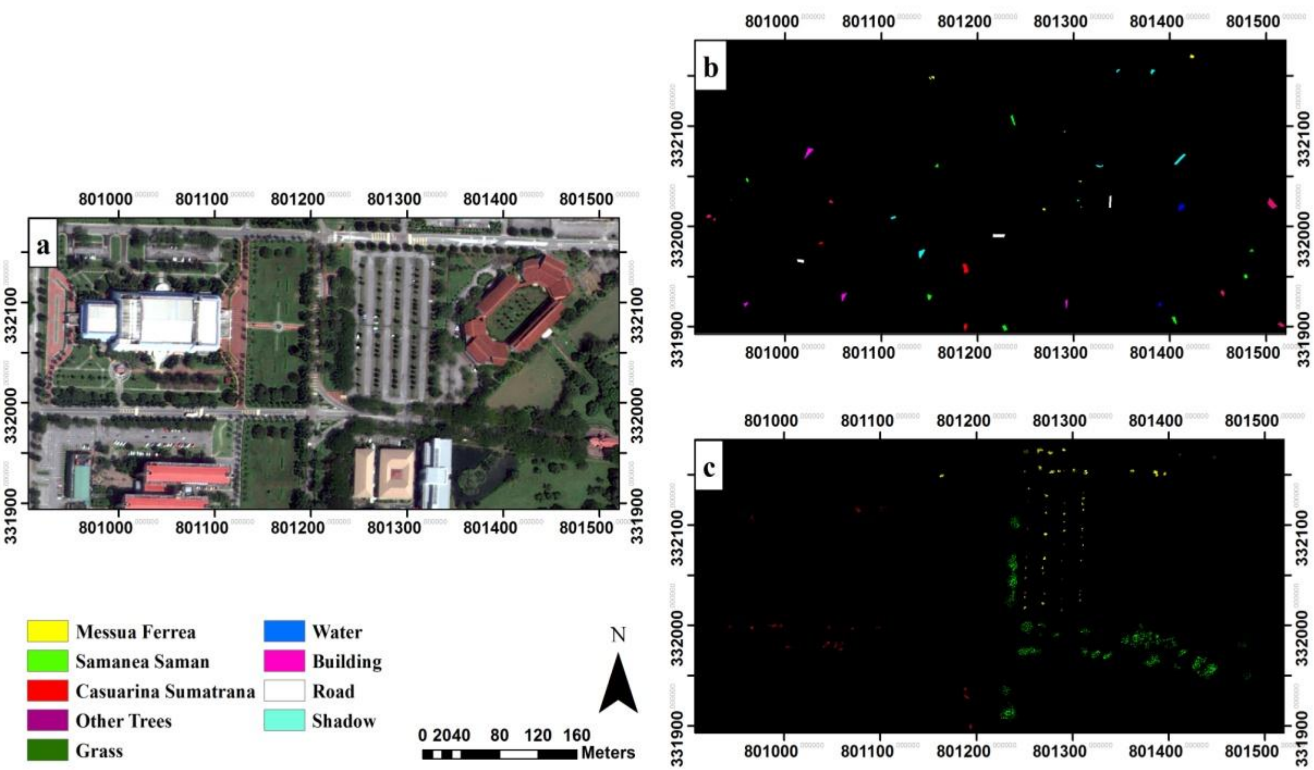

Figure 4.1: Study areas which is part of UPM campus (a), ground truth image as a training data (b) and ground truth image as a testing data (c)

Table 4.1: Number of pixels as the training and testing ROI.

	M. Ferrea (No. of Pixels)	*S.Saman* (No. of Pixels)	C.Sumatrana (No. of Pixels)
Training (UPM Campus)	134	243	239
Test (UPM Campus)	731	1929	362
Test (Jalan Syed Putra, KL)	-	1003	-
Test (Mardi, Serdang)	-	-	174
Test (Jalan Sungai Besi, Serdang)	358	-	-

4.3 Spectral-Based Classification

Spectral-based classification or pixel-based classification can classify images more quickly than object-based classification. In this research, ML and SVM were used to illustrate the level of improvement achieved by object-based classification. The results of these two methods indicate that the ML classifier misclassified many pixels. Figure 4.2 shows the result of ML classification. The misclassified parts are shown by red circles.

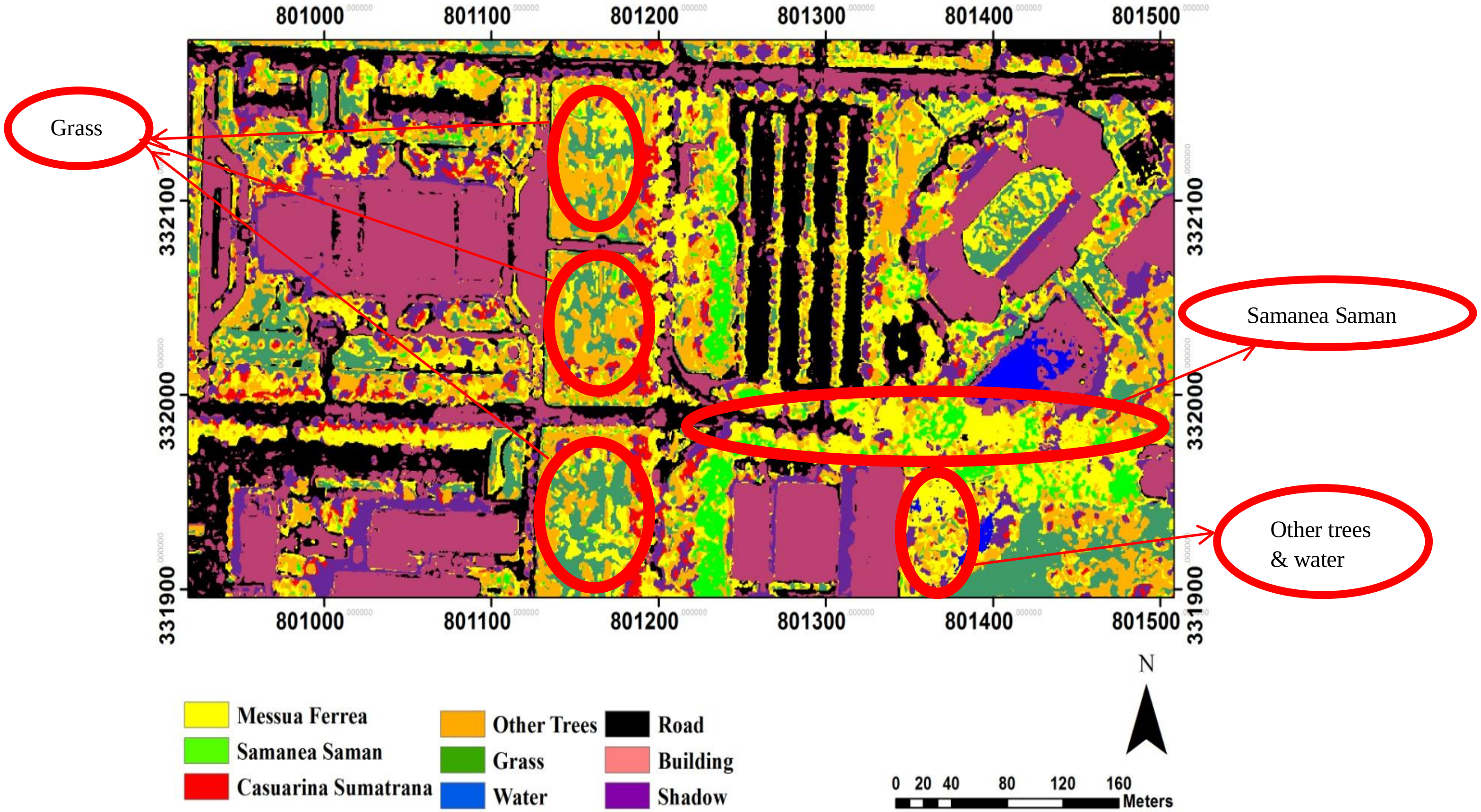

Figure 4.2: Maximum Likelihood Classification (UPM campus).

As mentioned previously, accuracy assessment is based on the confusion matrix. The overall accuracy of ML classification is 65.68%, with a Kappa coefficient of 0.3980. Table 4.2 shows the accuracy assessment of ML classification.

Table 4.2: Accuracy assessment of ML classification.

	ML	
	Prod. Acc (%)	User Acc. (%)
M. Ferrea	85.71	28.66
S. Saman	63.93	97.86
C.Sumatrana	50.40	83.01
Overall Accuracy	65.68 %	
Kappa Coefficients	0.3980	

The non-parametric algorithm known as the SVM classifier was used to measure the efficiency of machine learning. As it mentioned in Chapter 3, this method generated better results than ML classification did. Nevertheless, the SVM classifier still classified some images inappropriately because of the lack of awareness regarding fine spatial and textural features. Figure 4.3 shows the result of SVM classification, which utilized RBF as a kernel parameter.

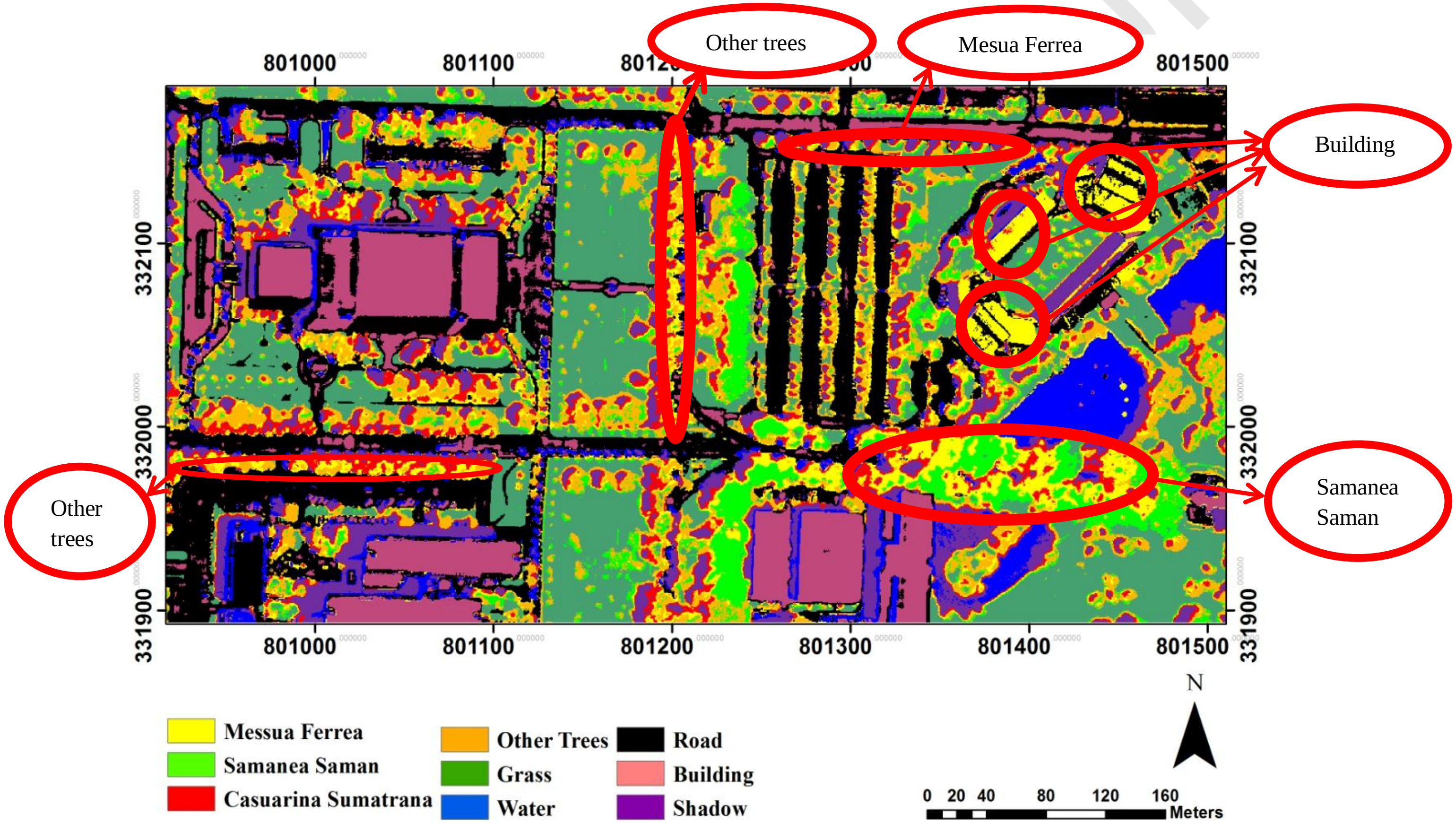

Figure 4.3: SVM classification (UPM campus).

On the basis of the confusion matrix, the overall accuracy of the SVM classifier 71.07%, with a Kappa of 0.4523. As it mentioned before, ground truth data was also obtained for accuracy assessment through in situ observation. Table 4.3 presents the accuracy of SVM classification.

Table 4.3: Accuracy assessment of SVM classification.

	SVM	
	Prod. Acc. (%)	User Acc. (%)
M. Ferrea	48.88	36.28
S. Saman	78.00	95.56
C.Sumatrana	67.60	41.94
Overall Accuracy	71.07 %	
Kappa Coefficients	0.4523	

The accuracy of both ML and SVM classification was low with respect to identifying all tree species, including *S.Saman*, *M.Ferrea*, and *C.Sumatrana*. Furthermore, a visual interpretation indicated many misclassifications of *S.Saman* and *M.Ferrea*, as well as of other tree species. Given the spectral similarity between these classes, misclassification is a common error. Figure 4.4 shows the spectral profile of one sample of each class including *M.Ferrea*, *S.Saman*, *C.Sumatrana*, other tree and grass. This figure demonstrates that the spectral profile of the classes is near together, so the spectral similarity leads to the misclassification between classes. Therefore, methods of discriminating different tree species through pixel-based classification were difficult to develop.

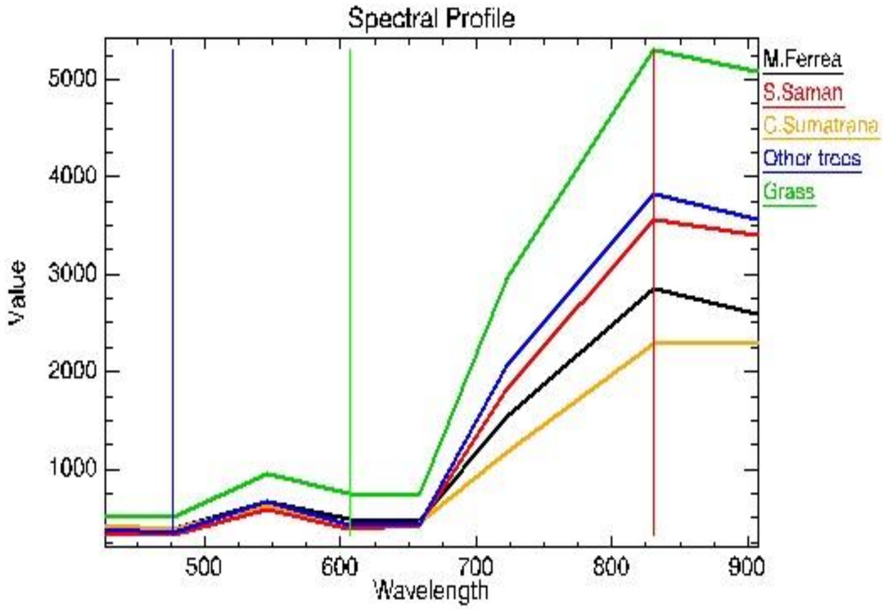

Figure 4.4: Spectral profile of M.Ferrea, S.Saman, C.Sumatrana, other trees and grass.

4.4 Manual Object-Based Classification (Based on Trial and Error)

After image segmentation and merging, the attributes were computed in order to create a rule to discriminate urban tree species. Spatial, spectral, color, band ratio and textural attributes were applied to develop new rule sets manually of object-based classification. The definitions of all attributes computed in manually rule-sets are presented in Table 4.4.

Table 4.4: Definition of all attributes, which are used in manually rule-sets.

Attribute	Description
Minband_x	**Spectral** - The minimum value of the pixels comprising the region in band x.
Maxband_x	**Spectral** - The maximum value of the pixels comprising the region in band x.
Avgband_x	**Spectral** - The average value of the pixels comprising the region in band x.
Area	**Spatial** - Total area of the polygon, minus the area of the holes.
Compact	**Spatial** - A shape measure that indicates the compactness of the polygon.
Form_Factor	**Spatial** - A shape measure that compares the area of the polygon to the square of the total perimeter.
Majaxislen	**Spatial** - The length of the major axis of an oriented bounding box enclosing the polygon.
Roundness	**Spatial** – A shape measure that compares the area of the polygon to the square of the maximum diameter of the polygon.
Rectangular_Fit	**Spatial** - A shape measure that indicates how well the shape is described by a rectangle.
Solidity	**Spatial** - A shape measure that compares the area of the polygon to the area of a convex hull surrounding the polygon.
Tx_range	**Texture** - Average data range of the pixels comprising the region inside the kernel.
Tx_mean	**Texture** - Average value of the pixels comprising the region inside the kernel.
Tx_entropy	**Texture** – Average entropy value of the pixels comprising the region inside the kernel.
Band Ratio (NDVI)	**Band Ratio** - Computes a normalized band ratio between two bands, using the following equation: (B2– B1) / (B2 + B1 + eps)
Color	**Color Space** - Compute HSI color space attributes.
Hue	**Color Space** – Hue is often used as a color filter and is measured in degrees from 0 to 360.
Saturation	**Color Space** – Saturation is often used as a color filter and is measured in floating-point values that range from 0 to 10.

Figure 4.5 shows the rule set attributes of the *M.Ferrea*, *S.Saman* and *C.Sumatrana* species.

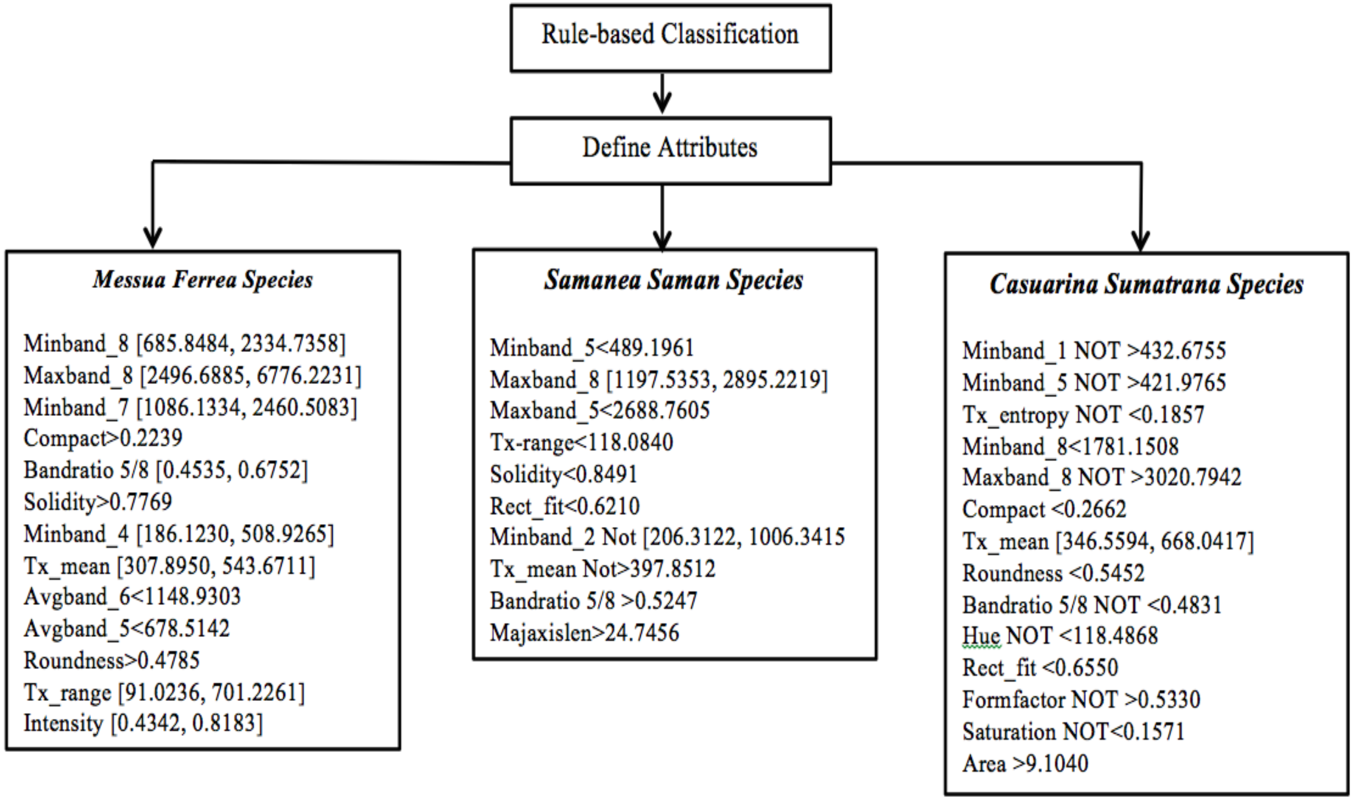

Figure 4.5: The manually rule sets for *M.Ferrea, S.Saman* and *C.Sumatrana*.

On the basis of the confusion matrix, the overall accuracy assessment of manually rule-based classification was 83.62%, with a Kappa of 0.6307. Nonetheless, some segments were not detected by object-based classification because of spectral similarities among classes and the confusion among different urban materials. Nevertheless, this type of classification effectively reduced the number of misidentified objects. Figure 4.6 shows the result of manually OB classification to detect urban tree species, and Table 4.5 highlights the accuracy assessment of that based on the confusion matrix.

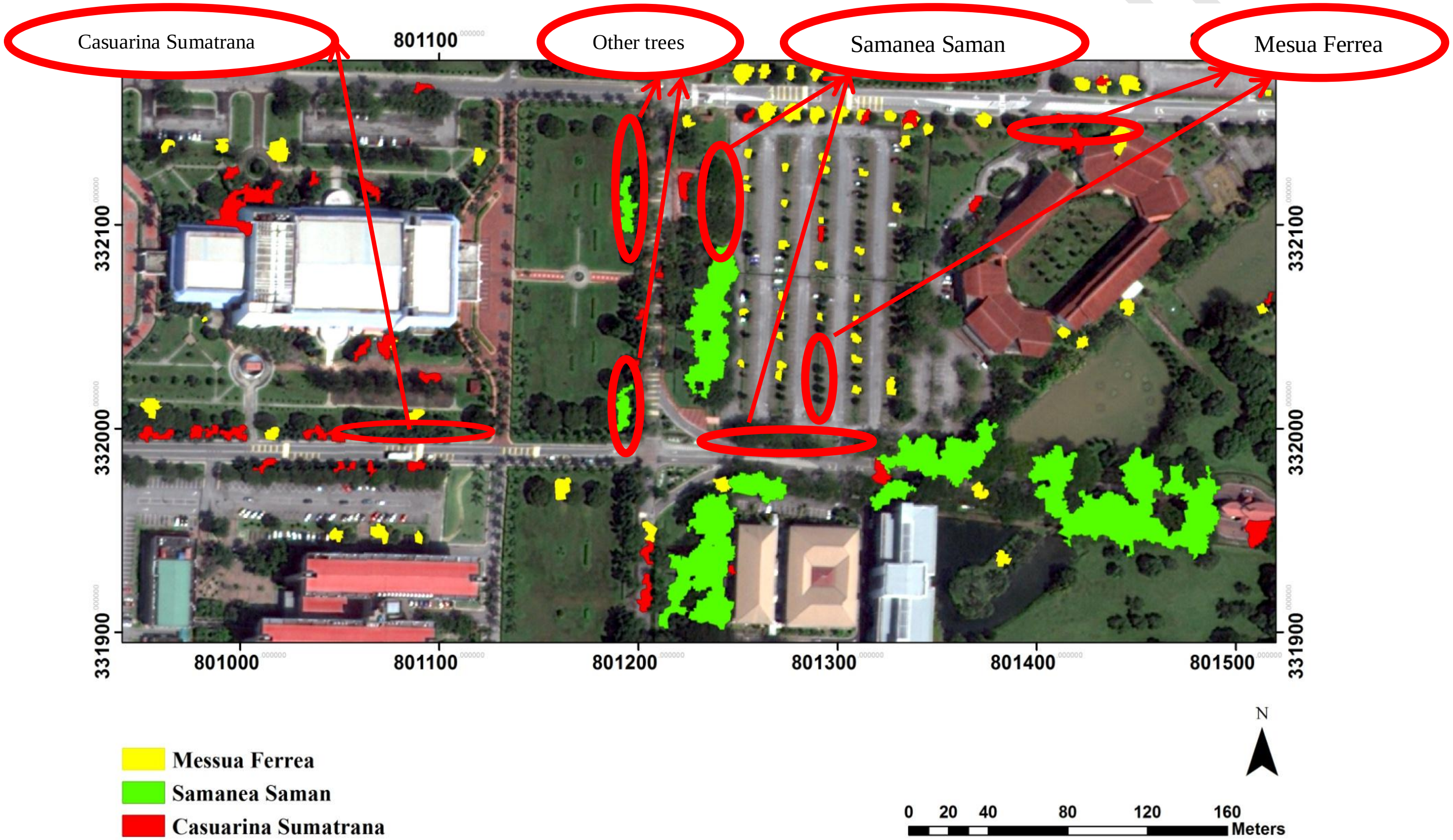

Figure 4.6: Result of *Mesua Ferrea, Samanea Saman* and *Casuarina Sumatrana* species detection by manually OB classification.

Table 4.5: Accuracy assessment of manually OB classification to detect *M.Ferrea, S.Saman* and *C.Sumatrana*.

	OB Classification (Manually)	
	Prod. Acc. (%)	User Acc. (%)
M. Ferrea	71.31	100
S. Saman	86.97	100
C.Sumatrana	73.76	98
Overall Accuracy	83.62 %	
Kappa Coefficients	0.6307	

4.5 Automatic Object-Based Classification (Based on Generic Rule-Sets)

Spatial, spectral, textural and colour attributes were applied to develop new generic rule sets of object-based classification. In order to utilize the attributes, the segmentation and merging which were the most important steps in OB classification were done by Envi Ex software. Figure 4.7 shows the image segmentation and merging by their suitable scale that were used in this study. Since segment scale was larger, the boundary of the objects would be larger and small objects could not be detected. Thus in this study, the segment scale was defined as a small value in order to detect the smaller tree species. The segment scale was 20, and the merging level was 65.

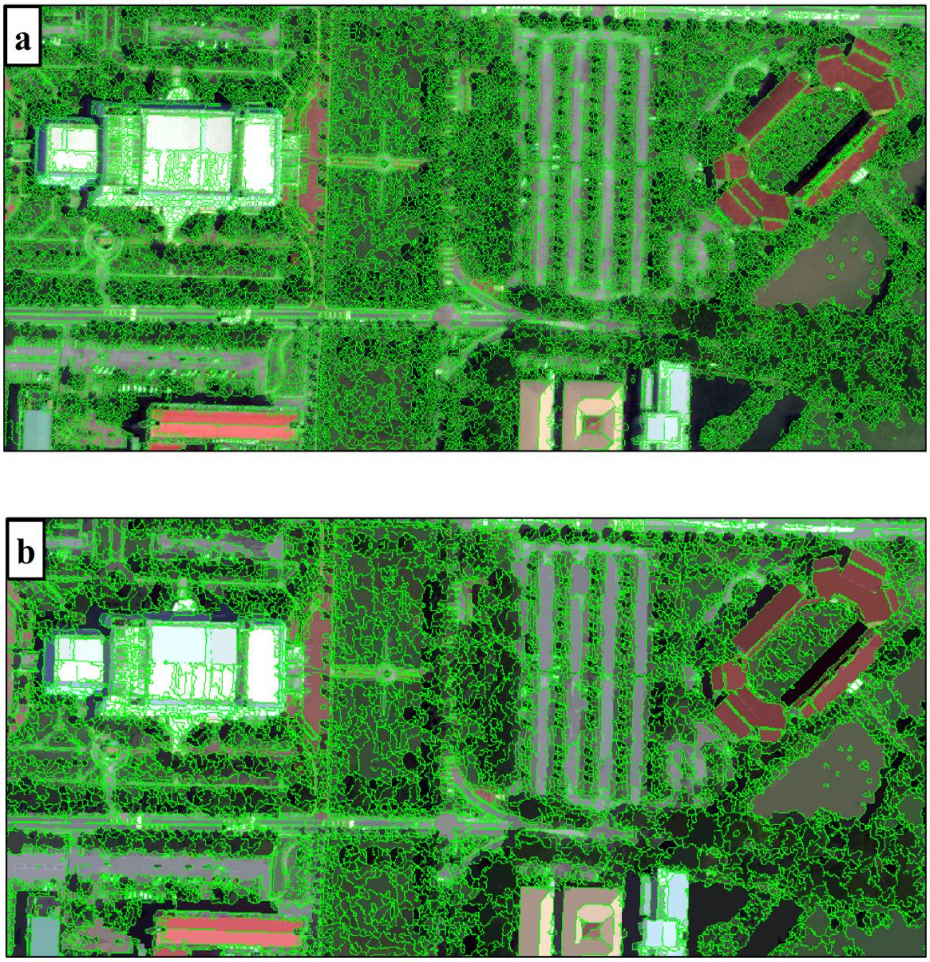

Figure 4.7: Segmentation scale preview, which was 20 (a) and merging scale preview, which was 65 (b).

The very high resolution satellite imagery such as WV-2 image was helpful and provided important information to distinguish different objects. This information, which was inherent, can be divided to 4 main classes and they were spectral, spatial, texture and colour attributes.

Each one was also separated to its own classes. The WV-2 imagery has 8 spectral bands, so spectral information of this imagery included 32 attributes and they were minband_x, maxband_x, avgband_x and stdband_x. In table 4.6 the definition of each spectral attribute is explained.

Table 4.6: Definition of spectral attributes for each band.

Attribute	Description
Minband_*x*	**Spectral** - The minimum value of the pixels comprising the region in band x.
Maxband_*x*	**Spectral** - The maximum value of the pixels comprising the region in band x.
Avgband_*x*	**Spectral** - The average value of the pixels comprising the region in band x.
Stdband_*x*	**Spectral** - The standard deviation value of the pixels comprising the region in band *x*.

The second inherent information of the image was spatial attributes. Spatial information was divided to 14 attributes, which included area, length, compact, convexity, solidity, roundness, form_factor, elongation, rect_fit, maindir, majaxislen, minaxislen, numholes and holsolrat. Different trees have different area and length, so the related information could not be useful to discriminate tree species. Thus in this study, area and length were not considered for feature selection, so only 12 spatial attributes were used. The definition of each spatial attributes is demonstrated in table 4.7.

Table 4.7: Definition of spatial attributes.

Attribute	Description
Area	**Spatial -** Total area of the polygon, minus the area of the holes.
Length	**Spatial -** The combined length of all boundaries of the polygon, including the boundaries of the holes.
Compact	**Spatial -** A shape measure that indicates the compactness of the polygon.
Convexity	**Spatial** - Polygons are either convex or concave. This attribute measures the convexity of the polygon.
Solidity	**Spatial -** A shape measure that compares the area of the polygon to the area of a convex hull surrounding the polygon.
Roundness	**Spatial –** A shape measure that compares the area of the polygon to the square of the maximum diameter of the polygon.
Form_Factor	**Spatial -** A shape measure that compares the area of the polygon to the square of the total perimeter.
Elongation	**Spatial -** A shape measure that indicates the ratio of the major axis of the polygon to the minor axis of the polygon.
Rectangular_Fit	**Spatial -** A shape measure that indicates how well the shape is described by a rectangle.

Maindir	**Spatial -** The angle subtended by the major axis of the polygon and the x-axis in degrees.
Majaxislen	**Spatial -** The length of the major axis of an oriented bounding box enclosing the polygon.
Minaxislen	**Spatial -** The length of the minor axis of an oriented bounding box enclosing the polygon.
Numholes	**Spatial -** The number of holes in the polygon. Integer value.
Holesolrat	**Spatial -** The ratio of the total area of the polygon to the area of the outer contour of the polygon.

The third information which is extracted from WV-2 image was texture attributes. Since the trees have different texture, the textural attributes can be helpful to discriminate different tree species. The definition of the texture attributes is defined in table 4.8.

Table 4.8: Definition of texture attribures.

Attribute	Description
Tx_range	**Texture -** Average data range of the pixels comprising the region inside the kernel.
Tx_mean	**Texture -** Average value of the pixels comprising the region inside the kernel.
Tx_variance	**Texture -** Average variance of the pixels comprising the region inside the kernel.
Tx_entropy	**Texture –** Average entropy value of the pixels comprising the region inside the kernel.

The last and very important attributes in this study was colour space and band ratio attributes. Two new bands of WV-2 imagery (Red-edge and NIR2) were effective to detect vegetation, thus in this study not only the common band ratio of vegetation which is NDVI index [(Red-NIR1)/(Red+NIR1)] is used, but also the band ratio of the Red-edge and NIR2 is considered, which are as following:

Band ratio 5/7: (NIR1- Red) / (NIR1+Red)

Band ratio 5/8: (NIR2 - Red) / (NIR2+ Red)

Band ratio 6/7: (NIR1- Red Edge) / (NIR1+ Red Edge)

Band ratio 6/8: (NIR2 - Red Edge) / (NIR2+ Red Edge)

In conclusion the total number of attributes before feature selection that were used in this study was 55 attributes (32 spectral, 12 spatial, 4 texture, 4 band ratio and 3 color space). The definition of the color space and band ratio attributes is explained in table 4.9.

Table 4.9: Definition of the color space and band ratio attributes.

Attribute	Description
Band Ratio	**Band Ratio -** Computes a normalized band ratio between two bands, using the following equation: (B2– B1) / (B2 + B1 + eps)
Color	**Color Space -** Compute HSI color space attributes.
Hue	**Color Space –** Hue is often used as a color filter and is measured in degrees from 0 to 360.
Saturation	**Color Space –** Saturation is often used as a color filter and is measured in floating-point values that range from 0 to 10.

After computation of all attributes, in order to utilize the attribute variables of each segment the ArcGIS software was used to export the segments to a vector layer. Figure 4.6 shows part of the vector layer, which was extracted by Envi Ex and was opened in ArcGIS. In the figure the segments that their boundary is light blue (means selected), some of them are defined as a training data, which was used for attribute selection by WEKA software.

In the attribute table of the vector layer each row demonstrate each segment with its computed attributes, and each field or column shows all values of one attribute. In order to create a training data, in situ observation was done and 9 classes were categorized, and then based on the field survey some segments are defined as a training data. The number of segments that was allocated for training data is mentioned in Table 4.10, and the extracted attributes of some training segments are shown in appendix C.

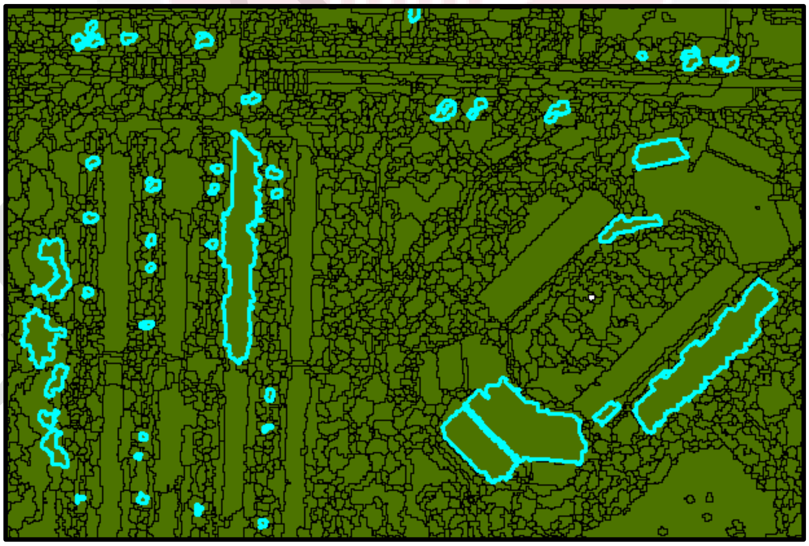

Figure 4.8 Part of vector layer which, was exported from feature extraction module. Some segments were selected and defined as a training data.

Table 4.10: The number of segments for each class in the training data.

Training (UPM Campus)	Number of Segments
M. Ferrea	70
S. Saman	52
C. Sumatrana	42
Other trees	60
Grass	110
Water	2
Road	42
Building	55
Shadow	80

Since the analysis of 55 attributes to develop a generic rule sets was hard and time consuming, thus the attribute selection module by WEKA software was utilized to deduct some attributes and select the most efficient attributes to discriminate urban classes. In this study the CfsSubsetEval was used as a subset evaluator to define which attributes were the most appropriate to distinguish different urban classes.

The results show that from 55 attributes, only 26 were selected which were:

Compact, Maindir, Minaxislen, Band ratio5/7, Band ratio 5/8, Band ratio 6/7, Hue, Saturation, Tx_range, Tx_variance, Tx_entropy, Minband_1, 3, 5 and 6, Maxband_1, Avgband_1, 2, 3, 4 and 8, Stdband_2, 3 , 6, 7 and 8.

Table 4.11 shows the definition of the selected attributes by Cfs Subset Evaluator in WEKA software.

Table 4.11: Definition of selected attribute by Cfs Subset Evaluator.

Attribute	**Description**
Minband_x	**Spectral** - The minimum value of the pixels comprising the region in band x.
Maxband_x	**Spectral** - The maximum value of the pixels comprising the region in band x.
Avgband_x	**Spectral** - The average value of the pixels comprising the

	region in band x.
Stdband_*x*	**Spectral** - The standard deviation value of the pixels comprising the region in band *x*.
Compact	**Spatial -** A shape measure that indicates the compactness of the polygon.
Maindir	**Spatial -** The angle subtended by the major axis of the polygon and the x-axis in degrees.
Minaxislen	**Spatial -** The length of the minor axis of an oriented bounding box enclosing the polygon.
Tx_range	**Texture** - Average data range of the pixels comprising the region inside the kernel.
Tx_variance	**Texture -** Average variance of the pixels comprising the region inside.
Tx_entropy	**Texture –** Average entropy value of the pixels comprising the region inside the kernel.
Band Ratio	**Band Ratio -** Computes a normalized band ratio between two bands, using the following equation: (B2– B1) / (B2 + B1 + eps)
Hue	**Color Space –** Hue is often used as a color filter and is measured in degrees from 0 to 360.
Saturation	**Color Space –** Saturation is often used as a color filter and is measured in floating-point values that range from 0 to 10.

After attribute selection by Cfs Subset Evaluator, with the aim to gain the attribute coefficients, the fisher's model in SPSS was used to discriminate the attributes to achieve the coefficients. Eight functions were achieved by SPSS analysis. After that unstandardized coefficient results were considered as the attributes coefficients.

In this research the attributes coefficients for *Samanea Saman* species were different from *Casuarina Sumatrana* and *Mesua Ferrea* Species. For computing the attribute coefficients for *C.Sumatrana*, 4 random segments of this species were selected and were added to the training data for SPSS analysis. Tables 4.12 and 4.13 show the attributes coefficients of each function for *S. Saman*, *C.Sumatrana* and *M.Ferrea* respectively.

Table 4.12: Attributes Coefficients for *Samanea Saman* species.

	Function 1	Function 2	Function 3	Function 4	Function 5	Function 6	Function 7	Function 8
COMPACT	1.37	1.849	7.661	0.533	-6.365	12.765	-1.327	-1.412
MAINDIR	-0.001	-0.001	0.001	-0.001	0.002	-0.004	0.005	0.001
MINAXISLEN	.001	-.078	.359	.180	-.093	.028	-.026	-.025
BANDRATIO 5/7	27.736	2.815	3.620	35.912	36.427	30.692	28.332	31.865
BANDRATIO 5/8	-5.972	14.725	-8.358	-19.566	-22.888	-44.417	-14.146	-31.560
BANDRATIO 6/7	-24.833	1.925	-3.365	-1.878	-10.881	33.856	-37.204	-11.815
HUE	-.003	.002	.002	-.012	.018	.009	-.002	-.005
SATURATION	1.873	6.937	.633	-8.812	-2.905	-1.036	1.140	2.216
TX_RANGE	-.012	.002	.003	.009	-.012	.000	-.005	-.002
TX_VARIANC	.000	.000	.000	.000	.000	.000	.000	.000
TX_ENTROPY	13.839	14.090	-7.268	25.187	28.733	-10.944	-13.614	124.497
MINBAND_1	.004	-.002	-.001	.005	-.009	.017	.003	.018
MAXBAND_1	-.004	-.004	-.005	.002	.004	.000	-.002	.005
AVGBAND_1	.006	.012	.022	-.015	.007	-.030	-.036	.000
AVGBAND_2	-.007	.000	-.016	.014	-.016	.005	.038	-.016
STDBAND_2	.012	-.003	-.006	-.025	.016	-.010	-.013	.003
MINBAND_3	-.001	-.005	-.003	.004	-.004	-.004	-.020	.005
AVGBAND_3	-.003	-.002	.008	-.011	-.004	-.003	-.017	.004
STDBAND_3	.006	.007	.008	.039	.001	-.007	.030	.000
AVGBAND_4	.003	.003	-.006	.007	.013	.009	-.001	.000
MINBAND_5	.001	.003	.002	-.003	.007	-.003	.015	-.005
MINBAND_6	-.002	-.001	.003	-.001	-.001	.001	.001	-.002
STDBAND_6	-.007	.000	-.006	.004	-.014	.020	-.008	.004
STDBAND_7	.000	-.001	.003	-.004	-.002	-.010	-.007	-.006
AVGBAND_8	.001	-.004	-.001	-.001	-.001	.000	.001	.002
STDBAND_8	-0.001	-0.001	0.005	-0.005	0.004	0.007	0.014	0.003
(Constant)	-7.413	-8.845	-3.804	-8.965	-2.140	1.734	16.358	-30.644

Table 4.13: Attributes Coefficients for *Mesua Ferrea* and *Casuarina Sumatrana* species.

	Function 1	Function 2	Function 3	Function 4	Function 5	Function 6	Function 7	Function 8
COMPACT	1.575	1.687	8.090	1.079	-6.070	12.978	-.249	-2.857
MAINDIR	-.001	-.001	.001	-.002	.002	-.003	.005	.001
MINAXISLEN	-.001	-.071	.356	.185	-.087	.029	-.019	-.032
BANDRATIO 5/7	27.203	3.323	2.593	34.614	37.844	31.012	23.932	34.934
BANDRATIO 5/8	-5.527	14.380	-7.911	-18.858	-23.744	-44.060	-9.020	-34.323
BANDRATIO 6/7	-24.981	2.011	-3.268	-1.966	-11.108	32.219	-39.493	-11.990
HUE	-.003	.002	.002	-.012	.018	.009	-.003	-.005
SATURATION	2.327	6.540	.825	-8.017	-3.025	-1.166	-.011	3.046
TX_RANGE	-.012	.002	.002	.010	-.012	.000	-.006	-.002
TX_VARIANC	.000	.000	.000	.000	.000	.000	.000	.000
TX_ENTROPY	13.021	15.080	-7.991	22.938	29.146	-12.622	-14.460	120.541
MINBAND_1	.003	-.001	.000	.004	-.009	.017	.005	.016
MAXBAND_1	-.004	-.004	-.005	.002	.004	.000	-.002	.005
AVGBAND_1	.007	.013	.022	-.016	.006	-.032	-.034	-.002
AVGBAND_2	-.006	.000	-.016	.015	-.015	.006	.036	-.013
STDBAND_2	.011	-.003	-.005	-.026	.015	-.009	-.008	-.002
MINBAND_3	-.001	-.004	-.003	.004	-.004	-.006	-.021	.005
AVGBAND_3	-.003	-.002	.009	-.010	-.005	-.004	-.016	.002
STDBAND_3	.006	.008	.006	.038	.002	-.006	.027	.004
AVGBAND_4	.003	.004	-.006	.006	.013	.009	-.002	.000
MINBAND_5	.001	.003	.002	-.003	.007	-.002	.015	-.004
MINBAND_6	-.002	-.001	.004	-.001	-.001	.001	.001	-.002
STDBAND_6	-.007	-.001	-.005	.005	-.014	.020	-.009	.004
STDBAND_7	.000	-.001	.003	-.004	-.003	-.010	-.007	-.006
AVGBAND_8	.002	-.004	-.001	-.001	-.001	.000	.001	.002
STDBAND_8	-.001	-.001	.005	-.006	.004	.007	.014	.004
(Constant)	-5.964	-9.203	-3.685	-8.482	-2.266	2.512	15.740	-28.334

Moreover in order to develop the generic rule, the functions at group centroids were utilized. Group centroids were the unstandardized canonical discriminant functions, which were evaluated at group means. Tables 4.14 and 4.15 demonstrate the group centroids of *S.Saman*, *M.Ferrea* and *C.Sumatrana* respectively.

Table 4.14: Functions at group centroids for *Samanea Saman* species genric rule.

	Function 1	Function 2	Function 3	Function 4	Function 5	Function 6	Function 7	Function 8
M.Ferrea	1.123	2.352	-0.673	0.505	0.345	1.105	0.146	0.128
S.Saman	2.936	0.457	0.513	1.102	0.653	-0.995	0.57	0.108
C.Sumatrana	0.348	2.422	-0.386	0.156	-0.108	-0.68	-0.932	0.238
Other trees	1.791	1.17	-0.296	0.42	0.192	-0.058	-0.201	-0.454
Grass	3.067	-3.236	-0.144	-0.492	-0.364	0.15	-0.067	0.04
Water	-2.783	-3.208	17.061	6.164	-2.169	2.06	-1.052	0.006
Road	-5.225	-2.05	0.551	-0.637	2.205	0.062	-0.125	-0.002
Building	-6.083	-1.444	-1.218	1.173	-1.075	-0.115	0.127	-0.009
Shadow	-1.64	2.095	1	-1.505	-0.678	-0.131	0.239	-0.015

Table 4.15: Functions at group centroids for *Mesua Ferrea* and *Casuarina Sumatrana* species generic rule.

	Function 1	Function 2	Function 3	Function 4	Function 5	Function 6	Function 7	Function 8
M.Ferrea	1.127	2.325	-.695	.476	.369	1.133	.096	.141
S.Saman	2.923	.459	.468	1.077	.688	-.959	.619	.114
C.Sumatrana	.299	2.402	-.327	.132	-.121	-.766	-.892	.212
Other trees	1.787	1.152	-.317	.400	.205	-.044	-.169	-.472
Grass	3.047	-3.274	-.118	-.462	-.376	.141	-.080	.042
Water	-2.816	-2.929	16.930	6.388	-1.956	2.003	-1.103	-.013
Road	-5.226	-2.051	.570	-.708	2.189	.043	-.131	-.003
Building	-6.084	-1.445	-1.230	1.184	-1.046	-.099	.136	-.008
Shadow	-1.590	2.067	1.016	-1.460	-.719	-.093	.266	-.015

Figure 4.9 shows plot analysis of *M.Ferrea*, *S.Saman* and *C.Sumatrana*, which are the example of correlation between two functions and their group centroids. Whatever the circles (tree species) are gathered near the group centroid, it means the function coefficients is more suitable to distinguish the mentioned class from the other classes. Thus the figure shows that the mentioned function coefficients were appropriate to detect tree species due to the high correlation between the group centroid and the species.

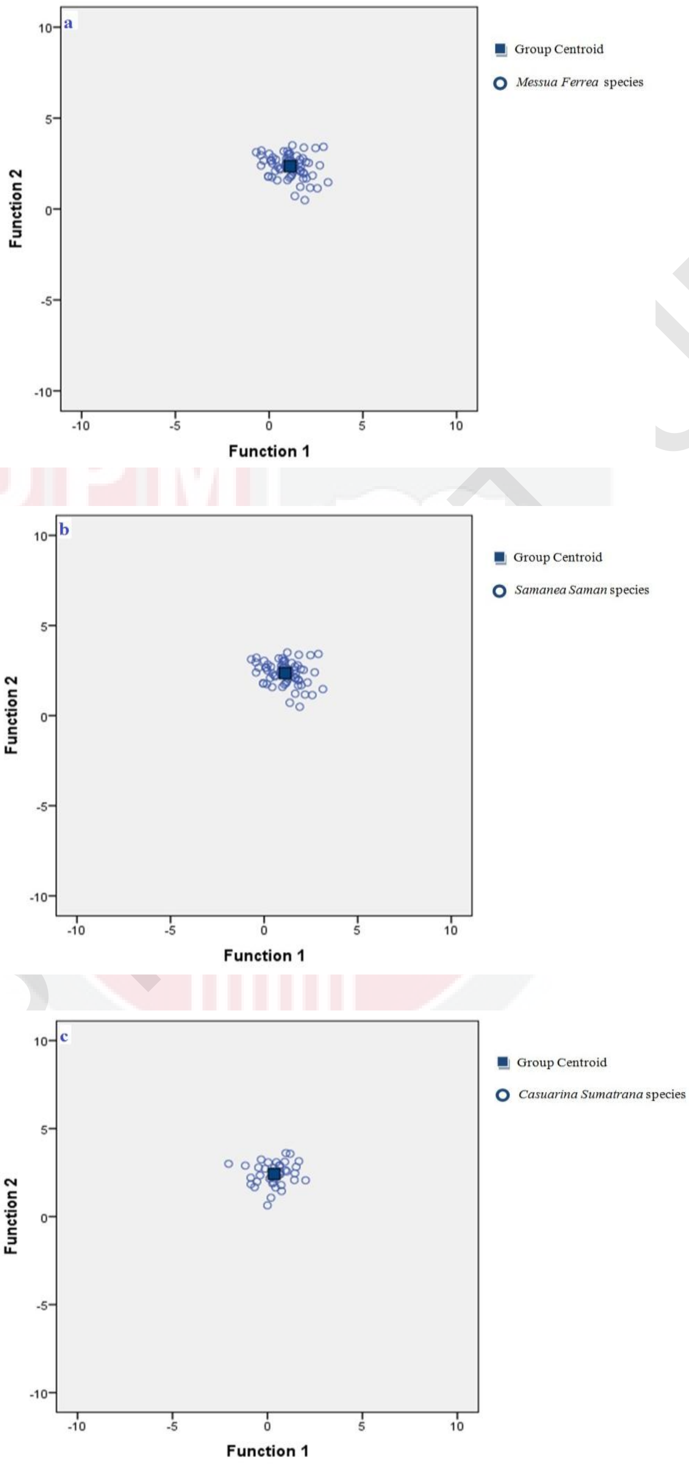

Figure 4.9: Discriminate functions analysis in related to group centroids, for *M.Ferrea* (a), *S.Saman* (b) and *C.Sumatrana* (c).

To assess and consider the significance of the functions that were extracted from the fisher's model result the eigenvalue table was used which showed the model make possible to predict the *S.Saman*, *M.Ferrea* and *C.Sumatrana* with 100% accuracy statistically respectively by utilizing all these eight functions (APPENDX E and F).

In this study, 26 predictor variables in 8 different functions, which came after fisher's model, were extracted based on the training data. In order to compare the influence of using all 8 functions and less than 8 functions, the generic rule was applied two times. The first time all 8 functions, and the second time only 6 functions were used.
As an example, some functions of *Samanea Saman* were calculated as follows:

Function1 for Segment1: (Compact_Segment1) *1.37+(Maindir_Segment1)*-0.001+ (Minaxislen_Segment1)*0.001+(BandRatio5/7_Segment1)*27.736+…+(Stdband_8_Segment1)*-0.001+ (-7.413)

Function2 for Segment1:
(Compact_Segment1)*1.849+(Maindir_Segment1)*-0.001+ (Minaxislen_Segment1) *-.078+(BandRatio5/7_Segment1)*2.815+…+(Stdband_8_Segment1)*-0.001+ (-8.845)

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Function8 for Segment(n): (Compact_Segment(n))*-1.412 + (Maindir_Segment(n))*0.001+(Minaxislen_Segment(n)) * -0.025 + (BandRatio5/7_Segment(n)) * 31.865 + … + (Stdband_8_Segment(n))* 0.003 + (-30.644)

After calculation of all functions for each segment, in order to predict the classes of the segments, the Cartesian distance according to the group centroids, which were given in Tables 4.14 and 4.15 was computed. The generic rule sets were applied on the UPM campus image to evaluate the accuracy of the new model to predict *S.Saman*, *M.Ferrea* and *C.Sumatrana* species. Figure 4.10 and 4.11 shows the predicted result of the tree species (from 8 functions and 6 functions respectively) based on the generic rule sets in UPM campus.

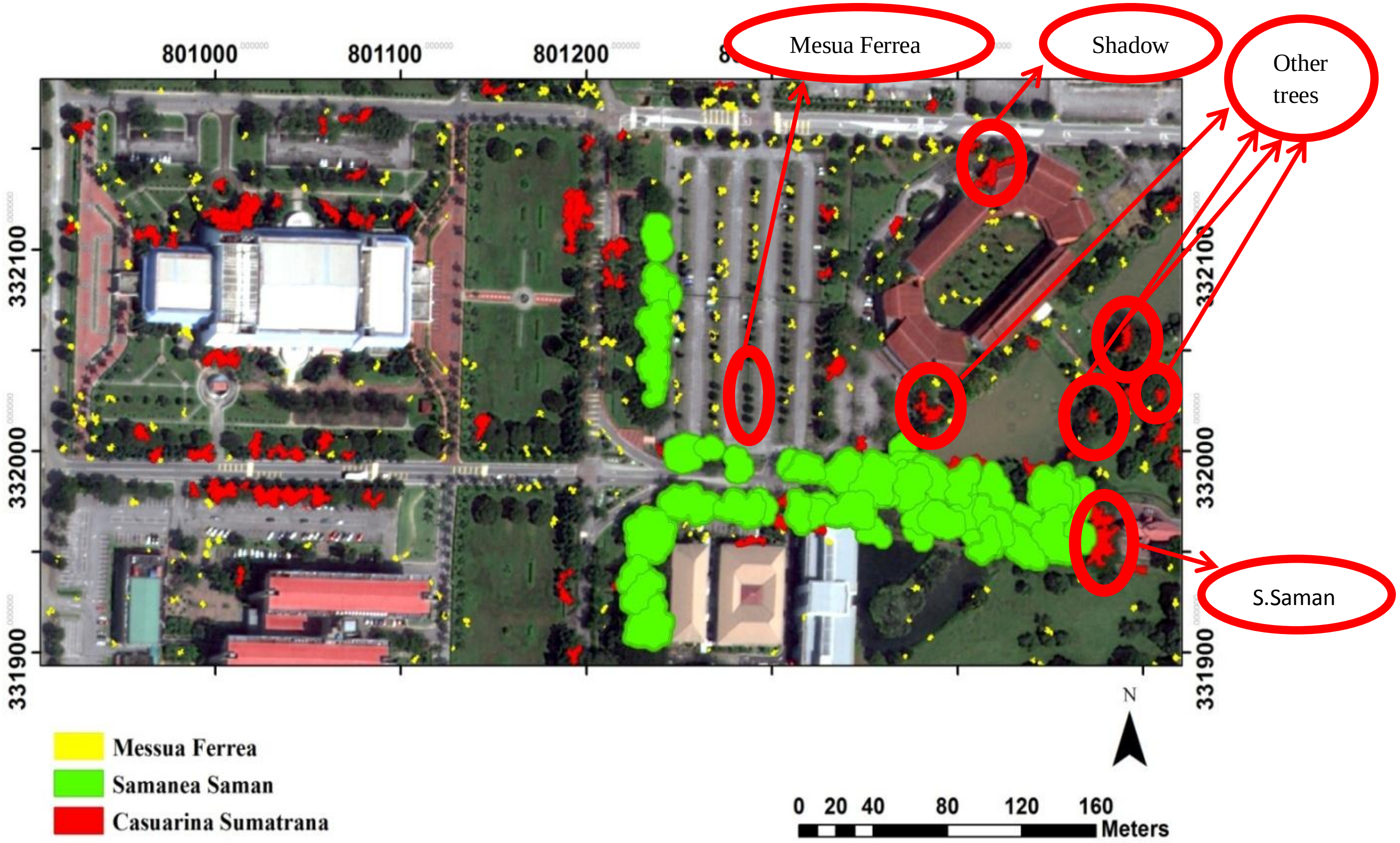

Figure 4.10: Predicted results of Mesua Ferrea, Samanea Saman and Casuarina Sumatrana species based on the new generic rule sets (8 functions).

Figure 4.11: Predicted results of Mesua Ferrea, Samanea Saman and Casuarina Sumatrana species based on the new generic rule sets (6 functions).

Before applying the generic rule sets to predict the tree species, the rule sets depended on each tree species can be filtered by area attribute to improve the generic model. For instance for *S.Saman* trees, since this tree was large, so the segments which their area was roughly larger than 30 meters was filtered for *S.Saman* rule sets.

A standard confusion matrix was used in combination with ground truth data obtained through in situ observation to define the quantitative accuracy of the results. Table 4.16 exhibits the accuracy of the generic rule sets based on the 8 and 6 functions to detect urban tree species.

Since the overall accuracy of the rule set by using 8 functions were significantly higher than using 6 functions (about 68.40% higher), so the generic rule set was defined based on all 8 functions.
To verify the transferability and accuracy of the model in a more comprehensive way and without using training data, the model was applied to different WV-2 images and independent area. For this purpose part of Kuala Lumpur and Serdang were selected as the validation area. The following figures (figures 4.12, 4.13 and 4.14) have shown the predicted results of the tree species in different areas.

Table 4.16: Accuracy of the rule sets to predict urban tree species, including *M.Ferrea, S.Saman* and *C.Sumatrana,* based on 8 and 6 functions.

	Prod. Acc (%)		**User Acc. (%)**	
	(8 functions)	**(6 functions)**	**(8 functions)**	**(6 functions)**
M. Ferrea	63.20	33.52	100	95.70
S. Saman	97.87	8.55	100	100
C.Sumatrana	73.84	45.36	96.96	32.70
Overall Accuracy	86.87		18.47	
Kappa Coefficients	0.7561		0.12	

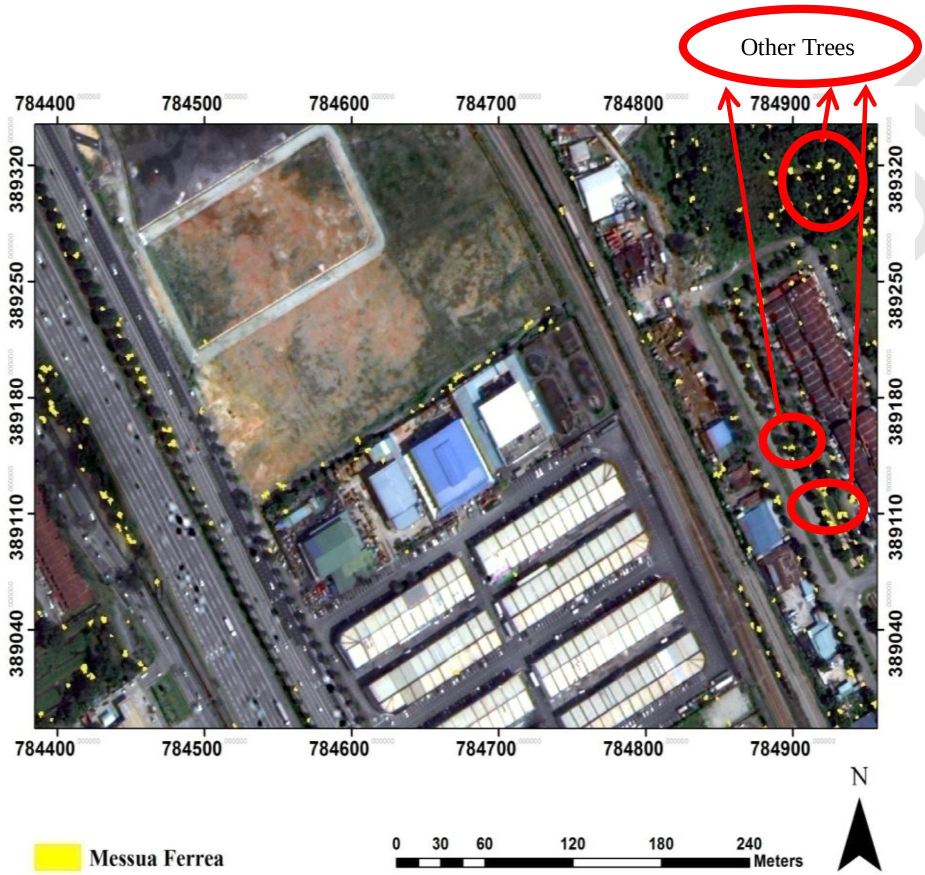

Figure 4.12: Transferability of the generic rule-sets to detect *Messua Ferrea* species in the validation area (Jalan Sungai Besi, Serdang) without any training data.

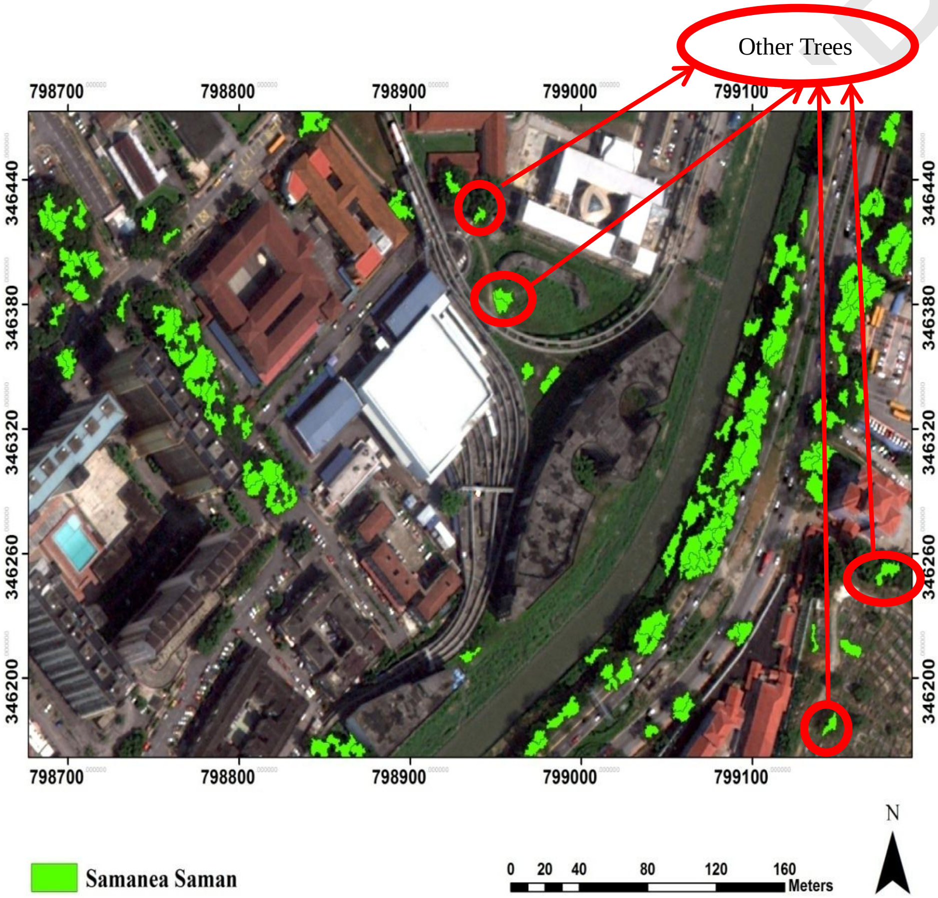

Figure 4.13: Transferability of the generic rule-sets to detect *Samanea Saman* species in the validation area (Jalan Syed Putra, Kuala Lumpur) without any training data.

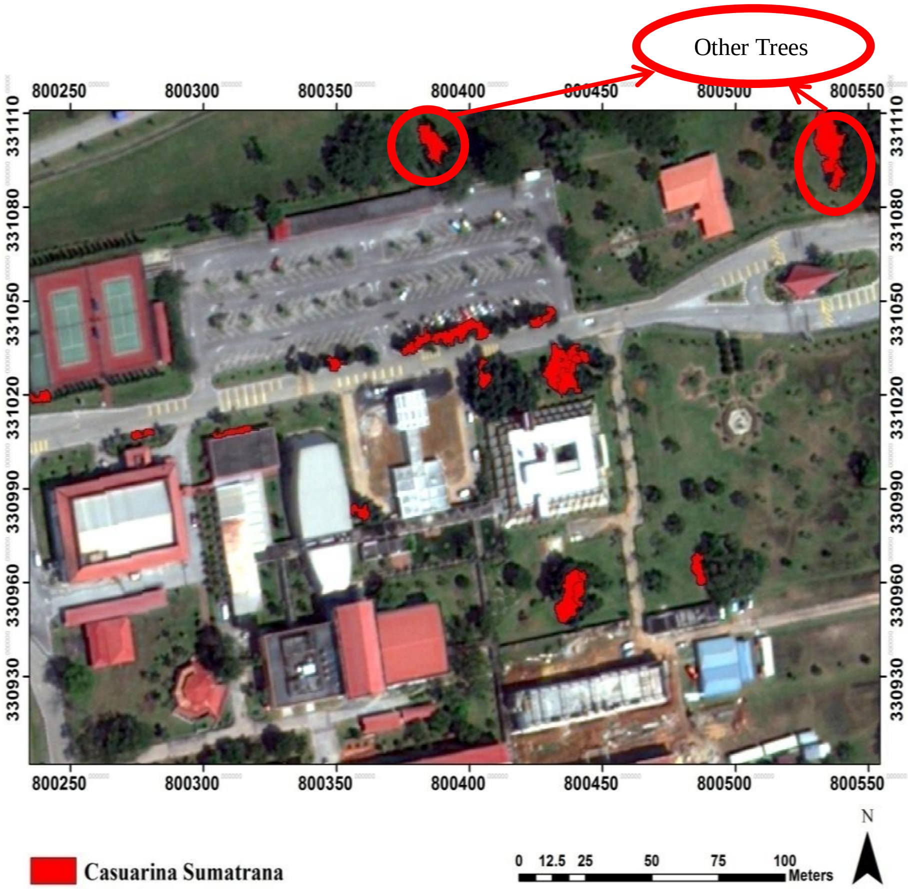

Figure 4.14: Transferability of the generic rule-sets to detect *Casuarina Sumatrana* species in the validation area (MARDI, Serdang) without any training data.

The accuracy, which was achieved by the new model to predict tree species on the validation areas are shown in table 4.17.

Table 4.17: Accuracy of the generic rule sets to predict urban tree species on the validation areas, without any training data.

	Jalan Syed Putra, KL		Mardi, Serdang		Jalan Sungai Besi, Serdang	
	Prod. Acc(%)	User Acc.(%)	Prod. Acc(%)	User Acc. (%)	Prod. Acc(%)	User Acc. (%)
M. Ferrea	-	-	-	-	62.85	100
S. Saman	94.92	100	-	-	-	-
C.Sumatrana	-	-	70.69	100	-	-
Overal Accuracy	81.80		76.79		70.84	
Kappa Coefficients	0.7639		0.6742		0.6063	

4.6 Discussion

The main objective of this research was to develop a new generic rule sets that had the transferability on different areas to detect urban tree species namely *Mesua Ferrea*, *Samanea Saman* and *Casuarina Sumatrana*, based on the limited training data by using the economical VHR imagery such as World View-2 image. Pixel-based classification can classify images more quickly than object-based classification. Thus in this research, ML and SVM were used to illustrate and evaluate the level of improvement achieved by object-based classification.

In this study, ML and SVM spectral-based classifiers were applied on the UPM campus image and they were lead to low-accuracy results. The pixel-based SVM performed better than the ML classifier because of the limitation of the latter in terms of extracting the spectral characteristics of each pixel.

The accuracy assessment of the pixel-based classifications clearly demonstrated the potential of SVM techniques for detection of urban trees in comparison to ML classifier. Although the producer's accuracy of *M.Ferrea* detection by ML classifier was higher than SVM, the other classes' accuracy was less. Moreover the difference between producer's and user's accuracy for whole classes by MLC is too high, from 32.61% to 57.05% that means this classification is not suitable to classify urban areas. 71.07% Overall classification accuracy (k= 0.45) was achieved using SVM in contrast to the overall accuracy of ML classification which was 65.68%, with a kappa coefficient of 0.39. The highest and lowest accurcy of urban tree species by SVM classifier was for *S.Saman* and *M.Ferrea* respectively. Nevertheless, the SVM classifier still classified image inappropriately due to the lack of awareness regarding fine spatial and textural features.

Summary of the pixel-based classifications shows that overall accuracy increased from 65.68% to 71.07% (up to 5.39%) with SVM classification. Thus, SVM may be superior to the ML classifier when the spectral similarity of urban targets was high. The poor accuracy in both ML and SVM was recognized to the fact of spectral similarity between these classes, including *S.Saman*, *M.Ferrea*, *C.Sumatrana*, other trees and grass. In addition a visual interpretation indicates many misclassifications of *S.Saman* and *M.Ferrea*, as well as of other tree species, also the boundary of the tree edges is difficult to detect. Therefore based on the spectral-based classifications the methods of discriminating different tree species are difficult to develop.

Hence, the object-based classification was used to overcome the pixel-based classification limitation. To this end, information on various spectral, spatial, textural and colour attributes was used. The high spatial resolution of WV-2 imagery provides high-level spatial heterogeneity from natural surfaces. The spectral diversity of the land cover classes was also highlighted in terms of the increased spectral resolution in this type of imagery and new bands in WV-2 imagery facilitated the discrimination of different tree species.

Segmentation and merging in object-based classification were important steps in generating image objects and computing attributes. The selection of low segmentation (20) and moderate merging scales (65) which combined the similar adjacent segments to overcome over-segmentation assisted in the detection of the boundaries and shapes of different tree species. Therefore, the value of the segmentation and merging will be affected on the final result of the object-based classification.

In order to evaluate the potential of WV-2 imagery, at first the object-based classification based on trial and error (manually) was applied. The first specific objective of this research was to evaluate the performance of pixel-based and object-based image analysis (OBIA) methods for detection of urban tree species. Thus the result of object-based classification manually shows that the overall accuracy of detecting tree species was enhanced by up to 12.55% in compare to pixel-based classification, and the result emphasis on the object-based classification power to discriminate urban tree species.

The next step was developing a generic model to detect urban tree species through OB classification. In order to utilize and optimise the attributes information of the segments to prepare the attributes for developing the generic rule-sets to predict the urban tree species, Cfs Subset Evaluator was applied to select the most effective attributes for discriminating urban classes, especially urban tree species. The result of the mentioned method for attribute selection was demonstrated that from 55 attributes, 26 of them were selected which included 3 spatial, 5 color, 3 texture, 15 spectral. To achieve the coefficients of the selected attributes, Fisher's method analysis was applied on the selected attributes and 8 functions were extracted from the analysis results. The eigenvalue table shows that if the all 8 functions used as the generic rule, this model can predict the tree species with 100% accuracy statistically.

However the number of spectral attributes which were selected, was more than other attributes, the weight of coefficients has shown that band ratio 5/7, band ratio 5/8, band ratio 6/7, tx_entropy, saturation and compact were more significant attributes than others to discriminate urban tree species. Therefore, the band ratio, texture and spatial attributes were more effective than spectral attributes to discriminate urban tree species. Moreover, the attributes have shown the new bands of WV-2 imagery are obviously effective to discriminate urban tree species.

Finally based on the 8 functions and by considering the Cartesian distance, the new generic model was developed from WV-2 UPM imagery. At first to evaluate the generic rule accuracy, the model was applied on the UPM imagery, and then to assess the prediction accuracy and the transferability of the rule, it was applied on different areas.

The overall accuracy of this generic model was significantly higher than pixel-based classification. By utilization of object-based classification in WV-2 the discriminating accuracy of the species for *M.Ferrea*, *S.Saman*, and *C.Sumatrana* species was enhanced by up to 15.54% and the number of misidentified objects also reduces. The results confirmed the efficiency of derive information means 26 attributes related to spatial, spectral, color and textural information extracted from the WorldView-2 image, rather than the traditional method (ML) and SVM which utilizes the spectral information with approximately 65.68% and 71.07% overall accuracy respectively. Therefore by pixel-based classifications urban tree species are difficult to detect because of the spectral similarities among classes and the confusion among different urban materials. Moreover in compare to manually object-based classification, the accuracy of generic model was improved about 3.25%.

The second specific objective of this study was to develop a new generic rule set to discriminate urban tree species based on an OBIA by utilizing spectral, spatial, color and texture information. Accordingly the results of the generic rule show that the model can predict the mentioned trees with an overall accuracy of approximately 86.87% and a Kappa coefficient of 0.76. Thus the second objective of this research is achieved by the mentioned results. Based on the literature review (chapter 2), the study on urban tree species detection by using WV-2 and OBIA were too rare. By the way, two recent studies, which were more similar to this research, were considered for comparison. The first difference was the classification method through OBIA. In study by Verlic et al. (2014) and Li et al. (2015), the SVM method applied, but in this research the OBIA was done based on the creating a rule set. The second difference was the ancillary data (satellite imageries or LiDAR data), which were used in the previous studies, however in this research only WV-2 imagery was used which is more economical. Finally the last and most important difference is the transferability of the generic rule sets. The previous studies classifications were not transferable to other study areas; conversely the generic rule set that is achieved through this study is transferable on different study areas.

Consequently to verify accuracy of the model in a more comprehensive way and without using training data, the model was applied to different WV-2 images and independent area. The results that achieved by generic rule-sets on the validation areas (Jalan Syed Putra /Kuala Lumpur, Mardi/Serdang, and Jalan Sungai Besi/Serdang), has proved the transferability of the generic model to predict urban tree species (*M.Ferrea*, *S.Saman* and *C.Sumatrana*) producer's accuracies for the image 62.85%, 94.92%, 70.69%, and user accuracies'100% for all images. So the third specific objective of this study, which was to validate the transferability of the new generic rule set in other study areas, is achieved. These results demonstrate various advantages of the OB approach such as the extracting all attributes information from the segments and its capability of combining spatial, texture, color and band ratio as well as spectral information into the classification.

By assessing the accuracy of the OB classification on UPM imagery and validation areas, it should be noted that both accuracy is high for *S.Saman* so it can be said the rule set acquired for S.Saman based on segmentation can detect this type of tree with 94.92% accuracy. Since the accuracy of S.Saman detection is high and the number of *S.Saman* segments is near to the real numbers, thus the OB classification based on the segments could be helpful for counting trees in urban area. In this study based on the field measurement in UPM campus area, 41 *S.Saman* species is detected, however the number of segments of *S.Saman* by generic rule is 45 segments. Thus if we consider each segment equal to one tree, the number of S.Saman trees by the generic rule is 45, and the error in counting can be occurred due to the large width of *S.Saman* trees which leads to divided some trees into two or more segments. Therefore the OB classification specially the segmentation step might be helpful for urban tree counting.

Among the urban tree species in this study, the lowest accuracy allocated to *M.Ferrea* species. This misclassification is caused by the size of the *M.Ferrea* trees which were too young and small, so the different segmentation scale might be improved the accuracy of *M.Ferrea* species. Moreover similarities in texture and high-grade spectral variability within classes that are affected by sun angle, and shadows might be lead to the misclassification.

In conclusion, spectral, spatial, color, band ratio and textural attributes are applied to develop new generic model in order to discriminate urban tree species. This model demonstrates a good potential for predicting and discriminating different urban tree species such as *Mesua Ferrea, Samanea Saman* and *Casuarina Sumatrana* trees from the WV-2 imagery.

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

5.1 Introduction

The general conclusion of this thesis is the successfulness in automated urban tree species detection by developing a new generic rule using World View-2 imagery. The first section of this chapter will discuss the important conclusions of this research. The second part of the chapter will discuss about recommendations for further research in developing the methods to extract different tree species in urban areas using VHR resolution imagery.

5.2 Conclusion

Urban vegetation management has become an important issue because of rapid urban development. Rapid urbanization has prompted people to control urban green spaces for ecological purposes. Accurate and reliable information on different tree species is crucial to urban vegetation studies. This information assists urban planners and researchers in urban planning and disaster management.

Urban spaces are complex areas; hence, accessibility to all trees by field survey is extremely difficult and time-consuming. Several studies have been conducted to detect tree species; however, the lack of generic rule sets for conducting this detection process in urban areas remains a major setback. This study proposed the detection of urban tree species from WV-2 imagery by utilizing spectral, spatial, color, band ratio and texture information. The species of this research were selected among the most effective and popular species of urban trees in tropical areas such as Malaysia which widely used to save much energy (*Mesua Ferrea* and *Samanea Saman*) and act as effective windbreakers (*Casuarina Sumatrana*).

With regard to the general objective of this study, that was evaluating the object-based classification to detect urban tree species, different classification methods were applied to the UPM image which includes the spectral-based classifier methods such as traditional methods (ML), advanced method (SVM) and OB classification method which was done manually. The results show that the spectral information only, is not sufficient for detecting and discriminating between the urban classes especially tree species. The overall accuracy of pixel-based analysis increased from 65.68% to 71.07% with SVM, and subsequently the object-based method produced more accurate results than ML and SVM did at approximately 83.62%. Thus OB approach has potential to discriminate urban tree species as the result demonstrated the overall accuracy of the tree species were enhanced up to 12.55%.

One of the limitations in detecting urban tree species using remote sensing data is a lack of sufficient training data. Collecting the training data, especially for the different tree species is a very difficult task and time consuming. Furthermore, lack of the generic model to predict the urban tree species by utilizing very high resolution imagery is another gap in urban studies.

Hence the main objective of this study is to develop a generic rule for automated urban tree species detection based on object-based image analysis (OBIA) methodology on WV-2 imagery. The generic model acquired over the UPM campus imagery that considers the spectral, spatial, color, texture information of tree species.

To train the model, the training data were prepared based on a field survey, and all training data were extracted only from the UPM image. The segmentation was applied to extract the spectral, spatial, texture and color attributes, and then feature selection were shown that CfsSubsetEval method is a sufficient attribute evaluator which could selected 26 attributes from 56 attributes, which were most effective attributes to detect and discriminate urban tree species. These attributes by utilizing fisher's method were able to discriminate different urban trees in terms of eight functions and different coefficients. The Cartesian distance was used to develop a generic model based on the attributes and their coefficients by considering eight fuctions. The results of the generic rule show that the model can predict the mentioned trees with an overall accuracy of approximately 86.87% and a Kappa coefficient of 0.76.

Finally to assess the transferability of the generic rule sets, the model was applied to some other image with no training data in the urban space such as part of Kuala Lumpur and Serdang. The results of the generic rule over the validation areas show producer's accuracy of 62.85%, 94.92%, and 70.69% respectively for tree species, namely, M.Ferrea, S.Saman, and C.Sumatrana.

The result of the main objective shows that this model has a good potential to predict and detect three urban tree species (*M.Ferrea*, *S.Saman*, and *C.Sumatrana*) without using training data from WV-2 images.

The innovation and benefits of this model are as following: firstly it was developed based on the multispectral satellite data which is economical and its processing is fast. Secondly this generic model was created based on the statistical approach not by trial and error. Thirdly the model fully utilized the attributes information of segments which is acquired from WV-2 imagery that includes the spatial, spectral, color, band ratio and texture information. Lastly the transferability of this generic model can predict the urban tree species without using training data.

Nevertheless, there are still some limitations that can affect on the result. For instance since the study area is an urban area, thus the shadows on the trees which is created by high-rise buildings can lead to the misclassification. Moreover according to the fact that the segmentation is the most important step in the object-based classification, and there is not any absolute scale for the classes, thus the different segment scales can affect on the results.

5.3 Recommendations for Future Research

The recommended future research is provided to further improve the proposed method. In this study three tropical urban tree species which widely used to save much energy and act as effective windbreakers is considered for developing the generic rule, and the future work is needed to apply and improve the proposed method to detect and discriminate other urban tree species.

According to the fact that the accuracy of object-based classification is highly dependent on segmentation; thus, a new scale might be adjusted for the segmentation step to optimize the generic model.

In the future works the generic model can be developed based on the new high resolution satellite imagery such as World View-3 and ancillary data such as LiDAR can be utilized to improve the classification accuracy in shadows. Finally this generic model currently was applied on different part of Malaysia, and it would be applied on different areas outside Malaysia.

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APPENDIX A

Satellite and airborne sensors, which were investigated for urban forest studies.

	Spatial Resolution	Band	Dynamic Range	Methods	References
Hyperspectral	5 m	15 nm		ICARE (3D atmospheric correction code), NDVI-LAI relationship, DSM (0.25 resolution)	Adeline et al. 2013
				Decision tree (DT) classifier	Zhang and Qiu 2012
				LAI	Hao et al. 2011
QuickBird	2.44 m	multispectral	16 bit	Super-resolution mapping (SRM) based on Markov random fields (MRF), maximum likelihood classifier (MLC)	Ardila et al. 2010
	0.61 m	panchromatic		SRM based on MRF and SVM	Ardila et al. 2011
				Reproducible geographic object-based image analysis (GEOBIA)	Ardila et al. 2012
				GLCM, VTI building, and NDVI	Hong et al. 2009
					Hu 2011
				Global environment monitoring index (GEMI) and NDVI	Huang et al. 2007
		R,G,B, NIR		Fuzzy multi-threshold classification	Li et al. 2010
				DT classifier	Zhang et al. 2012

				MSAVI	Puissant et al. 2014
				NDVI, Principle Components Transformation, DT classifier, MLC	Ouma and Tateishi 2008
					Hashiba et al. 2004
					Tooke et al. 2009
MODIS	250	band 1-2	12 bit	MODIS EVI and DT classifier	Zheng and Qui 2012
	500	band 3-7			
	1000	band 8-36			Hao et al. 2011
Color Infrared (CIR)				DSM (3D), GLCM, SVM	Iovan et al. 2008
				Random Forest (RF)	Johnson and Xie 2013
SPOT	10 m		8 bit		Kong and Nakagoshi 2005
	20 m				
					Zhang et al. 2007
					Liu et al. 2008
IKONOS	1 m	panchromatic		NDVI, SR, ARVI, SAVI, LAI	Ma and Ju 2011
	4 m	multispectral			

SAR					Maksymiuk et al. 2014
LIDAR					Zhu et al. 2012
					Nicholas et al. 2012
					Zhang and Qiu 2012
					Niemeyer et al. 2013
					Sung 2012
					Oshio et al. 2012 and 2013
					Adeline et al. 2013
					Zhou 2013
Landsat				NDVI and GEMI	Huang et al. 2007
MSS	60 m				Zhang et al. 2007
TM	30 m			MLC, NDVI	Shouse et al. 2013
ETM+	15-30 m			MLC, NDVI	Peijun et al. 2010
					Hasmadi and Jusoff 2004
					Gong et al., 2013
				RVI, NDVI, PVI, NDBI	Cai et al. 2010

World-View 2	0.5 m	panchromatic	11 bit	(RF) classification, Linear discriminant analysis (LDA)	Immitzer et al. 2012
					Abd Latif et al. 2012
	2 m	multispectral		Minimum Distance (MD) classification, Spectral Angle Mapper (SAM), NDVI	Nouri et al. 2014

APPENDIX B

Summary of urban tree species detection through remote sensing and different classification methods.

Sensor	Acquisition date	LiDAR	Classification algorithm	Species no.	Overall Acc.	Tree species	Tree counting	References
ADS40, MIVIS	Dec 2011	X	ML> SAM, SID	10	92.57	herbaceous, heatland, arundo donax, poplar, oak, pine, cypressus, spruce, willow, and olive		Forzieri et al. 2013
Landsat TM	May 1996		Supervised > Unsupervised	3	61	Oil Palm, Rubber Tree, Bush, Grass (+ 6 different landcover types)		Ismail and Jusoff 2004
RIEGL LMS-Q560	Winter 2006/2007	X	DT / ANN	6	DT: 72 / ANN: 95	Fagus sylvatica, Acer platanoides, Platanus acerifolia, Tilia cordata, platyphyllos, Aesculus hippocastanum,		Hofle et al. 2012
CIR Sensor	2004		SVM (texture measure)	2		Plane tree (Platanus Hispanica), lime tree (Tilia)	Tree Crown delineation	Iovan et al. 2008
CIR Sensor	2004		SVM	6		Platanus, Sophora, Tilia, Celtis, Pinus, Cupressus	Tree Crown delineation	Iovan et al. 2014
World View-2	January 2010		MD, SAM & segmentation	8	0 – 87	Hopean, Odorata Roxb, Shorea Leprosula, Neobalanocarpus Heimii, Gymnacranthera Bancana (Ihiq) Sinclair, Rusty Sterculia,Palaqium Rostratum, Eugenia Oleina, and Dyera Costulata.	Tree Counting	Abd Latif et al. 2012
QuickBird	2007		Segmentation & fuzzy multi-thresholds classification	2	93.72	Forest, Grassland, Thick grassland		Li et al. 2010
IKONOS & World View 2	IKO: April 2006 / WV-2: May 2011		LDA/ Regression Trees	7	16% to 18% improved	Sand live oak, Laural oak, Live oak, Pine, Palm, Camphor, Magnolia		Pu and Landry 2012

					by WV-2 (compared with Ikonos)			
Aerial & LandSat TM 5	Aerial: 2006 & 2009 / LandSat: 2005 & 2007		OB > PB	1	Aerial (HSR): 94.2 / Landsat (MSR): 74.6	Bush honeysuckle (Lonicera maackii)		Shouse et al. 2013
RapidEye	2009, LiDAR: 2007	X	SVM	8		Pinus, Aesculus, Platanus, Tilia, Acer, Populus, Fagus, Quercus		Tigges et al. 2013
QuickBird	2008	X	SMA	2		Evergreen & Deciduous species		Tooke et al. 2009
QuickBird	March 2007	X	SMA / DT	2	Evergreen: 80%, Deci: 67%	Evergreen & Deciduous species		Tooke et al., 2009
AISA	July 2004 & Oct 2006, LiDAR: April 2006	X	Segmentation	7	Summer: 57% / Fall: 56%, adding LiDAR improved 19%	Deciduous trees: Gleditsia triacanthos, Acer saccharum, Tilia Americana, Quercus palustris, Pinus strobus, and Picea glauca		Voss & Sugumaran, 2008
Hyperspectral, LiDAR(Terra Remote Sensing) TRSI	2008	X	ANN / AGFLVQ / SAM	20	AGFLVQ: 68.8% / SAM: 39.95	American Elm, Hackberry, Pecan, Eastern Red Cedar, Shumard Red Oak, Tree of Heaven, Cedar Elm, Green Ash, Red Mulberry, Chinaberry, Gum Bumelia, Bald Cypress, Cherry Laurel, Boxelder, Post	Individual Tree detection	Zhang & Qiu, 2012

						Oak, Live Oak, Bur Oak, Cottonwood, Crepe Myrtle, Black Willow		

APPENDIX C

Extracted attributes of some training segments from attribute table in ArcGIS.

AREA	LENGTH	COMPACT	CONVEXITY	SOLIDITY	ROUNDNESS	FORMFACTOR
30.125000	25.113466	0.246611	1.103701	0.839721	0.533302	0.600238
60.875000	42.860438	0.205408	1.185872	0.710949	0.418176	0.416424
331.375000	138.823207	0.147963	1.668304	0.688035	0.403854	0.216075

ELONGATION	RECT_FIT	MAINDIR	MAJAXISLEN	MINAXISLEN	NUMHOLES	HOLESOLRAT
1.481744	0.620635	43.118198	8.480705	5.723463	0.000000	1.000000
1.607464	0.527947	139.459811	13.614287	8.469422	0.000000	1.000000
1.343264	0.426065	28.606544	32.322322	24.062516	0.000000	1.000000

BANDRATIO	HUE	SATURATION	INTENSITY	TX_RANGE	TX_MEAN	TX_VARIANC
0.490368	198.741720	0.171151	0.780583	92.438017	919.727272	2064.350776
0.401151	198.741126	0.331200	0.718157	63.776423	874.958898	888.134147
0.576211	195.805167	0.225869	0.839824	28.538346	858.240685	114.804031

TX_ENTROPY	MINBAND_1	MAXBAND_1	AVGBAND_1	STDBAND_1	MINBAND_2	MAXBAND_2
0.182930	850.000000	1064.000000	911.231405	44.594424	813.000000	1183.000000
0.186265	787.000000	1109.000000	871.439024	35.500882	728.000000	1167.000000
0.181086	816.000000	955.000000	859.256391	15.779509	758.000000	982.000000

AVGBAND_2	STDBAND_2	MINBAND_3	MAXBAND_3	AVGBAND_3	STDBAND_3	MINBAND_4
923.429752	82.128642	656.000000	1072.000000	792.049587	102.566470	564.000000
838.089431	50.878568	590.000000	1035.000000	666.398374	59.836886	477.000000
824.706767	23.904683	611.000000	892.000000	704.551128	30.077740	514.000000

MAXBAND_4	AVGBAND_4	STDBAND_4	MINBAND_5	MAXBAND_5	AVGBAND_5	STDBAND_5
1128.000000	731.661157	124.494548	556.000000	1192.000000	771.206612	148.403556
1103.000000	586.597561	80.500048	424.000000	1228.000000	589.813008	97.187498
866.000000	620.521805	41.898188	453.000000	921.000000	598.772932	52.595647

MINBAND_6	MAXBAND_6	AVGBAND_6	STDBAND_6	MINBAND_7	MAXBAND_7	AVGBAND_7
1173.000000	1618.000000	1404.388430	85.377336	2131.000000	2860.000000	2462.148760
706.000000	1700.000000	966.398374	180.608619	995.000000	2744.000000	1460.943089
1146.000000	1700.000000	1441.290977	81.475429	1675.000000	2927.000000	2384.931579

STDBAND_7	MINBAND_8	MAXBAND_8	AVGBAND_8	STDBAND_8
159.770808	1847.000000	2583.000000	2255.314050	167.060570
285.137942	957.000000	2748.000000	1380.008130	296.869352
178.206095	1526.000000	2688.000000	2227.035338	159.790037

APPENDIX D

Eigenvalues (*Samanea Saman*)

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	10.281[a]	53.8	53.8	.955
2	5.044[a]	26.4	80.3	.914
3	1.619[a]	8.5	88.7	.786
4	.931[a]	4.9	93.6	.694
5	.717[a]	3.8	97.4	.646
6	.337[a]	1.8	99.1	.502
7	.131[a]	.7	99.8	.341
8	.033[a]	.2	100.0	.179

APPENDIX E

Eigenvalues (*Mesua Ferrea* and *Casuarina Sumatrana*)

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	10.140[a]	53.6	53.6	.954
2	5.048[a]	26.7	80.3	.914
3	1.595[a]	8.4	88.7	.784
4	.906[a]	4.8	93.5	.689
5	.715[a]	3.8	97.3	.646
6	.347[a]	1.8	99.1	.508
7	.137[a]	.7	99.8	.347
8	.035[a]	.2	100.0	.184

Wilks' Lambda table (*Samanea Saman*)

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 8	.001	3377.305	208	.000
2 through 8	.012	2179.091	175	.000
3 through 8	.074	1289.490	144	.000

4 through 8	.193	813.446	115	.000
5 through 8	.373	488.123	88	.000
6 through 8	.640	220.690	63	.000
7 through 8	.856	77.097	40	.000
8	.968	16.133	19	.648

Wilks' Lambda table (*Mesua Ferrea* and *Casuarina Sumatrana*)

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 8	.001	3394.166	208	.000
2 through 8	.012	2192.512	175	.000
3 through 8	.074	1295.389	144	.000
4 through 8	.193	819.975	115	.000
5 through 8	.368	498.405	88	.000
6 through 8	.631	229.436	63	.000
7 through 8	.850	80.959	40	.000
8	.966	17.112	19	.582

BIODATA OF STUDENT

Razieh Shojanoori was born on the twenty-seventh of June 1986 in Tehran, Iran. She studied at Science Faculty of the Islamic Azad University of Tehran (North Branch), Iran from 2004 to 2008, where she obtained her bachelor degree in Geology. She completed her master degree in the Remote Sensing and Geographic Information Systems (RS and GIS) from 2010 to 2011 at Faculty of Engineering, Universiti Putra Malaysia (UPM), Malaysia. Later she has carried out a doctoral study in Remote Sensing at UPM. Her Ph.D. topic is “Object-Based Imagery Analysis For Automatic Urban Tree Species Detection Using High Resolution Satellite Image”. Her research interest includes urban forest, remote sensing, geographic information systems and geology.

LIST OF PUBLICATIONS

Shojanoori, R., Shafri, H.Z.M., Shattri, M. and Ismail, M.H. (2016). The Use of WorldView-2 Satellite Data in Urban Tree Species Mapping by Object-Based Image Analysis Technique. *Sains Malaysiana*, 45(7): 1027-1036.

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