URBAN TREE SPECIES CLASSIFICATION ON PIXEL AND OBJECT LEVEL WITH WORLDVIEW-2 IMAGE, USING MAXIMUM LIKELIHOOD CLASSIFIER AND SUPPORT VECTOR MACHINE

LUCY CHEPKOSGEI CHEPKOCHEI
March, 2014

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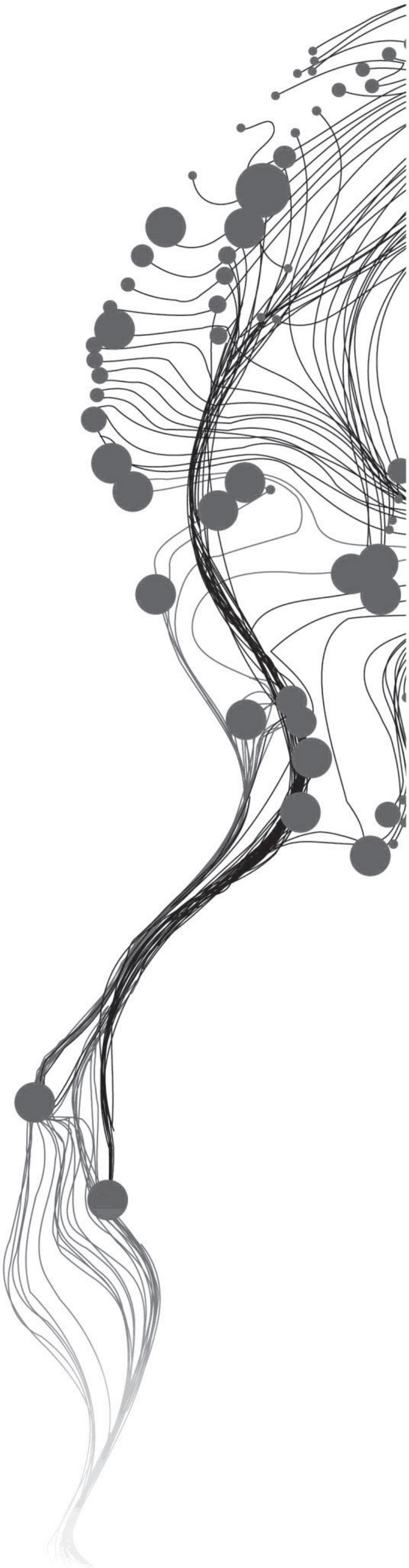

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Enschede, The Netherlands, [March, 2014]

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Geoinformatics

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ABSTRACT

Urban areas do have a mixed environment of land cover. classification using traditional techniques like ground survey, aerial photography are time-consuming, costly and limited. In recent years, sensors have continually been launched and very-high resolution images relevant to sustainable development of urban land-use are increasingly being captured. This has resulted in increased multispectral data with broader spectral bands, higher radiometric and temporal resolution and high spatial resolution. High spatial resolution imagery, however, brings in a new challenge of spectral response of individual trees being influenced by variation in canopy illumination, the surrounding and background effects. This is a challenge in classification of tree species using ordinary pixel based classification (e.g. maximum likelihood classification). This study investigated the classification of urban tree species using maximum likelihood classification and support vector machine on the WorldView-2 satellite image using object and pixels in both methods. Object and pixel based analysis was used in both classification methods. MLC performed better than SVM in both object and pixel based calssification. MLC pixel based overall accuracy was 66.93% with Kappa of 0.54 and 51.24% with Kappa of 0.36 for SVM pixel based. MLC object based overall accuracy was 71.17% with Kappa of 0.66 and 44.62% with Kappa of 0.31 for SVM object based analysis. Even though MLC perfoms better than SVM, the accuracy is still low compared to generally accepted accuracy. This indicates that both methods are still not satisfactory techniques of classifying high resolution images for Delft city. MLC, however, has been used for many years in image classification. It is straightforward and does not require extreme expert skills to apply. MLC algorithm can be found in most of the remote sensing application software. Examples of this software are ERDAS, ENVI and ILWIS (open source) among others. This makes MLC an easy available method for classification. MLC pixel based classification is effective in classifying medium and large trees (e.g. *Plantanus Spp.* and *Fagus Spp.*). MLC relies on mean and covariance of samples hence calculation of covariance matrix in small tree crowns (> 10 pixels) could not be determined. Class separability using J-M distance measure and NDVI mean and variation evaluation were the same. This gives the possibilty of use of NDVI in separating tree species. SVM does not operate based on data distribution making it applicable to any type of data (i.e. normal or non-normal distribution. Its performance relies on kernel parameters. In this study, C value of 5 and value 5 for δ were used. Experimenting on optimum parameters values of C and δ can give satisfactory classification results. Though the study area is in The Netherlands, classification of tree species using MLC and SVM brings up possibilities to apply the same approach in other urban areas and to other species.

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Mungu yuko.

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1. INTRODUCTION

1.1. Background

Remote sensing provides useful information to assist challenges in environmental, hydrological, ecological, agricultural and development aspects. Satellite imagery has the reflectance information of the Earth's surface within the electromagnetic spectrum. Remote sensing classification techniques help to assign a class to specific reflectance information in a pixel. Mixed pixel, however, is one of the major problems encountered when extracting that information from the image (Ling et al., 2013). Successful classification is dependent on heterogeneity of a pixel, pixel size and class variance. Some common land cover classes are vegetation, built up areas, water bodies, desert, soil and bare ground. The same classes mentioned do have sub-classes, for example, vegetation can be sub-divided into various vegetation types of forests, grassland and cropfields. To classify the said classes, human beings can use visual interpretation techniques like the human-knowledge, patterns, size, association and colors on the image. Visual interpretation techniques are time-consuming, prone to human error and costly over large areas. Supervised classification is a common classification method where the user selects training samples (Kuckartz, 2007). Unsupervised classification uses the algorithm to define which pixel belongs to which class based on the feature space.

Classification methods can be grouped into either hard or soft classification. In hard classifications methods, each pixel belongs to the class it most closely resembles. Hard classifications examples are Iterative Self Organized Data Analysis and Transfer Algorithm (ISODATA), centroid (e.g. K-means), maximum likelihood methods. It is easier to do hard classification of homogenous areas (e.g. pure croplands, pure waterbodies). Hard classification, however, is dependent on spatial scale and variance of the classes. In soft classification each pixel can belong to more than one class and has membership grades for each class. Moreover, it takes into concideration the heterogeneous (mixed) nature of the real world. Soft classification methods include the linear mixture modeling and fuzzy classification.

In many applications (e.g. maximum likelihood), datasets could be described as normally distributed. In reality, however, the data in some cases may not be normally distributed. This calls for non-parametric classification technique. The commonly non-parametric mehods are parallepiped, minimum distance, neural networks among others. Support Vector machine (SVM) is one of the emerging non-parametric technique. SVM is a supervised non-parametric learning kernel based. SVM makes differenciation of classes based on decision boundary, i.e. hyper-plane.

1.2. Motivation and problem statement

Urban forests play a major role in cities and towns in improving air quality and climate protection, energy saving, recreation and human connection with nature (McPherson, 2006). Trees reduce carbon-dioxide in the atmosphere through assimilation (Myeong et al., 2006). Information of tree species location and distribution is important for sustainable trees management and helps in giving knowledge pertaining to functioning of the forested ecosystems. The health and diversity of trees species in urban forests is important. Moreover, tree diseases and pests cause tree health problems and eventually death (Boyd et al., 2013). Abiotic factors like the un-favorable soil properties, moisture and temperature extremes, chemical toxicity, physical injuries reduces plant health, cause decay. Guarding against disasters like Dutch elm disease that destroyed many elm trees in the 1960s and 70s (Tomlinson & Potter, 2010) is important. Practices of fertilization, mulching, watering, pruning to get certain landscapes and thinning influences growth of trees. The urban authority monitors and manages urban forests. There is a need to plan the costs to replace the sick or dead trees. It also assist to "put the right tree in the right place" (Santamour Jr, 2004). As a result, it is vital to map tree species in urban areas with the help of remote sensing imagery.

Urban areas do have a mixed environment of land cover (e.g. grass, gardens, scrublands, and impervious areas) and continuously changing infrastructure. The urban environment is also characterized by heterogeneous mosaics of small features made up of materials with different physical properties (Mathieu et al., 2007). Urban trees inventory is necessary to identify tree location, to gain information about species and their spatial distributions. This information can be collected using traditional techniques for example ground survey and aerial photography. However, ground survey techniques (for example GPS survey) are time-consuming, costly and limited, especially when one has to work over large areas. Aerial photography, visual map interpretation are similarly slow and expensive, especially when it has to be done for large scale mapping which translate to detailed over small areas (Suárez et al., 2005). In addition, a field survey is limited to accessible areas like public places; it is not easy in some cases to collect tree information in private properties and dangerous or inaccessible areas.

In recent years, sensors have continually been launched and very-high resolution images relevant to sustainable development of urban land-use are increasingly being captured (Kong et al., 2006). This has resulted in increased multispectral data with broader spectral bands, higher radiometric and temporal resolution and high spatial resolution (Blaschke, 2010). High spatial resolution imagery, however, brings in a new challenge of spectral response of individual trees being influenced by variation in canopy illumination, the surrounding and background effects (Quackenbush, 2000). This is a challenge in classification of tree species using ordinary pixel based classification (e.g. maximum likelihood classification). Moreover, these data are only information sources and requires data processing, analysis and information extraction to get useful information. In tree crown classification, tree structural characteristics, for example; height, crown shape, crown diameter and canopy cover are considered. A tree crown, however, may not occupy a whole pixel and in some cases can partially occupy more than one pixel leading to mixed pixels. Accordingly, high spatial resolution of data does not fully solve capturing of trees since in reality in geographical space; trees do not exactly fit in a pixel. Thus it reduces the accuracy when using conventional pixel-based classifications.

The aim of the present study is to classify urban tree species using high resolution image, Worldview-2. Apart from Red band, WorldView-2 has additional Red-Edge spectral band which is considered sensitive in plant studies. The Red-Edge band (680 nm to 750 nm) is the transition between the minimum and maximum reflectance. Worlview-1 has panchromatic (black and white) at 0.50 m resolution imagery and QuickBird has the standard four spectral bands (red, blue, green and near infrared). The unique bands with spectral resolution helps in feature extraction and classification methods in support land-cover mapping, in particular urban areas mapping. This will facilitate better planning and monitoring of urban forests and other green areas within cities. To achieve this, maximum likelihood classification and support vector machine approaches were applied to determine the suitability of the 8-band Worldview-2. In addition, the object based and pixels based classification was done on the urban tree species and accuracy evaluated.

1.3. Research identification

The main objective of this research was to classify urban tree species using object and pixel based using maximum likelihood classification and support vector machine on the WorldView-2 satellite image.

1.3.1. Research objectives

The following are the specific objectives:

i. To detect urban tree species on the Worldview-2 multispectral image.
ii. To determine the accuracy of application of Maximum Likelihood Classification (MLC) pixels analysis and tree objects analysis on Worldview-2 multispectral image in urban tree species classification
iii. To determine the accuracy of Support Vector Machine (SVM) pixel in classifying tree species
iv. To determine if Worldview-2 Normalized Difference Vegetation Index (NDVI) can be used to separate the tree species

1.3.2. Research questions

i. Which tree species can be successfully detected and separated from other species?
ii. Can MLC object and pixel based analysis classify tree species?
iii. Can SVM pixels analysis and tree objects analysis classify tree species successfully?
iv. Can Worldview-2 Normalized Difference Vegetation Index (NDVI) be used to detect different tree species?

1.4. Innovation aimed at

This research aimed at examining the suitability of 8-band Worldview-2 multispectral image in urban tree species classification. The pixels and tree objects were separately as applied as training samples on the image. Class separability was done using J-M distance and NDVI mean and standard deviation to how distinct the tree species classes were. Optimum parameters values were chosen and used for SVM classification. MLC to some extent classified medium and large trees. SVM classified all tree species including small trees that could not be classified by MLC.

1.5. Research approach

The research started with literature review on maximum likelihood classification and support vector machine to identify gaps on images and methods of urban tree species classification. To attain the stated objectives and answer the research questions, the following major steps were taken, which included data pre-processing, use of NDVI to determine class separability, classification using MLC and SVM based on pixel and objects and apply accuracy assessment. Finally the results were evaluated. The general flow of research activities are as shown in figure 1.

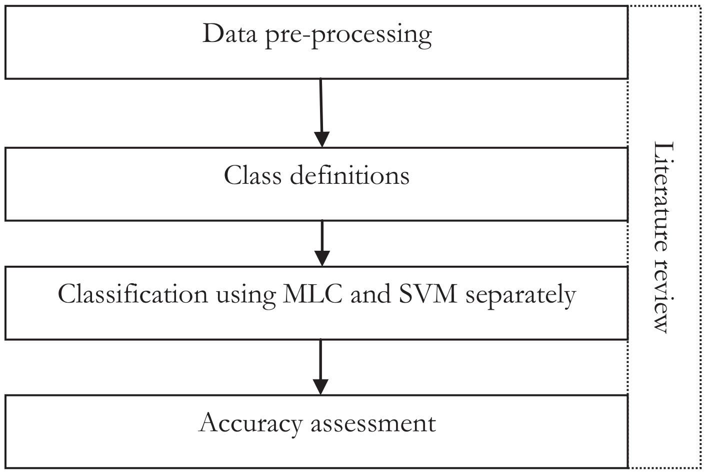

Figure 1: General framework of research activities

1.6. Thesis outline

The thesis is structured into seven chapters. The first chapter deals with the background of research study, problem statement, research objectives, research questions to be answered, innovation that was aimed at and general research framework. The second chapter gives literature review of the research which is related maximum likelihood classification and support vector machine and tree species classification. The third chapter deals with study area location, data and software used. Chapter four of the thesis explains the concepts and methodology applied in the research and chapter five gives the results. Chapter six gives the analysis of the results. The thesis ends with chapter 7, making conclusion and recommendations for future research.

2. LITERATURE REVIEW

2.1. Tree species mapping and Remote sensing

Remote sensing is a valuable tool in forest management; giving up-to-date information about land cover/use. Following advancement of technology in remote sensing, there has been increased availability of satellite images. Vegetation mapping using remote sensing applications has improved majorly because of significant importance in monitoring, protection and restoration programs (Xie et al., 2008). In the recent past, (80s and 90s), mapping and classification of tree species were done using the interpretation and mapping of aerial photographs (Engler et al., 2013). Over the last decade, however, use of high spatial and spectral resolution satellite imagery became increasingly common. This made research on classifying tree species at the individual tree level possible (Brandtberg, 2002). Previous studies on mapping tree species composition have demonstrated the advantages of remote sensing techniques. For example, Ke and Quackenbush (2007) got improved accuracy of about 66% in classifying 5 species of trees (i.e. spruce, pine, hemlock, larch and deciduous) of New York city, USA.

Several studies have demonstrated the ability of discriminating tree species with multispectral data. Multi-spectral images like the Landsat TM, SPOT, IRS, MOS among others with spatial resolution ranging from 20 m to 60 m were helpful in classification of tree species (Roller, 2000). The majority of the studies were restricted to single spatial resolution and few spectral bands. Among the challenges faced by then (around 2000) was the spatial and spectral resolution of the available satellite images which was incompatible with the geometrical precision and level of details needed for mapping at a local scale (Carleer & Wolff, 2004). Dalponte et al. (2009) investigated the role of spectral resolution in forested areas and found that there is a relationship between the spectral resolution, the classifier and the classification accuracy. Tree species mapping in remote sensing is based on knowledge that species have unique spectral signatures associated with bio-physical properties. However, different tree species sometimes have similar spectral signatures which increases the challenges for successful tree species mapping (Leckie et al., 2005). The review of the literature reveals that classification accuracy depended on spectral resolution, spatial resolution, classifier and the study site.

Over the recent years, more satellites with higher spatial and spectral resolution have been launched. Most of the multispectral sensors like the IKONOS or QuickBird have a high spatial resolution and the four standard spectral bands (Blue, Green, Red, Near Infrared). On the other hand, some like MODIS, Landsat, ASTER, and SPOT have more bands with lower spatial resolution. For some time most tree species mapping using high resolution images were based on IKONOS, QuickBird and Light Detection and Ranging (LiDAR) data (Chen., 2010; Hájek, 2006; Mora et al., 2010; Voss & Sugumaran, 2008). Worldview-2 is among the new satellite imageries launched in 2009. According to Chen. (2010), there were still few studies using Worldview- 2 data that had appeared in peer reviewed publications. However, with time more research work continued to be done on tree species using WorldView-2 data, with promising results obtained (Latif et al., 2012). Pu and Landry (2012) got a 16–18% higher classification accuracy using Worldview- 2 imagery compared to IKONOS imagery in mapping seven urban tree species (i.e. sand live oak, laurel oak, live oak pine, palm, camphor and magnolia). Immitzer et al. (2012) classified 10 tree species in a forest in Austria which showed suitability of WorldView-2 images for tree species classification. Cho et al. (2012) used maximum likelihood classifier to map savannah tree species in South Arica. Zhang and Hu (2012) used the longitudinal profiles of each tree to map six tree species (i.e. Maple, Ash, Birch, Oak, Spruce, Pine) of trees in Ontario, Canada.

The literature review suggests that maximum likelihood classification and support vector machine using high resolution satellite imagery, like QuickBird, IKONOS, and now the new WorldView-2 offers promising results in identifying and mappin group or individual tree species. In more recent studies Ardila et al. (2010) extracted individual tree crowns in an urban setting using super resolution mapping on Quick bird images. In the study, 73% of the trees in the study area were identified. In addition, Ardila et al. (2011) used Markov-random-field-based super-resolution mapping to identify urban trees in Quick bird image getting an accuracy of about 66%. Experiments was done using end member model on satellite imagery using SRM by Wu et al. (2011). The experimental results proved that the algorithm gives improved accuracy compared to the traditional methods. This gave reason to expect that worldview-2 will yields better results in tree species mapping.

2.2. Maximum likelihood classification

The remote sensing literature presents several methods for supervised classification for multispectral data. Maximum likelihood classification (MLC) has found wide application in the field of remote sensing. MLC is a supervised classification method based on the Bayesian theorem. Its main inputs are class mean vector and covariance matrix. The main steps are as follows; the number of classes required in the study area are determined and the training pixels for each of the desired classes are chosen based on land cover information for the study area.

Even though MLC is perhaps the most widely used pixel based classification method, the class showing the highest likelihood is alway allocated to a pixel, thus resulting to wrong classification making errors unavoidable. Alesheikh (2003) modified the MLC by estimating a prior probability so as to improve mis-classification errors using data fusion model. The results of the study demonstrated that data fusion model was effective to deminish misclassification errors.

Mahbooba (2011) categorized and classified forest tree species on SPOT imageries based on difference of each species based on optical properties. The study found that it was easier to distinguish tree species at a higher level (i.e coniferous and broadleaved) than at individual tree species level. Kubatko et al. (2009) estimated the use of maximum likelihood for species trees. They recomended that while the availability of more data for inference of species trees increases, there is need for development of procedures to model relationships between methods and the tree species.

2.3. Support vector machines

SVM is a non-parametric classifier (SVM) and was first studied for the purpose of problem pattern recognition by Vapnik (1979). It has been increasingly applied in remote sensing applications (Camps-Valls et al., 2004; Melgani & Bruzzone, 2004; Mercier & Lennon, 2003; Mountrakis et al., 2011). The attractiveness of SVM is because of higher accuracy achieved in comparison to traditional methods (e.g., maximum likelihood, decision tree classifiers) and low sensitivity to high dimensionality i.e. the Hughes effect consequently reducing the impact of the "curse of dimensionality" (Bazi & Melgani, 2006).

Recently, SVM classifiers have been used and a higher accuracy achieved in tree species mapping especially in combination with kernel functions. Colgan et al. (2012) applied SVM to make decisions boundaries on coniferous and deciduous trees and classify four tree species; scots, pine, Norway spruce and Birch. The study applies supervised grade of membership model (GoM) with SVM and achieves accuracy of 89%.

SVM has been to study performance of the different spectral features based on tree species namely *Pinus sylvestris*, *Picea abies*, *Betula pubescens*, *Betula pendula* (Heikkinen et al., 2010). This was done on multi spectral four band sensor data of Leica ADS80. The results without SVM showed that the four band sensor data had inadequate classification information to classify the three tree species. However, when simulation is applied with SVM, it demonstrated an average 5-15% higher accuracy in classification. Turhan and Serdar (2013) used SVM to differentiate salix tree species namely *Salix alba, Salix caprea,* and *Salix alaeagnos* in Turkey. With a linear kernel function, the study successfully made an optimal decision boundaries for the three classes in a decision plane. The achieved accuracy was 80.6% and 95.2% for training group and testing group respectively.

The literature review suggest there is little research publications on application of SVM on Worldview-2. Ebrahim et al. (2012) compared Worldview-2 image and hyperspectral data for urban area land-cover classification. Even though the interest of study was impervious areas, the study revealed the Worldview-2 images for detection of vegetation. Xiaonan (2012) used SVM on WorldView-2 image to identify and classify saltcedar. The results indicated successful classification despite their spectral similarity.

3. CONCEPT AND METHODOLOGY

This chapter explains the methods applied to achieve the objectives and answer the research questions. The methodology framework is as shown in figure 2.

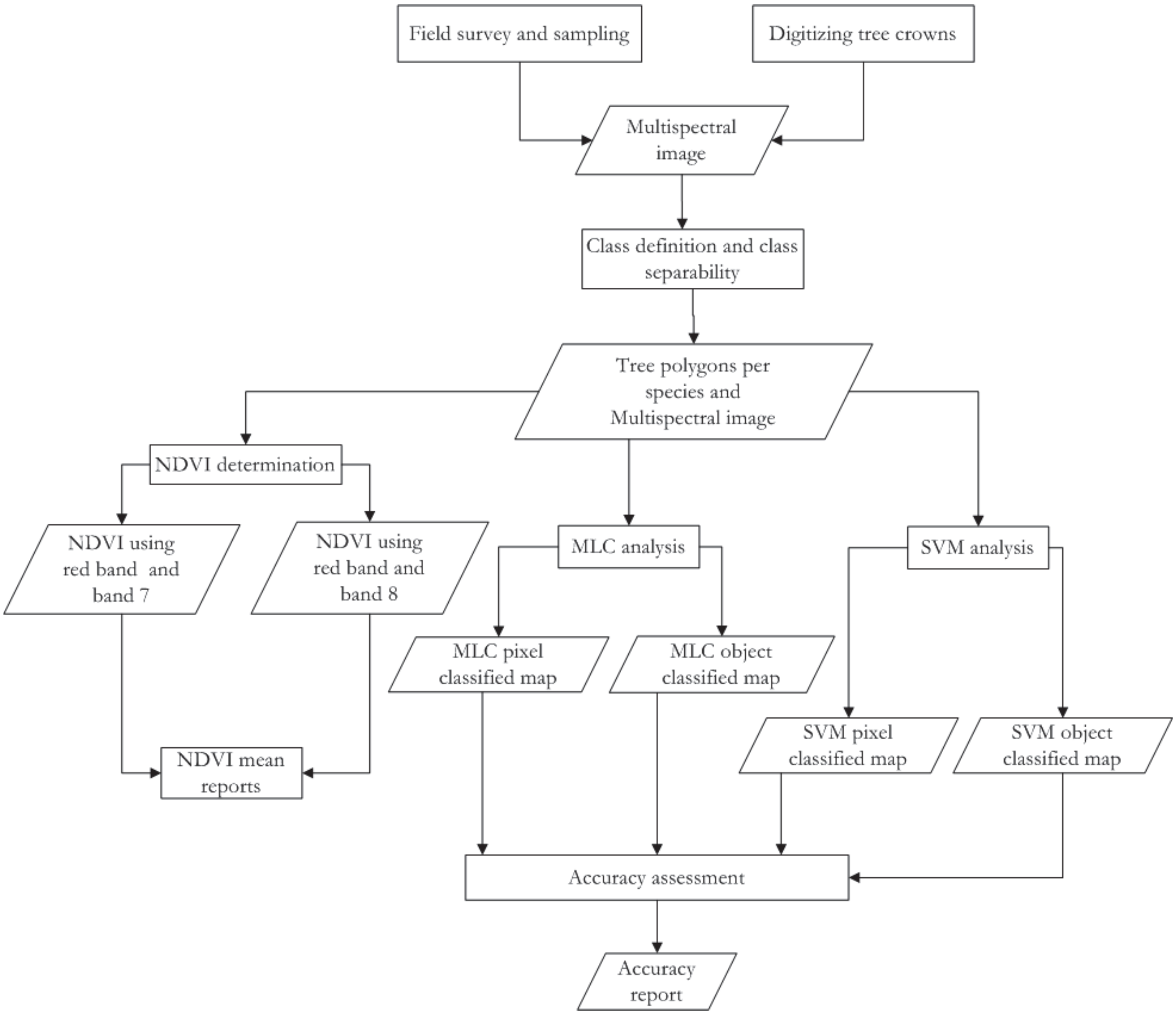

Figure 2: Methodology framework

3.1. Detection and dis-aggregation of different urban tree species

3.1.1. Sampling and Field visit

Trees were identified in the satellite image by visual/human interpreation. Literature review on tree species and their locations in the selected study site was compiled. One day visit on 19th October 2013 was done to verify information already available and to sample more trees. The simple random sampling was used. The positions of trees were selected randomly from the trees already identified on the image and spread out over the whole selected study site.

3.1.2. Polygons digitization and Class definition

Class definition involved identification and selection of tree species of interest in the image. Training sites for each tree species were determined using field collected data and literature review of the tree species.

Polygons were delineated based on the images. The training samples of the listed tree species are as shown in table 1.

Table 1: Class definition of the seven tree species

Species	Common Name
Acer Spp.	Maple
Aesculus Spp.	Horse-chestnut
Alnus Spp.	Alder
Corylus Spp.	Hazels
Fagus Spp.	Beech
Plantanus Spp.	London plane
Tilia Spp.	Linden

3.1.3. Class separability

In remote sensing, class separablity allows one to determine how distinct, and thus separable, different classes are from each other. It helps to determine how similar the distributions of two or more groups of pixels are and measures statistical difference or distance between two or more class distributions. When classes are spectrally distinct, then classification will be easier. Several class separability methods exist; some of the methods is based on the distance between class means (for example Euclidean Distance, Divergence). The other method are based on the differences between class means and the distribution of the values around the means, for example Jeffries-Matusita (JM) Distance, Bhattacharyya Distance (Ullah et al., 2012). In this regard, methods like the Euclidean Distance only work with one band at a time while measure like the JM Distance work on any number of bands.

For normally distributed classes, JM distance, Divergence, Transformed Divergence and Bhattacharyya distance are are presented in sub-sections 3.1.3.1 – 3.1.3.3.

3.1.3.1. Jeffries-Matusita distance (JM)

Jeffries-Matusita distance (JM) is a function of separablity that directly relates to the probability of how good a resultant classification will be (Chen, 1976). JM_{ij} distance separability measure for class i and class j JM is :

$$JM_{ij=} \sqrt{2(1-e^{-\alpha}})\qquad (1)$$

Where α is the Bhattacharyya distance and is given by

$$\alpha \ = \frac{1}{8}\,(\mu_i - \mu_j)^t\,(\left(\frac{C_i+C_j}{2}\right))^{-1}\,(\mu_i - \mu_j) + \frac{1}{2}\ln\,\frac{\left(\frac{C_i+C_j}{2}\right)}{\sqrt{|C_i|+|C_j|}}\qquad (2)$$

where, i and j are the two classes, C_i is the covariance matrix of i, u is the mean vector of u and t indicates the transposition.

JM_{ij} ranges from 0 to 2, where $JM_{ij} > 1.9$ is considered good separability of classes, moderate separability for $1.0 \leq JM_{ij} \leq 1.9$ and poor separability for $JM_{ij} < 1.0$ (Gambarova et al., 2010; Jensen, 1996). The class regions are separated by decision boundaries, whereby, the decision boundary between class *i* and class *j* occurs as shown in equation (3).

$$g_i(\omega) = g_j(\omega) \tag{3}$$

3.1.3.2. Divergence measure

As the value of separation between classes, divergence increases. Divergence and Bhattacharyya distance have values between 0 to ∞.

$$D\alpha\beta = \frac{1}{2}(u_\alpha - u_\beta)'(C_\propto^{-1} + C_\beta^{-1})(u_\propto - u_\beta) + \frac{1}{2}\mathrm{Tr}\,[(C_\propto^{-1} - C_\beta^{-1})'(C_\propto^{-1} + C_\beta^{-1})] \tag{4}$$

where $u_\propto$ and u_β are the covariance matrix of class 1 and class 2, $C_\propto^{-1}$ and C_β^{-1} are inverted covariance matrix for classes 1 and 2.

3.1.3.3. Transformed Divergence (TD)

According to experiments done by Chen (1976), the transformed divergence performed better than the divergence and Bhattacharyya coefficient. *TD* has both upper and lower bounds between 0 and 2. TD is as:

$$TD_{\propto B} = 2[1 - exp^{\frac{-D_{\alpha\beta}}{8}}] \tag{5}$$

The following quantitative measures of class separability were used; Divergence (D), Transformed Divergence (TD), Bhattacharyya distance (B), Jeffries-Matusita distance (JM) and Euclidean Distance (ED). According to Jensen (1996), Transformed Divergence (TD) and Jeffries-Matusita distance (JM) are preffered and widely used compared to the other three measures. Although for completeness purposes, the five measures are presented in data processing for calculating class separability.

3.2. MLC application of pixels and tree objects analysis

3.2.1. MLC pixel classification

Maximum Likelihood classification (MLC) is based on the Bayesian theorem. In Bayesian theorem, the posterior distribution P$(i|\omega)$ i.e. the probability that a pixel with vector ω belongs to a class$_i$ is as shown in equation (6).

$$P(i|\omega) = \mathrm{P}\frac{(\omega|i)P(i)}{P(\omega)} \tag{6}$$

where P $(\omega \mid i)$ is the likelihood function, P(i) is the a priori information (the probability that class i occurs) and P (ω) is the probability that ω is observed.
Assuming each observation has a set of measurements, then pixel x is assigned to class i when equation 7 applies.

$$x\epsilon\, i \text{ If } \mathrm{P}\,(i \mid \omega) > P(\mathrm{j} \mid \omega), \text{ for all } j \neq i \tag{7}$$

Equation 6 can be re-written as shown in equation 8 where M is the number of classes; P (w) is the normalisation constant which ensures that $\sum_{i=1}^{M}$ P sums up to 1.

$$\mathrm{P}(w) = \sum_{i=1}^{M} \mathrm{P}\,(\omega|i)P(i) \tag{8}$$

The MLC assumption is that the distribution of a class training sample is normal (Gaussian). A class is determined based on mean and covariance. The pixel with highest probability is allocated to a class or unclassified if the pixel does not fit any of the classes. A pixel can be unclassified also if it is below threshold probability values set as shown in equation 9.

$x\epsilon\ i$ If $g_i(\omega) > g_j(\omega)$ for all $j \neq i$ (9)

Normal distribution, the above becomes as (10).

$$\frac{1}{2}(w-u_i)^t C_i^{-1}(w-u_i) - \frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln(|C_1|) - \left(\left(\frac{1}{2}(w-u_i)\mathrm{t}\right) - \frac{1}{2}(w-u_i)\mathrm{t}\, C_j - {}^1 w - ui - N2\ln(2\pi) - 12\ln(|C_1|) - 12\, w - ut\right) = 0$$

3.2.2. MLC object classification

The following steps were followed in MLC tree object classification.

i. Consider pixels inside each polygon. Boundary pixels and pixels on vertices are not included.
ii. Take the mean and covariance of pixel DN values for pixels inside the polygon.
iii. JM distance is computed between the polygon and each class
iv. The class with the smallest JM distance is assigned to the polygon.

3.2.3. Small and big trees

The decision of minimum mapping size was influenced by the minimum number of samples to estimate the covariance matrix. MLC uses mean and covariance to determine likelihood of a pixel class. Any number of pixels can give the mean but difficult to get the covariance. Small trees were considered to be trees species that are smaller than 10 pixels. Big trees are trees bigger than 10 pixels.

3.3. Support Vector Machine

Support Vector Machine (SVM) is kernel-based supervised non-parametric statistical learning technique in the field of machine learning. SVM, a linear binary classifier do not have assumptions based on data distribution, rather it gives a training sample a class of one of the likely label.

SVM algorithm relies on parameters. The parameter denoted as C controls of the trade-off of margin maximization and error minimization. In non-linear classification there is kernel parameter. This is to ensure, all parameters can be treated in a unified framework (Gaspar et al., 2012). For this study, the radial Gaussian kernel was used. The parameter σ is the only kernel parameter. SVM model selection is the the adaptation of the hyperparameters.

The hyperplane is the decision boundary which minimizes mis-classifications and errors that were obtained during the training process. The SVM algorithm targets to find a hyperplane which separates the data into specific classes in a manner that it is consistent with the training samples. To find a hyper plane, in linear separable SVM that maximizes the margin figure 3 and equation (10a) and (10b) applies. For support vectors, it is as given in equation 11.

m_i Positive $(y_i = 1)$: $m_i .w + b = \geq 1$ (10a)

m_i Negative $(y_i = -1)$: $m_i .w + b = \leq 1$ (10b) and for support vectors: $m_i \, .w + b = \pm 1$ (11)

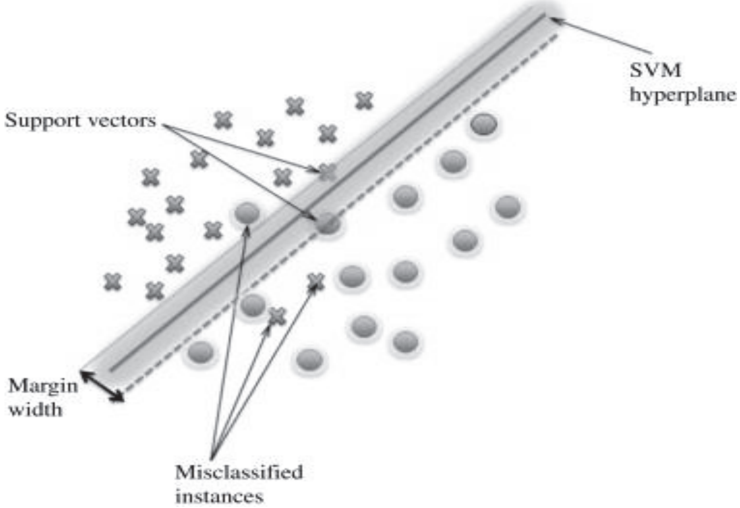

Figure 3: Example of linear SVM: Source: Mountrakis et al. (2011) and Cristianini and Shawe-Taylor (2000)

To get the decision boundary then equation 12:

$$w.m+b = \sum_i \propto_i y_i m_i \cdot m+b \ , \qquad (12)$$

It relies on the product of the training sample point m and the support vectors m_i and computation of inner products ($m_i \ \cdot m_j$) between the pairs of training sample points.

To get the distance between the training sample point and the hyperplane, the equation 13;

$$\frac{m_i \ .w + b}{\|w\|} \qquad (13)$$

Thus, the margin is $\frac{2}{\|w\|}$ and to maximize it, the $w = \sum_i \propto_i y_i m_i$, where $\propto_i$ is learned weight and x_i is support vector.

Hence, for separable linear data, the equation is equation 14:

$$\min_{w,b} \frac{1}{2} \ \|w\|^2 \quad \text{subject to } y_i(w.m_i + b) \geq 1 \qquad (14)$$

For Non-linear separable SVM, the equation (15)(

$$\min_{w,b} \frac{1}{2} \ \|w\|^2 \ + C \sum_{i=n}^{n} \xi_i \ \text{ subject to } y_i(w.m_i + b) \text{ -1 } + \xi_i \leq 0 \qquad (15)$$

where C: tradeoff constant, ξ_i is the slack variable (positive), when margin is ≥1 then $\xi_i = 0$ and when margin is < 1, pay linear penalty and the hinges loss is equation (16).

$$\xi_i = \max(0, 1 - y_i(w.m_i + b) - 1 + \xi_i \leq 0 \tag{16}$$

Gaussian kernel functions also named radial basis function (RBF) kernel is as shown equation (17).

$$K(m, y) = \left(-\frac{1}{\sigma^2} \ \|\mathrm{m} - \mathrm{y}\|^2\right) \tag{17}$$

In estimation of optimum value for σ, all pairs of training input vector from the positive class and a training input vector from the negative class are used. The difference in both is computed in input space between all pairs. The median of distances is applied as a measure of scale thus as a good guess for σ.

3.3.1. SVM object analysis

The following was done in SVM object classification

i. Consider pixels inside each polygon. Boundary pixels and pixels on vertices are not included.
ii. Determine the probability of every pixel inside the polygon to a certain class, probabilities are taken from SVM
iii. Compute the sum of the pixel probabilities to this class
iv. Repeat for all other classes
v. The class with highest total probability is assigned to the polygon.

3.4. Determination of the Worldview-2 NDVI to separate the tree species

The Normalized Difference Vegetation Index (NDVI) relies on the principle that green plants absorb solar radiation for use as a source of energy in the process of photosynthesis. The green plant leaves cells scatter solar radiation in the near-infrared. The green plants appear relatively dark in bands where they are photosynthetically active and bright in the near-infrared (David M. Gates, 1980). Therefore, the identification of vegetation cover is achieved by measuring the said reflectance change.

WorldView-2 has two bands in the near-infrared range of the spectrum region, (i.e. band 7), near infrared1in 0.77–0.895 µm named NIR1 in this study and band 8, near-infrared2 in 0.86–1.04 µm named NIR2. Bothe bands were used separately. The formula are 18a and 18b.

$$\frac{\mathrm{NIR1-Red}}{\mathrm{NIR1+Red}} \text{ in using NIR1 and red band} \tag{18a}$$

$$\frac{\mathrm{NIR2-Red}}{\mathrm{NIR2+Red}} \text{ in using NIR2 and red band} \tag{18b}$$

The NDVI mean and standard deviation values of WorldView-2 data were derived for each of the tree species.

The t-test was calculated to determine the *p*-value of NDVI mean between each of the tree species.

3.5. Accuracy assessment

The tree species classification accuracies were estimated based on cross validation matrix on seven stratified pairs of training test sets collected as described in the approach by Witten and Frank (2005). Congalton and Green (1998) gives many more detailed confusion matrices. Site-specific error analysis method applies only one accuracy value given as a percentage for the whole satellite image. However, in this study it was not possible to apply most of them. Non-site-specific assessment is the simplest method, but does not provide no information on pixel mis-classification (Senseman et al., 1995). Site-specific error analysis requires conciders locational accuracy of the classification. This makes it susceptible to gross errors from control points boundaries and pixel mis-classification (Ramlal & Drummond). In practical applications, analysis is inter-class based and confusion (error matrix) achieves this as it gives the overall accuracy analysis.

An error matrix is a square matrix having equal number of rows, columns and the seven classes of tree species. The major diagonal of the error matrix represents the properly classified class of tree sample species. The non-diagonal values of the matrix show the errors of omission or commission. Omission errors correspond to non diagonal column totals and commission errors are represented by non diagonal row totals. A comparison of the seven tree species mapped was done from all the verification datasets and the already classified image to get an error matrix (or confusion matrix).

Overall accuracy (total accuracy), is the total number of correctly classified sample points by the total number of points. The user accuracy compared the classified map with the field collected data which gives the probability that the point is correctly mapped. Producer accuracy compared field data with the classified map, indicating the probability that a randomly selected point from the reference data is correctly mapped. Mean accuracy combines the user and producer accuracy by dividing the number of correctly classified points multiplied by two by the sum of the number of field data points and map data points for each class. This helps to indicate the accuracy for a class which falls in between the two values of user and producer accuracy. Areal difference is used to compare areas of different classes on the map with the reference data. The areas are always related to the true (reference data) area. Kappa (k) index compares the agreement against which might be expected by chance The k value of 0 is random agreement, value of -1 means map does not correspond to the ground truth and 1 means that the map and the verification data have exactly the same attribute values.

4. MATERIALS AND STUDY AREA

This chapter gives information about the data used i.e. the satellite image, subset image, training samples reference data. It also explains the study area including its location.

4.1. Study area location

The research was conducted in the city of Delft, in the province of South Holland, The Netherlands. Delft lies 52° 00' 30.89" N 4° 18' 18.24" E , 52° 01' 59.67" N 4° 22' 26.15" E, 51° 58' 08.06" N 4° 24' 29.11" E and 51° 58' 23.32" N, 4° 20' 25.81" E, at an elevation above sea level of about -2 m to -6 m.The location map is as presented in figure 4. The city has several tree stands, especially in parks and nature areas such as the Delftse Hout and Botanical garden. The Botanical Garden of Delft University of Technology (TU Delft) has a wide variety of plants, trees, herbs and spices. Over the years exotic plants have been introduced in the garden. Within the city centre (central park) there are several parks like the Nieuwe Plantage, Agnetapark and Kalverbos.

The urban landscape is a mixture of heterogeneous land-cover. It has diverse surfaces like roads, trees, parking lots, and water canals. The surfaces, too, are made of different materials like concrete, asphalt, metal, plastic, glass, grass, shrubs, water and soil among other materials. Trees are of varying species and age, hence varying sizes of crowns. The trees in a city face urban stresses (Dwyer et al., 1992). These stresses include compacted soil, and city streets and driveways which can constrain root growth. The road salt, environmental pollution and pesticides used to treat lawns can also contaminate their air and water. Moreover, tall buildings block sunlight to trees, the use of lawn mowers, weed trimmers, snow plows and and human interactions affects their health and growth. Though the study area is in The Netherlands, classification of tree species using MLC and SVM brings up possibilities to apply the same approach in other parts of the world.

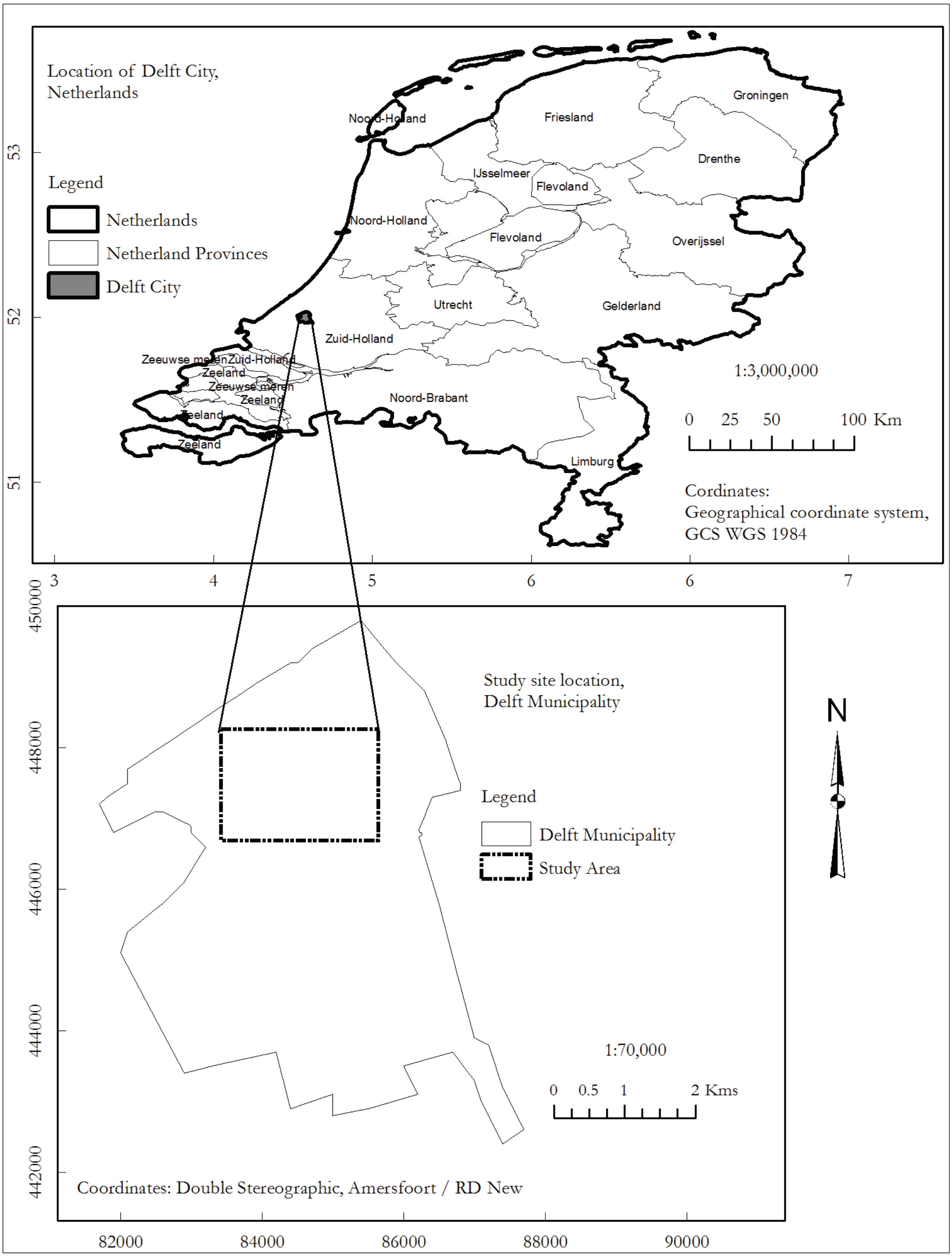

Figure 4: Location of study area, Delft City, The Netherlands

4.2. Data

In this study, the datasets used included reference data and satellite images and are explained in detail below.

4.2.1. Reference data

Delft tree species guide by That et al. (2006) was used to create a database of main trees species that occur in Delft city. Delft Municipality (2007) report of the list of monumental trees gave locations in Delft streets and parks, scientific names, Dutch names, status as at year 2007 and who manages them (private property or municipality). Volunteer information on the monumental trees (large, old and/or very beautiful trees) in Belgium and Netherlands (Monumental Trees, 2013) was useful in visual interpretation (especially very large trees) which aided verification of trees species.

Fieldwork was done at study area on 19th October 2013 to verify locations using hand-held GPS. Tree species information was collected from the earlier sources and new information in parts of the study site that had no information. The result, reference data was divided into two sets; one set for use in training samples and the other for validation as shown in table 2.

Table 2: Sampled tree objects and pixels and their totals

Species	Tree objects		Pixels	
	training set	verification set	training set	verification set
Acer Spp.	15	15	1004	869
Aesculus Spp.	30	14	918	481
Alnus Spp.	43	31	283	222
Corylus Spp.	19	14	808	499
Fagus Spp.	17	11	947	516
Plantanus Spp.	26	26	1552	2396
Tilia Spp.	74	76	933	882
Total	224	187	6445	5865

4.2.2. Satellite images

Worldview-2 satellite image of Delft City from DigitalGlobe's WorldView-2 Satellite acquired on 12th May 2013 was used. It provides Multispectral imagery of 8 bands at 1.84 m. The bands are the four standard bands: Blue (450-510nm), Green (510-580nm), Red (630-690) and NIR1 (770-895). In addition are four new bands namely Coastal Blue (400-450), Red-edge (705-745), Yellow (585-625nm) and NIR2 (860-1040nm)

4.2.3. Subset image

Figure 5 shows the area chosen to test the SRM method of classifying tree species. The area has complex heterogeneous mixture of grass, varieties of trees along water canals and roads and trees in private properties and open green spaces.

Figure 5: Subset of study area within Delft city centre, RGB: 5, 7 and 2

4.3. Software

The following are the softwares were used in this study. ERDAS Imagine 2013, version 13.0.2 was used in pre-processing stage for geo-referencing and sub-setting the study site. ArcGIS version 10.2 was used to process GPS reference data positions collected from the field for use as training samples and for validation and visualization of maps of study area.

R version 3.0.2, a free software environment for statistical computing and graphics(Bell Laboratories, 2013). The following packages were used; geoR (for geo-statistical analysis), rgdal (allow access to projections/transformations), rgl(for visualization like graphics), maptools (for reading and handling spatial objects and kernlab, kernel based machine learning.

5. RESULTS

5.1. Detection and dis-aggregation

5.1.1. Class separability

Class separability based on J-M distance is in table 3. The lowest class reparability of 0.325 was observed for *Alnus Spp.* and *Tilia Spp.* and highest was 1.925 for *Fagus Spp.* and *Plantanus Spp.* Moderate class separability of was observed between *Acer Spp.* and *Alnus Spp.* ,*Corylus Spp.*, *Fagus Spp.*, *Plantanus Spp* (1.050 to 1.594). A J-M distance of 1.023 to 1.835 was observed between *Aesculus Spp.* and *Alnus Spp.*, *Corylus Spp.*, *Plantanus Spp.* Poor class separability (0.325 and 0.992) was observed between *Tilia Spp.* and *Plantanus Spp.* , *Aesculus Spp.* and *Fagus Spp.* , *Acer Spp.* and *Tilia Spp.* , *Alnus Spp.* and *Plantanus Spp.* .

Table 3: Class separability using Jeffries-Matusita distance measure for the seven tree species

Species	*Acer Spp.*	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*
Acer Spp.		0.605	1.050	1.188	1.136	1.594	0.739
Aesculus Spp.	0.605		1.328	1.023	0.983	1.835	1.144
Alnus Spp.	1.050	1.328		1.340	1.730	0.992	0.325
Corylus Spp.	1.188	1.023	1.340		0.724	1.727	1.318
Fagus Spp.	1.136	0.983	1.730	0.724		1.925	1.603
Plantanus Spp.	1.594	1.835	0.992	1.727	1.925		1.051
Tilia Spp.	0.739	1.144	0.325	1.318	1.603	1.051	

Note: > 1.9: good separability, $1.0 \leq JM_{ij} \leq 1.9$: moderate separability and < 1.0: poor separability

5.1.2. Conditional probabilities

Figure 6 shows conditional likelihood probabilities that a given pixel is one of the seven tree species. The darkest (black) values indicate less likelihood for a tree and lighter (white) indicates higher likelihood of a presence of a tree. The highest probability was 0.86 and the lowest is value 0.

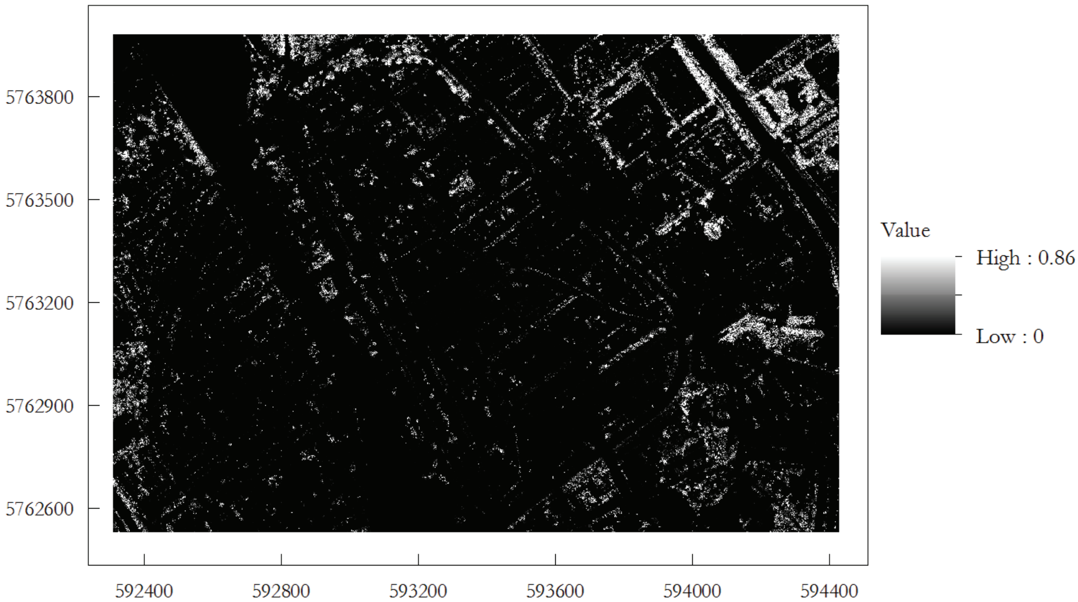

Figure 6: Conditional probabilities of the seven trees species

5.2. MLC object and pixel classification

The result of pixel based analysis and objects based analyses are as presented in figure 7 and figure 8 respectively (refer to section 3.1.3). Figure 7 show results of application of threshold value of 0.001, to remove areas of lowest probabilities (darkest in figure 6). This eliminates the undesired class memberships (example roads, pavements, buildings). The pixel based resulted in accuracy of 60.93% and kappa of 0.54 (Table 6) while object analysis had accuracy of 71.17% and kappa of 0.66 (Table 7). This reveals that MLC object analysis performed better than pixel analysis. Table 4 shows classification of pixels and mis-classification of pixels that occurred.

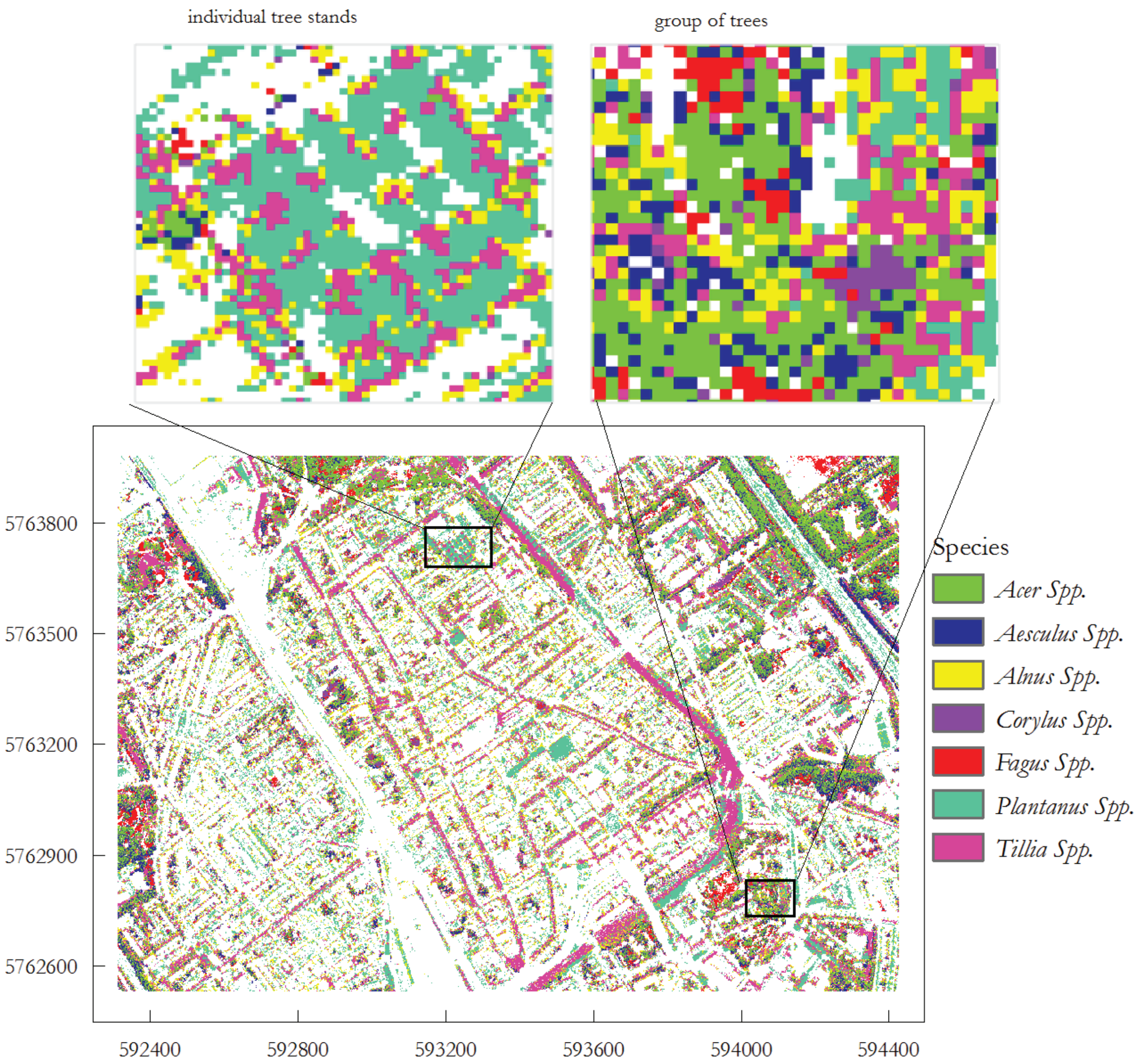

Figure 7: MLC pixel based classified results

Table 4: MLC contingency of pixel analysis of training set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*
Acer Spp.	654	94	59	8	40	8	141
Aesculus Spp.	216	539	23	41	66	2	31
Alnus Spp.	51	4	96	1	0	16	115
Corylus Spp.	119	66	39	442	114	12	16
Fagus Spp.	72	100	19	174	574	2	6
Plantanus Spp.	27	2	132	1	1	1129	260
Tilia Spp.	182	39	131	11	1	92	477

The classification results of big tree object based are presented in Table 5 and Figure 8 (refer to section 3.2.2). About 49% of the total 224 tree objects were not classified. This was because they were small sizes (> 10 pixels) as shown in figure 8. There were no mis-claasification for *Aesculus Spp.* and *Fagus Spp.* . They were successfuly (100%) classified. *Acer Spp.* was mis-classified as *Aesculus Spp.* while *Alnus Spp.* was classified into every species with most of its tree objects going to *Tilia Spp.* *Plantanus Spp.* had 2 of its tree objects mis-classified as *Tilia Spp.*

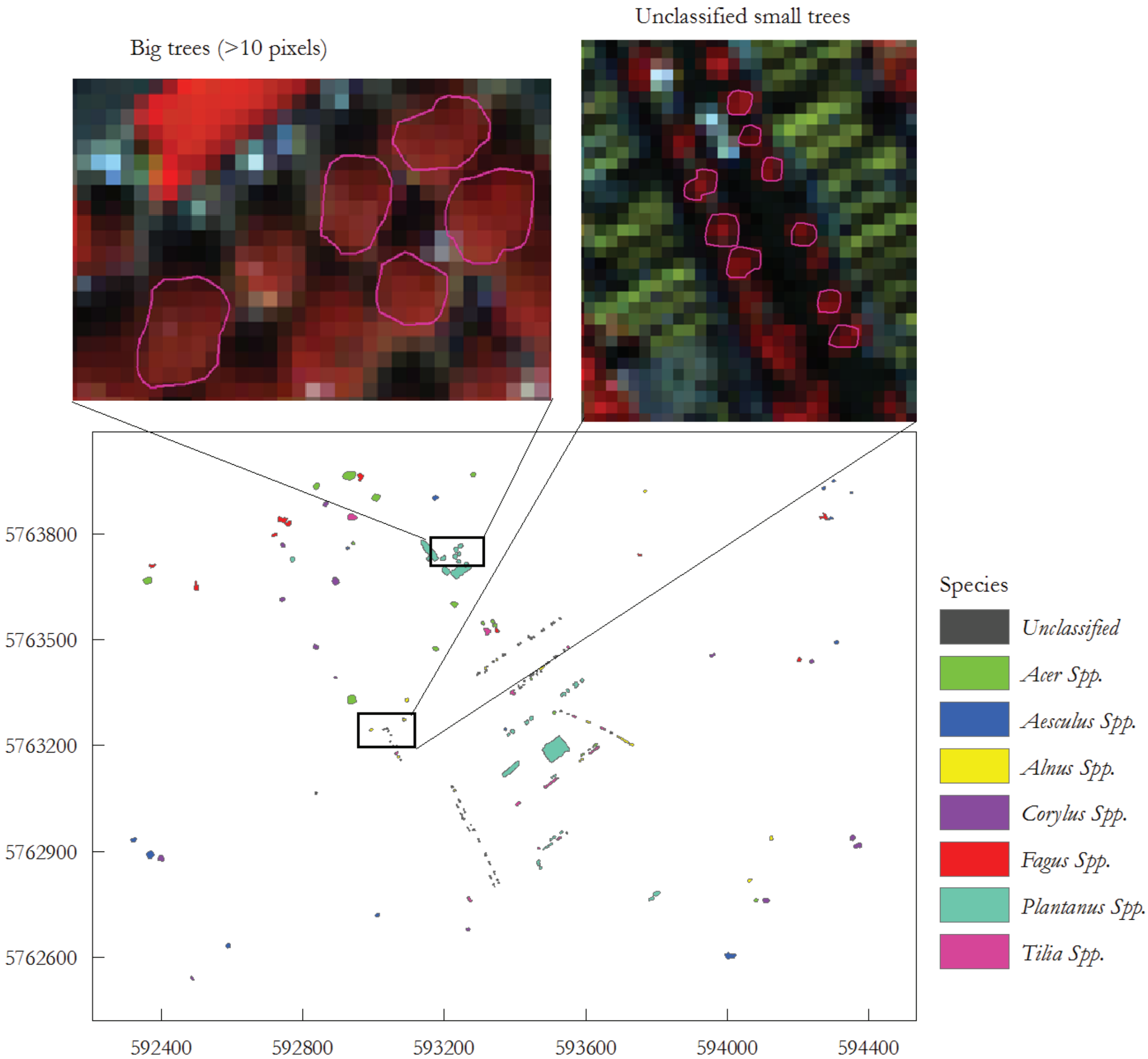

Figure 8: MLC object based classified results

Table 4: MLC tree objects contingency analysis of training set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*
Acer Spp.	12	5	0	0	0	0	0
Aesculus Spp.	0	24	0	0	0	0	0
Alnus Spp.	1	1	3	0	0	1	7
Corylus Spp.	0	0	0	19	2	0	0
Fagus Spp.	0	0	0	0	14	0	0
Plantanus Spp.	0	0	0	0	0	22	2
Tilia Spp.	2	0	2	0	1	1	10
Unclassified	0	0	38	0	0	0	55

5.2.1. MLC accuracy assessment

Table 5 and table 6 present results of accuracy assessment of pixel analysis and object analysis respectively. The overall accuracy was 60.93%, Kappa of 0.54 for pixel analysis. *Plantanus Spp.* had highest user accuracy of 89.52% with few pixels being mis-classified. *Alnus Spp. sp.* had most of its pixels being mis-classified (about 80%) with most pixels being classified as *Plantanus Spp.* and *Tilia Spp.* .

Table 5: MLC pixel accuracy contingency analysis of verification set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*	User accuracy	Overall Accuracy
Acer Spp.	656	213	51	120	73	26	181	49.70	60.93
Aesculus Spp.	94	543	5	65	97	2	40	64.18	
Alnus Spp.	59	23	98	38	19	133	129	19.64	
Corylus Spp.	8	41	1	446	174	1	11	65.40	
Fagus Spp.	40	65	0	112	576	1	1	72.45	
Plantanus Spp.	8	2	17	12	2	1128	91	89.52	
Tilia Spp.	139	31	111	15	6	261	480	46.02	
Producer accuracy	65.34	59.15	34.63	55.20	60.82	72.68	51.45		
Kappa statistic	0.54								

The overall accuracy for object based was 71.17% with a Kappa of 0.66 as shown in table 7. *Alnus Spp.* had the lowest in terms of user accuracy with 13% and the highest is *Aesculus Spp.* 92.31% with only 1 tree object classified as *Acer Spp.* The unclassified was 41% with *Alnus Spp.* leading at 77% followed by *Tilia Spp.* at 35%. The *Plantanus Spp.* had 14% classified as *Tilia Spp.*

Table 6: MLC object accuracy contingency analysis of verification set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*	User accuracy	Overall Accuracy
Acer Spp.	11	1	1	0	0	0	4	64.71	71.17
Aesculus Spp.	1	12	0	0	0	0	0	92.31	
Alnus Spp.	1	1	2	0	1	0	10	13.33	
Corylus Spp.	0	0	0	12	2	0	0	85.71	
Fagus Spp.	1	0	0	1	8	0	0	80.00	
Plantanus Spp.	0	0	0	0	0	25	4	86.21	
Tilia Spp.	1	0	2	0	0	1	9	69.23	
Unclassified	0	0	26	1	0	0	49		
Producer accuracy	73.33	85.71	40.00	92.31	72.73	96.15	33.33		
Kappa statistic	0.66								

5.3. Support Vector Machine

Figure 9 present results for optimum SVM parameter estimation. The optimum values estimation for σ and C are 5. Both gave highest overall accuracy of 51.41% for pixel analysis and 45.16 for object analysis.

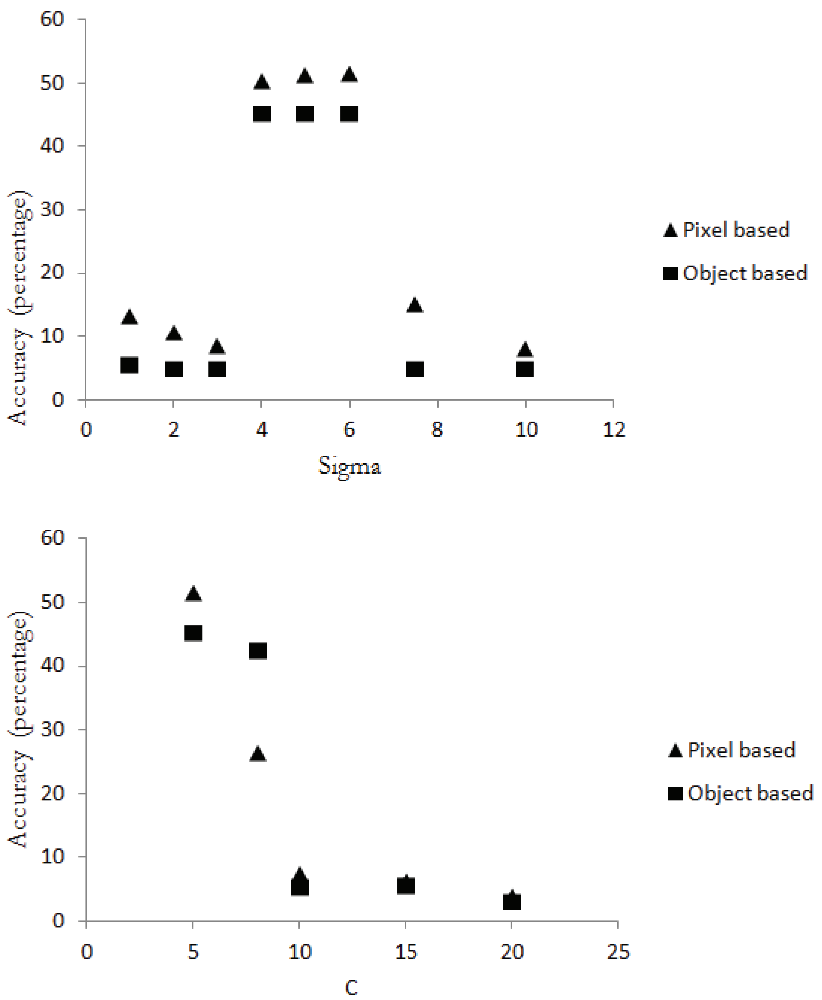

Figure 9: SVM parameter estimation of C and Sigma

Table 8, contingency pixel analysis shows that most pixels were successfully classified. *Aesculus Spp., Acer Spp. and Tilia Spp.* are mis-classified to all other species except *Plantanus Spp.* The rest of the species training samples are successfully classified (100%) to their corresponding species. Figure 10 of pixel based classified SVM does not seem to correspond to contingency pixels analysis in table 8. Visual interpretation reveals mis- classification occurred in all the species, individual and group of trees.

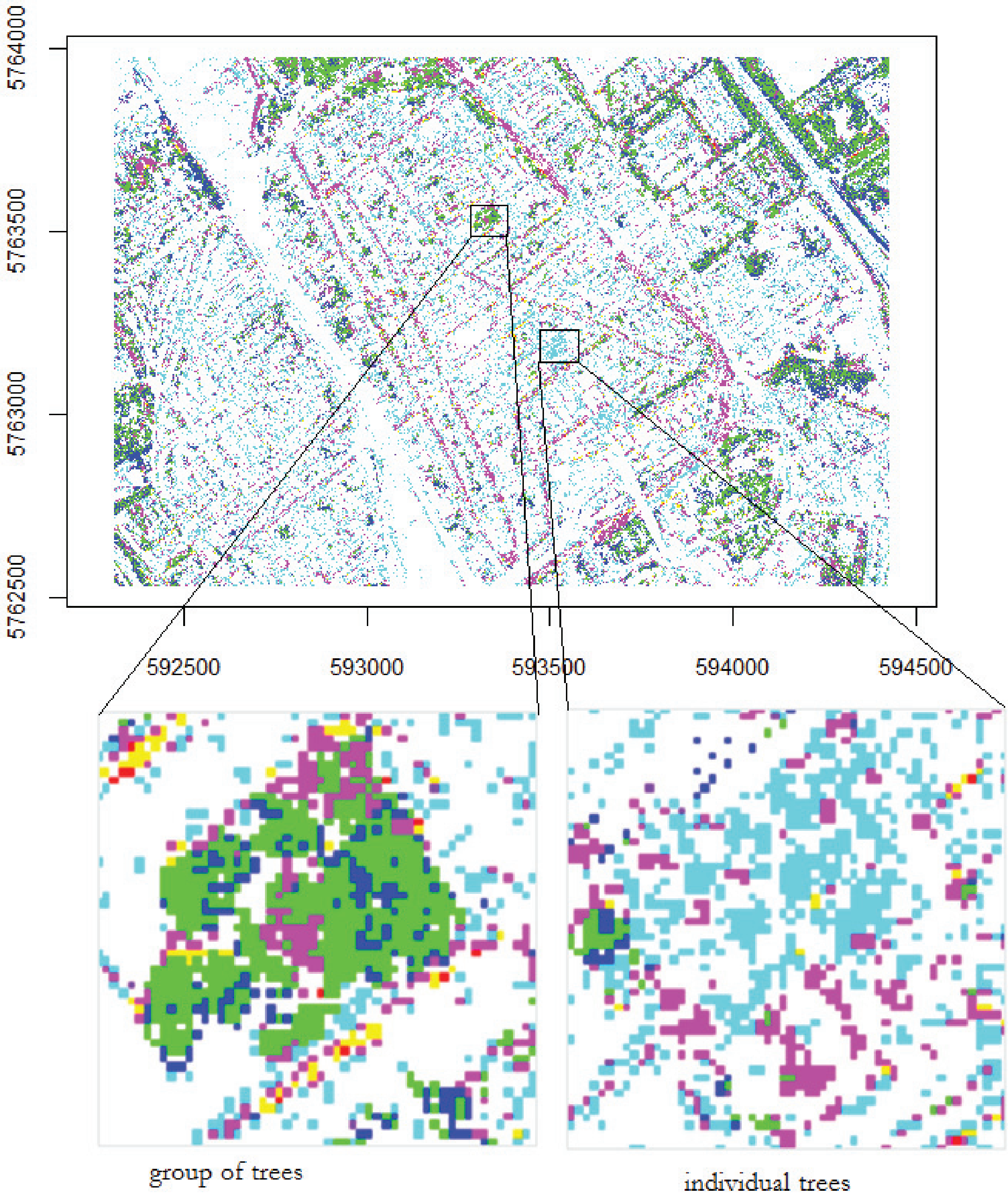

Figure 10: SVM pixel based classified results

Table 7: SVM pixel analysis contingency of training set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*
Acer Spp.	978	22	3	7	3	0	10
Aesculus Spp.	11	889	1	9	3	0	2
Alnus Spp.	0	1	270	0	0	0	0
Corylus Spp.	0	0	0	790	7	0	0
Fagus Spp.	0	3	0	2	934	0	0
Plantanus Spp.	1	0	6	0	0	1544	5
Tilia Spp.	14	3	3	0	0	8	916

Figure 11 show object based classification of tree object classification. Small trees were classified successfully. None of *Fagus Spp.* was classified. Table 9 shows mis-classification of objects in all classes except *Alnus Spp.* Visual interpretation on the map, however, shows that all species of tree species had mis-classified.

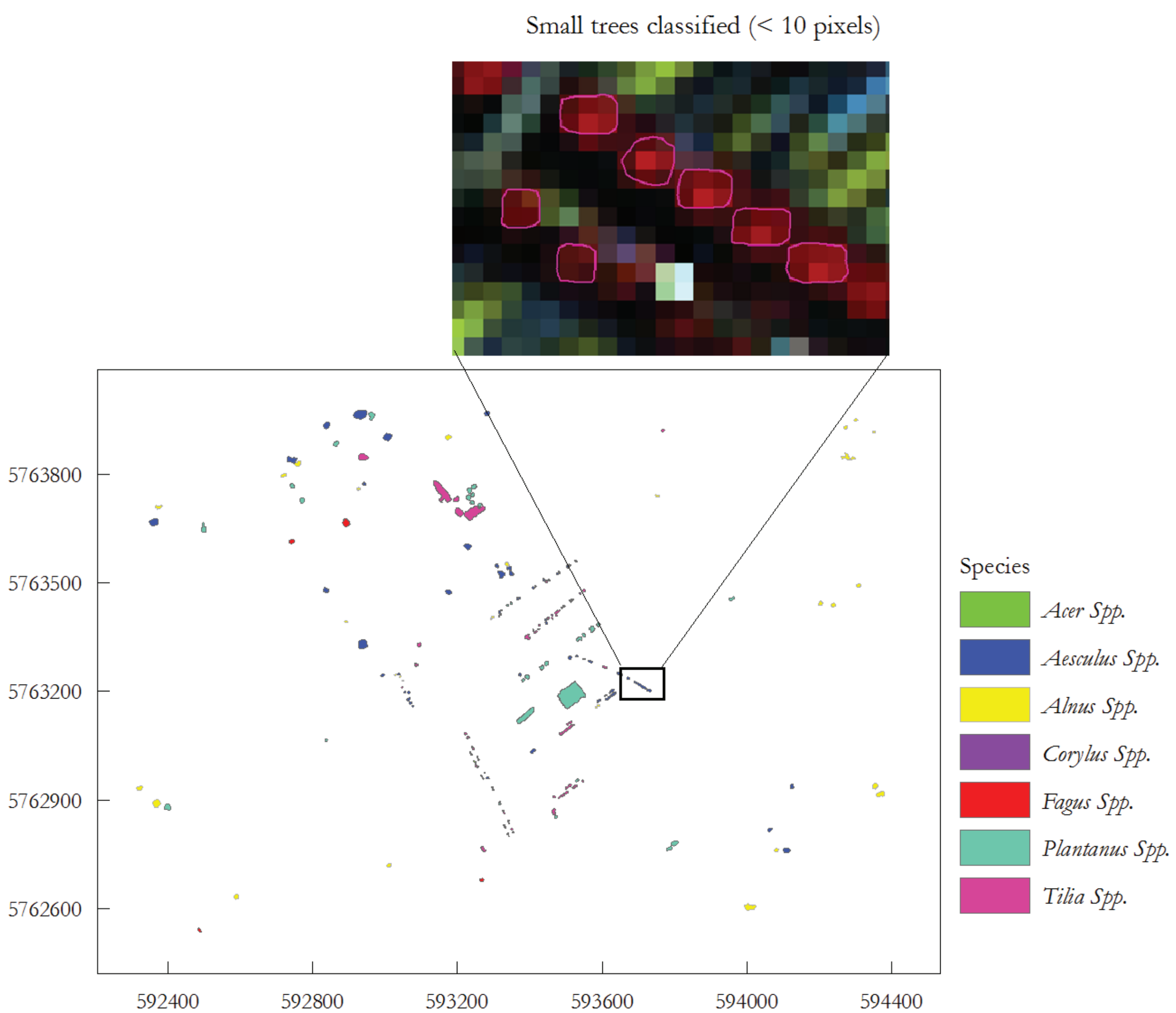

Figure 11: SVM object based classified results

Table 8: SVM object analysis contingency of training set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*
Acer Spp.	15	0	6	0	0	0	15
Aesculus Spp.	0	30	0	1	5	0	2
Alnus Spp.	0	0	17	0	0	0	0
Conylus Spp.	0	0	0	18	0	0	0
Fagus Spp.	0	0	0	0	0	0	0
Plantanus Spp.	0	0	0	1	13	22	2
Tilia Spp.	0	0	20	0	0	4	57

5.3.1. SVM accuracy assessment

Table 10 and 11 present contingency accuracy assessment results of pixel and object analysis respectively. It was observed that pixel analysis performed better than object analysis. Pixel analysis had overall accuracy of 51.24% and 0.36 kappa while object analysis had 44.62% overall accuracy and 0.31 kappa. Fagus is not classified at all in verification datasets.

Table 9: SVM accuracy pixel contingency analysis of verification set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*	User accuracy	Overall Accuracy
Acer Spp.	512	74	39	48	99	40	277	47.02	51.24
Aesculus Spp.	186	367	12	89	125	3	74	42.87	
Alnus Spp.	6	0	45	5	1	12	15	53.57	
Corylus Spp.	6	5	1	143	14	1	7	80.79	
Fagus Spp.	3	0	1	11	4	1	4	16.67	
Plantanus Spp.	99	13	17	192	269	1599	173	67.70	
Tilia Spp.	57	22	107	11	4	734	332	26.20	
Producer accuracy	58.92	76.30	20.27	28.66	0.78	66.90	37.64		
Kappa statistic	0.36								

Table 10: SVM accuracy object contingency analysis of verification set

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*	User accuracy	Overall Accuracy
Acer Spp.	12	1	5	2	2	0	27	24.49	44.62
Aesculus Spp.	2	12	0	4	4	0	5	44.44	
Alnus Spp.	0	0	4	0	0	0	1	80.00	
Corylus Spp.	0	0	0	2	0	0	0	100.00	
Fagus Spp.	0	0	0	0	0	0	0	0	
Plantanus Spp.	0	0	2	6	5	20	9	47.62	
Tilia Spp.	1	1	20	0	0	6	33	54.10	
Producer accuracy	80.00	85.71	12.90	14.29	0.00	76.92	44.00		
Kappa statistic	0.31								

5.4. Worldview-2 NDVI in separation of tree species

The results of comparison of NDVI mean and standard deviation using both band 7 (NIR1) and band 8 (NIR2) are as presented in table 12. The p-value of the mean of the different species is 0.4397. This revealed that the difference in the mean when using NIR1 and NIR2 is not statistically significant.

Table 12: NDVI mean and standard deviation per species using NIR1 and NIR2

	Mean		Standard deviation		Mean P Value
	NIR1	NIR2	NIR1	NIR2	0.4397
Acer Spp.	0.693	0.656	0.088	0.096	
Aeculus Spp.	0.701	0.676	0.074	0.08	
Alnus Spp.	0.565	0.515	0.152	0.163	
Corylus Spp.	0.706	0.668	0.125	0.138	
Fagus Spp.	0.763	0.735	0.073	0.082	
Plantanus Spp.	0.52	0.47	0.124	0.136	
Tilia Spp.	0.596	0.543	0.143	0.163	

The box plot of both NDVI mean and standard deviation of NIR1 is as presented figure 10. It was observed that the higher the mean, the lower the variability and the lower the mean, the higher the variability of NDVI.

The results of NDVI mean *p*-value determination between species are as presented in table 13. NDVI mean between *Acer Spp.*, *Aesculus Spp.* and *Corylus Spp.* was not statistically significant (*p*-values of 0.29 to 0.79). This was the same between *Tilia Spp.* with *Alnus Spp.* and *Plantanus Spp.* (*p*-value between 0.06 and 0.69). NDVI mean statistically significance was observed in most tree species (*p*-value of 0.0001) between *Acer Spp.* with *Alnus Spp. Plantanus Spp.* and *Tilia Spp.;* between *Aesculus Spp.* with *Alnus Spp., Plantanus Spp.* and *Tilia Spp.;* between *Alnus Spp.* with *Corylus Spp.*and *Fagus Spp.;* between *Corylus Spp. sp.* with *Plantanus Spp.* and *Tilia Spp.* and finally between *Fagus Spp.* with *Plantanus Spp.* and *Tilia Spp.* .

Table 13: NDVI mean *p*-value between the species

	Acer Spp.	*Aesculus Spp.*	*Alnus Spp.*	*Corylus Spp.*	*Fagus Spp.*	*Plantanus Spp.*	*Tilia Spp.*
Acer Spp.		0.7997	< 0.0001	0.2911	0.0024	< 0.0001	< 0.0001
Aesculus Spp.	0.7997		< 0.0001	0.5166	0.0072	< 0.0001	< 0.0001
Alnus Spp.	< 0.0001	< 0.0001		< 0.0001	< 0.0001	0.0402	0.0566
Corylus Spp.	0.2911	0.5166	< 0.0001		0.0112	< 0.0001	< 0.0001
Fagus Spp.	0.0024	0.0072	< 0.0001	0.0112		< 0.0001	< 0.0001
Plantanus Spp.	< 0.0001	< 0.0001	0.0402	< 0.0001	< 0.0001		0.6891
Tilia Spp.	< 0.0001	< 0.0001	0.0566	< 0.0001	< 0.0001	0.6891	

Note: < 0.0001: statistically significance and < 0.0001: no statistically significance

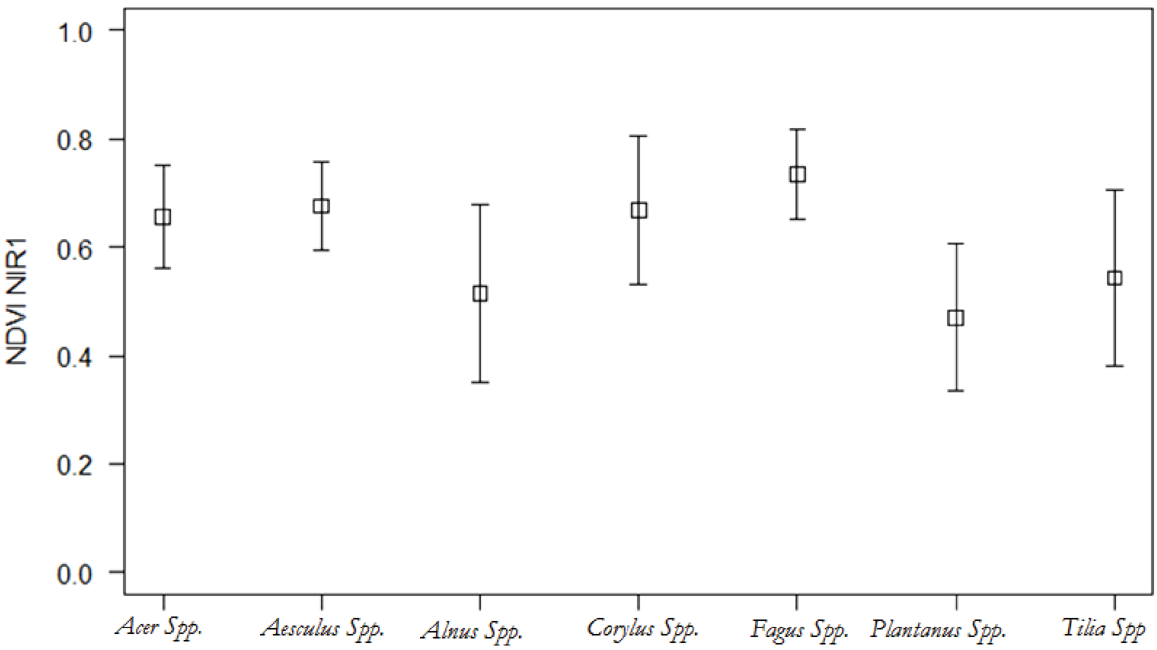

Figure 12: NDVI mean and standard deviation box plot

5.5. Summary

The result summary of the kappa coefficient and overall accuracy of the two classifications done are as presented in Table 14. *Plantanus Spp. Acer Spp., Aesculus Spp.* and *Fagus Spp.* are better classified. *Tilia Spp, Corylus Spp.* And *Alnus Spp.* are are easily confused.

Class separability by J-M distance measure and NDVI mean and variation show the *Plantanus Spp.* and *Fagus Spp.* are separable compared to the rest. *Tilia Spp and Alnus Spp.* were least separable.

Table 11: Summary accuracy assessment

Classification approach	Kappa (%)	Overall accuracy (%)
MLC Pixel analysis of tree species	0.54	60.93
MLC tree object analysis of big trees (>10 pixels)	0.66	71.17
Support Vector Machine pixel analysis	0.36	51.24
Support vector machine object analysis	0.31	44.62

6. DISCUSSION

6.1. Detection and dis-aggregation

The study has shown that multispectral data can be used for classifying four main species in an urban area in The Netherlands. The species that were well separated were *Plantanus Spp.*, *Fagus Spp.*, *Acer Spp.* and *Aesculus Spp.* In particular, *Plantanus Spp.* and *Fagus Spp.* showed high class separability with a distance of 1.925 obtained. MLC pixel analysis, *Plantanus Spp.* was classified with an accuracy of about 89%. *Fagus Spp.* achieved an accuracy of over 70%, which was caused by commission errors with *Corylus Spp.* class. As shown in MLC confusion matrix (Table 6), the proposed method offered fairly good user accuracy results for *Planatanus Spp* and *Fagus Spp.* The classification success of *Plantanus Spp.* is important for it is commonly used as an ornamental trees, in particular the urban areas and roadsides (Turner et al., 2012).

Low class separability was observed in *Alnus Spp.* and *Tilia Spp.*, a distance of 0.325. The two species are along the Delft water canals and are continouesly pruned annualy by the municipality to maintain specific tree crown size. Both do have similar textual properties. The adjacency effects caused by surrounding within a city causes spectral mixing thus making it difficult to distinguish the two species. In the study by Tolpekin and Stein (2009), lower classification accuracy was observed in parts of the image that had mixed pixels compared to parts that had pure pixels.

Studies show that it is possible to get high class separability for some species and low separability in other species (Carleer & Wolff, 2004; Latif et al., 2012; Naidoo et al., 2012). Stavretović et al. (2010) had higher accuracy for *Platanus acerifolia, Betula verrucosa* but lower accuracy for *Acer negundo, Acer platanoides* and F*raxinus ornus*. This was because the latter three species had the small sizes of the main growth elements in (i.e tree height, and crown size) in Mali Park in Obrenovac.

In this study, tree polygons of the training samples during class definations of tree crowns were manually delineated. This was effective for the study area was small. In practical applications, this would not be feasible especially if it deals with large area. An automatic tree crown extraction technique rather applied. The delineation errors that come with manual digitizing of the tree crowns can affect the image measures like mean and covariance. Unclear boundaries on inter-locking tree crowns when delineated as one causes errors because one tree crown could be having different characteristics than the other. Each tree species is modelled by the normal probability distribution, as mentioned earlier (see section 3.2). The successful application of MLC depends on correct delineation of the spectral classes of the tree species. Incorrect delineation leads to incorrect classification, consequently leading to low accuracy.

An automatic delineation of tree crowns is likely to reduce the omission and commission errors which occur due to human errors. This does not imply that automatic is accurate than manual deliniation because it eliminates human errors. Automatic may introduce its own errors but in some cases it will be more accurate and cheaper in cost especially in large areas for it will save labour. Many studies have been done on automatic tree crown extraction from satelite images using multispectral data (Ardila et al., 2011; Wang et al., 2004) , LIDAR data (Ene et al., 2012) and hyperspectral data (Bunting et al., 2010). The method of Ardila et al. (2012) can be used as an alternative approach to automatically extract tree crowns on high resolution imagery in an urban area.

6.2. MLC pixel and tree object based classification

The object analysis shows better results, nevertheless, a number of objects were unclassified. This was because they did not meet the criteria of big trees (<10 pixels). The tree species crowns had median crown sizes from 2 m² to 5 m². This meant a small cown or young tree covers approximately 4-6 pixels in the WorldView-2 image. Hengl (2006), recomended that at least four pixels represents the smallest objects. Considering Worldiew-2 2 m resolution, this rule, in this study was observed. MLC proofed effective for medium and large trees.

MLC pixel based accuarcy of small trees was low compared with accuracy of big trees. This could be because a small tree pixel often contains spectral information belonging to other classes like the grassland, water, bare ground i.e mixed pixel. This is due to spectral mixing because of adjacency effects and the surrounding. Small trees and shrubs pose a challenge in mapping the species tree crowns. Ardila et al. (2011) had commission and ommission errors on both even when he was using Markov random fields, a method that conciders neighbourhood system. For bigger trees, however, they occupy a much larger area with many pixels which are pure and spectral information on the pixels is more dominant than adjacency effects. This is in agreement with Ene et al. (2012) who observed that spatial resolution of the data strongly influences the tree crown extraction.

Research studies have been done on alternative methods that are not based on the limitations of spectral and spatial resolutions in urban area. In this research study, object analysis perfomed better than pixel analysis. Hard classification makes an assumption that the classes are discrete and mutually exclusive (Congalton; & Green, 1998). According to Foody (2002), in hard classification, a pixel is assigned unambiguously to a single class resulting in low classification accuracy in heterogeneous areas where a pixel is a mixture of several classes. Conditional probability (figure 6) gives 0.86 as the highest probability of one of the tree species. Threshold eliminates, however, the undesired membership classes of low probabilites (e.g. roads, water, impervious surfaces) as shown in in figure 7. The number of training samples and reference samples affects pixel classification in MLC. Congalton and Green (1998) recomends minimum 50 samples per class. The condition was in this study. One needs at least 100 pixels per band, image is 8 bands meaning 800 pixels per tree species for training. Combining these rules for pixel analysis leads to a minimum 283 pixels samples for *Alnus Spp.* species and 1552 pixels for *Plantanus Spp.* for training set. For the seven species, this led to a total of 6445 pixel samples for training set (tab;le 2). The minimum number of 800 training samples was not fulfilled for *Alnus Spp.* thus low accuracy. This is because during MLC classification, the estimated mean becomes biased and while the variance rely on the training samples in concideration of other classes (Lesparre & Gorte, 2006). It therefore suggests that increased training sample size will reduce the error in calculating accuracy of *Alnus Spp.*

6.3. Worldview-2 NDVI in separation of the tree species

NDVI mean values succesfully separated *Fagus Spp.* and *Plantanus Spp.* (*p*-value of 0.0001) but showed low separation in *Tilia Spp.* and *Alnus Spp.* (*p*-value of 0.0566). The poor separation could be perhaps be because NDVI was not able to provide accurate identification of species because of similarity in amount of photodynthetically active material. This corresponds with the findings in J-M distance class separability. There is no statistical significance in using either of the NearInfraRed bands. This is because both bands overlap (Satellite Imaging Corporation, 2013). NIR2, band 8 was used in determining NDVI successfully without NIR1 to separate vegetation areas using maximum likelihood (Maglione, 2013).

Delft city has different species of the same genus. The *Tilia Spp.* species had *Tilia tomentosa* genus and *Tilia x europaea pallida* sub-species. *Tilia x europea palida* is a hybrid between *Tilia europea* and *Tilia palida. Tilia Spp.* was under continuous annual pruning by the municipality. Both react differently to pruning practices (Bengtsson, 2005). This affects the growth hence leaf reflectance and consequently NDVI values. The common *Acer Spp.* species in Delft city of Netherands are the *Acer campestre*, *Acer negundo* and *Acer saccharum* and the common species for *Plantanus Spp.* are *Platanus × acerifolia* and *Platanus orientalis*. The indifference in NDVI mean separation could have been brought by each of species having species-specific chlorophyll content and leave structures (Abbasi et al., 2008). Gomes and Maillard (2013) studied the mapping problems of urban tree crowns on Worldvied-2 image. One of the methods used was vegetation indices (mainy NDVI). He suggested that NDVI is effective in separating trees at tree type level (i.e coniferous and deciduous) and not at specific individual tree species level. This could be because of leave strcuture of narrow and broad leaves respectively. Pettorelli et al. (2005) found out that NDVI is predominantly used in studies focusing on the effects of environmental change on plants more than on separation of tree species.

6.4. Support vector machine object and pixel based classification

SVM is considered to be resistant to over-fitting, has bias-variance trade-off and ability of capacity control (Melgani & Bruzzone, 2004; Mountrakis et al., 2011). The results however, did not demonstrate the said superiority. Pixel analysis had an overall accuracy of 51.24% and object based had 44.62%. Contingency analysis of training set in both pixel and object were excellent (Table 8 and 9). There was minimal mis-classification with most species having 90% to 100% user accuracy. The output classified maps however were not in agreement with the contingency analysis of the training set. This could be attributed to the SVM classifier in relation to high dimensionality and correlation to feature space (Bazi & Melgani, 2006). In this study, the SVM classifier was not tested for the curse of dimensionality, i.e. the Hughes effect. We cannot rule out, however, its consequences in classification.

Object based SVM classification did not classify *Fagus Spp.* both in the training and verification data. This may not be the problem of the dataset but how SVM operates. The performance of kernel based SVM relies on parameters. Few kernels used in SVM have been fully exploited because of complex parameter fine tuning that has to be done (Chapelle et al., 2002; Staelin, 2003). Parameters C and δ values of 5 for both gave reasonable results in the experiments. The perfomace of the used parameters suggest overall accuracy could be improved. This include more training samples, concidering data dimensionality and fine tuning to get optimal conditions that give satisfactory results. This mean more research work needs to be done to

The single largest increase in user accuracy was for Alnus, from 19% in MLC pixel analysis to 53.37% in SVM pixel analysis despite having the least number of training samples. This is in agreement with the findings of Mantero et al. (2005) that SVM can handle small training samples of a dataset. Roli and Fumera (2001) tested the performance of three classifiers neural networks, (i.e. K-NN and SVM) based on the number of training samples. The study demonstrated that SVM is less sensitive to small training samples. The SVM algorithm was not tested for curse of dimensionality i.e. the Hughes effect based on number of training samples. We cannot rule out that increase of training samples is likely to increase the overall accuracy.

6.5. Support vector machine and Maximum likelihood classification

MLC method performed better SVM in both pixel and object analysis. Compared to MLC, SVM is considered to have structural risk minimization (Tso & Mather, 2009). Furthermore, SVM does not work using the prior assumptions (*a priori)* made on the probability distribution of the data as MLC does. Literature gives weight to how to determine optimization parameters and the choice of kernel. This shifts the challenges of over-fitting from parameters and the choice of kernel to model selection. Kernel models, however, are sensitive to over-fitting the criteria of model selection. This problems are not unique to SVM kernel methods, most machine learning methods experience the same challenges (Cawley & Talbot, 2010). If one require a sparse kernel machine, it is advisable to use a kernel designed to be sparse from the beginning e.g. the Informative Vector Machine. SVM support vector loss functions used for regression do not have exact statistical interpretation (Roli & Fumera, 2001). This however, can be solved by use of expert knowledge of the problem encoded in the loss function (e.g. Poisson, Beta or Gaussian). In most cases, many classification challenges require the probability of class membership (Huang et al., 2002). Thus, methods like Kernel Logistic Regression would give class membership probability instead of results post-process of SVM so as to get probabilities.

The lower accuracies of SVM than MLC was probably because of SVM inability to transform non-linear class boundaries in the original space into linear space in high-dimensional space. According to SVM algorithm, non-linear decision boundaries depends on the factor of decision boundaries based on if they can be transformed to linear spaces (Zhong et al., 2013). This is achieved by mapping the input samples into a high-dimensional space. The SVM might have less success in transforming complex decision boundaries in the original input space into linear space in a high-dimensional space. MLC is less influenced by correlated feature space.

The application speeds of the two classifiers were different. In all training and classification, both pixel and object based, MLC took few minutes on (8 GB RAM, Core$_i$7). SVM took about 32 to 47 minutes on same computer using the same datasets. In the study areas, there were pure pixels (homogenous) and mixed pixels (heterogeneous). MLC assigns a class to a pixel that has highest likelihood while SVM depends on decision boundary. Study to assess the applicability of SVM on land cover classifications by Huang et al. (2002) demonstrated that training the SVM to classify mixed classes took several times longer than training pure pixels. This is because SVM training is influenced by noise level in data set, training data size, kernel parameters chosen and class separability.

Both methods in object based classification did not operate directly on single pixels, but on image objects which are considered homogeneous. The objects are classified to the classes to which they are most close to (refer to section 3.2.2 and 3.3.1). The classification accuracy depends on the quality of training samples. Objects likely extracted in-accurately leads to subsequent poor classification accuracy. The classification error can also accumulate from both the error in both training samples and clasification process. This means that when an object is mis-classified, all the pixels in that object will be mis-classified and consequently leads to poor classification results. This can be improved by advanced classification techniques that can combine spectral information with shape characteristics, texture and neighbourhood relationships in classification from an image (Stow et al., 2012).

Pixel and object based classifications required defination of several classes in application. Urban areas have a complex environment (e.g. impevious surfaces, grassland, pavements).Thisbrings the need to define many classes. Assuming a user required just one class. This means that it will involve a lot of unneccesary processes to get just that one class.

7. CONCLUSION AND RECOMENDATIONS

7.1. Conclusion

For urban tree species classification, MLC performed better than SVM in both object and pixel based calssification. MLC pixel based overall accuracy was 66.93% with Kappa of 0.54 and 51.24% with Kappa of 0.36 for SVM pixel based. MLC object based overall accuracy was 71.17% with Kappa of 0.66 and 44.62% with Kappa of 0.31 for SVM object based analysis. Even though MLC perfoms better than SVM, the accuracy is still low compared to generally accepted accuracy of 85% set by Anderson (1976). This indicates that both methods are still not satisfactory techniques of classifying high resolution images for Delft city. MLC, however, has been used for many years in image classification. It is straightforward and does not require extreme expert skills to apply. MLC algorithm can be found in most of the remote sensing application software. Examples of this software are ERDAS, ENVI and ILWIS (open source) among others. This makes MLC an easy available method for classification. MLC pixel based classification is effective in classifying medium and large trees (e.g. *Plantanus Spp. and Fagus Spp.*). MLC relies on mean and covariance of samples hence calculation of covariance matrix in small tree crowns (> 10 pixels) could not be determined. Class separability using J-M distance measure and NDVI mean and variation evaluation were the same. This gives the possibilty of use of NDVI in separating tree species. SVM does not operate based on data distribution making it applicable to any type of data (i.e. normal or non-normal distribution. Its performance relies on kernel parameters. Experimenting on optimum parameters values of C and δ can give satisfactory classification results. In conclusion, MLC and SVM can classify tree species on high resolution images and can be recommended for urban inventories. Though the study area is in The Netherlands, both methods need to be applied to other urban areas and other species for comparison and improvement towards optimal performance.

7.2. Recommendations

The research was done on WorldView-2 multispectral image. The Worldview-2 has additional panchromatic band of 0.46 m. Further research can be done to incorporate the panchromatic information including texture, shape charactersitic in tree species information so as to fully explore the capability of Worldview-2 image. The main drawback of SVM algorithm is the need of parameters to be set correctly so as to get the best reasonable classification results. Parameters that may give good results for one problem, may not give same good results in another problem. In most SVM algorithms, the user have to do experiments with different parameters through trial and error to get satisfactory results. It is recommended that an automatci parameter estimation method be further researched. There is increase in images with high spatial and spectral resolutions. Worldview-2 used in this study is one of them. This comes with challenges in classfication. This includes adjacency effects, the Hughes effect and illuminations of the species tree crowns. More,over tree crown boundaries are not precise i.e. they have fuzzy boundary. Further reseacrh needs to be done towards a solution of fuzzy boundary issue and canopy density which increases from boundary to the centre of the crown. Trees species have sub-species for each genus has species varieties. Trees too atimes occur in groups and can be tree crowns can be interlocked to each other. A multi-scale analysis is recommended to help map the tree crowns and species at different appropriate scales.

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