ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

DETERMINATION AND CLASSIFICATION OF IMPERVIOUS SURFACES AND THEIR DENSITY LEVELS WITH DIFFERENT TECHNIQUES AND DATA INTEGRATIONS

M.Sc. THESIS

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

SU GEÇİRMEZ YÜZEYLERİN VE BUNLARIN YOĞUNLUK DERECELERİNİN FARKLI YÖNTEM VE VERİ ENTEGRASYONLARI İLE BELİRLENMESİ VE SINIFLANDIRILMASI

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Beril VAROL, a M.Sc. student of ITU Graduate School of Science Engineering and Technology student ID 501171607, successfully defended the thesis entitled "DETERMINATION AND CLASSIFICATION OF IMPERVIOUS SURFACES AND THEIR DENSITY LEVELS WITH DIFFERENT TECHNIQUES AND DATA INTEGRATIONS", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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FOREWORD

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TABLE OF CONTENTS

Page

ABBREVIATIONS

ANN	: Artificial Neural Network
DTM	: Digital Terrain Model
GIS	: Geographic Information Systems
GLCM	: Grey Level Co-occurrence Matrix
GLDV	: Grey Level Difference Vector
GSD	: Ground Sampling Distance
IMD	: Imperviousness Density
LC/LU	: Land Cover Land Use
LiDAR	: Light Detection and Ranging
MMU	: Minimum Mapping Unit
NDVI	: Normalized Difference Vegetation Index
NDWI	: Normalized Difference Water Index
NIR	: Near Infrared
OSM	: OpenStreetMap
UTM	: Universal Transverse Mercator
WGS	: World Geodetic System

SYMBOLS

$P_{i,j}$: Digital number values of pixels i and j in P matrix.

LIST OF TABLES

Page

LIST OF FIGURES

Page

DETERMINATION AND CLASSIFICATION OF IMPERVIOUS SURFACES AND THEIR DENSITY LEVELS WITH DIFFERENT TECHNIQUES AND DATA INTEGRATIONS

SUMMARY

Land Cover/Land Use (LC/LU) maps are important sources of geo-information on observing and investigating the changes, developments in urban cities. Today, with the increase in population, urbanization, social and economic developments make the understanding of different levels of urban fabric more important. LC/LU maps are produced by classification. Classification mainly is divided into two methods being pixel/object-based classification. Recently, object-based classification has been used frequently as it allows the user to use image objects, which are clusters of pixels with similar spectral characteristics, and their relationships. In addition to spectral values used in pixel-based classification, it is possible to include different kinds of functions, features, indices to the classification. Also, it is possible to define manual functions, and object-object as well as class-class relationships can be used. The resulted LC/LU maps can be produced by different classification systems. The nomenclatures and detail levels on class definitions can be changed according to the purpose, extent and the data going to be used. One of the nomenclatures that have the most detailed levels and explanations on urban fabric is Urban Atlas of Copernicus. The urban fabric is divided into five classes and it is selected for use in this study. While it is possible to use open-source supportive data sources in classification, it is also possible to make use of different functions, features, indices and band values. Additionally, texture can be used in classifying and identifying objects and classes in images. The spatial resolution of the image is also important in this case. In high and very high-resolution images, the method is shaped by the resolution and the vector data can impact the classification accuracy. In this study, Bursa city is selected as the study area and the urban fabric is classified in detailed sub-classes. SPOT image with 1,5-meter resolution is used. Different methods of classification and impacts of different data integrations is tested. After the application, a total of 5 Urban Fabric density maps are produced and their total and class accuracies are compared.

SU GEÇİRMEZ YÜZEYLERİN VE BUNLARIN YOĞUNLUK DERECELERİNİN FARKLI YÖNTEM VE VERİ ENTEGRASYONLARI İLE BELİRLENMESİ VE SINIFLANDIRILMASI

ÖZET

Arazi Örtüsü/Arazi Kullanımı (AÖ/AK) haritaları özellikle kentsel alanların incelenmesinde ve bunların değişimini, gelişimini belirlemede önemli coğrafi bilgi kaynaklarıdır. Günümüzde nüfus artışı, kentleşme, sosyo-ekonomik gelişmeler gibi değişimler sebebiyle kent alanlarının farklı seviye ve yoğunluklarda incelenebilmesi de büyük önem taşımaktadır. Bu AO/AK haritaları sınıflandırma yöntemleri ile oluşturulmaktadır. Sınıflandırma temel olarak piksel tabanlı/nesne tabanlı sınıflandırma olarak iki alt başlığa ayrılmaktadır. Son zamanlarda oldukça fazla kullanılmakta ve geliştirilmekte olan nesne tabanlı sınıflandırmada, geleneksel piksel tabanlı sınılandmada kullanılan parlaklık bilgilerine ek olarak görüntü elemanları (piksel) benzer kümeler halinde segmente edilip görüntü nesneleri oluşturulmaktadır ve bu görüntü nesnelerinin bilgileri ve birbirleri arasındaki ilişkileri de dikkate alınarak sınıflandırma yapılabilmektedir. Görüntü nesnelerinin farklı öznitelik ve özellikleri kullanılıp çeşitli indisler tanımlanabilmekte ve nesneler arasındaki komşuluk ilişkileri, hiyerarşik ilişkiler de sınıflandırma yöntemleri içerisinde kullanılabilmektedir. Sınıflandırma sonucunda oluşturulacak AÖ/AK haritaları için değişik sınıflandırma sistemleri bulunmaktadır. Amaca, kapsama ve kullanılan veriye göre bunların sınıfları ve sınıf detay seviyeleri değişiklik gösterebilmektedir. Kent alanlarının sınıflandırılmasında en çok detay seviyesine sahip sınıflandırma sistemlerinden biri Copernicus'un Şehir Atlası (Urban Atlas) sınıflandırma sistemidir. Burada kent alanları Sürekli Kentsel Doku, Süreksiz Çok Yoğun Kentsel Doku, Süreksiz Orta Yoğunluklu Kentsel Doku, Süreksiz Düşük Yoğunluklu Kentsel Doku, Süreksiz Çok Düşük Yoğunluklu Kentsel Doku olmak üzere beş farklı seviyede belirlenmiştir. Bu çalışmada da bu sistem kullanılmıştır. Kentsel alanları sınıflandırırken yardımcı vektör verilerden faydalanabileceği gibi, nesnelerin parlaklık, renk bilgileri ve çeşitli indisler de kullanılarak bu sınıflandırma geliştirilebilir. Bu sebeple sınıflandırmaya açık kaynaklı coğrafi bilgi kaynaklarından olan OpenStreetMap, Wikimapia verileri de entegre edilmiştir ve bunlar segmentasyon ve sınıflandırma aşamalarında kullanılmıştır. Aynı zamanda doku (texture) bilgisi, nesneler arasındaki topolojik ilişkiler ve çevre arazi tipleri de sınıflandırma detayının doğruluğunu artırmak için kullanılabilecek yöntemler arasındadır. Görüntü içerisinde ve nesne içerisinde incelenen yeryüzü nesnelerinin aralarındaki yoğunluklar bunların dokuları incelendiğinde kendini göstermektedir. Özellikle kent dokusu ve doğal bitki örtüsü arasında bulunan kontrast farkları kentsel yoğunluk derecelerinin belirlenmesinde kullanım potansiyeli olabilmektedir ve çalışmada bu da incelenmiştir. Burada kullanılan görüntü çözünürlüğü de önem taşımaktadır. Özellikle yüksek ve çok yüksek mekânsal çözünürlüğe sahip uydu görüntülerinde vektör veri kullanımı ve seçilen metod sınıflandırma doğruluğunu etkilemektedir. Örneğin kullanılan vektör verinin çözünürlüğü görüntünün mekânsal çözünürlüğünden daha kötü ise bu sınıflandırmada

sorunlara ve yanlış sınıflandırma sonuçları elde edilmesine sebep olabilir. Literatürde bulunan çalışmalar genellikle günümüzde orta ve düşük çözünürlük olarak değerlendirilen görüntüler ile yapılmıştır ve daha yüksek çözünürlüklü görüntüler ile kentsel detay seviyelerini inceleyen çalışmalar az sayıda bulunmaktadır. Bu çalışmada Bursa ili çalışma alanı olarak seçilmiş ve kent sınıfları farklı yöntemler ile sınıflandırılmıştır. Bursa ilinin çalışma alanı olarak seçilme sebebi, hem Türkiye'deki en büyük illerden biri olması, hem çalışmada ele alınmak istenen kentsel yoğunluk derecelerinin hepsinin burada görünür olmasıdır. Şehirdeki kentsel yoğunluk kadar farklı arazi örtüsü ve arazi kullanımı sınıflarının varlığı da çalışmada kentsel alan tespiti için tercih edilmiştir. Ayrıca, çok yoğun kentsel alanlar olduğu gibi şehir merkezinden uzak, seyrek yerleşimler de şehirde görülebilmektedir. Yapılan sınıflandırmalarda, Copernicus tarafından sunulan Su Geçirmezlik Haritaları (IMD), Normalize Edilmiş Bitki Endeksi (NDVI), Parlaklık ve Haralick doku bilgileri kullanılmıştır. Her kentsel yoğunluk sınıfı için 10 ila 20 kontrol alanı seçilmiştir ve buradaki görüntü nesnelerinin bantlardaki istatistiksel değerleri hesaplanmıştır. Bu değerlerden yola çıkarak her yöntem için sınıfların ayrı ayrı tespit edilebilmesine sebep olabilecek sınıf bazında minimum ve maksimum eşik değerleri belirlenmiştir. Nesne tabanlı sınıflandırmada faydalanılan özellik ve fonksiyonlar ile görüntü nesneleri belirlenmiş ve bunlar belirlenen eşik değerleri kullanılarak sınıflandırılmıştır. Her yöntem ile nesne tabanlı sınıflandırma yapılarak üretilen haritalar üzerinde doğruluk analizi yapılmıştır ve bunların sonuçları karşılaştırılmıştır. Kullanılan veri pan-keskinleştirilmiş 1,5 metre mekânsal çözünürlüğe sahip SPOT görüntüsüdür. Bu görüntünün seçilme sebebi kentsel alanların incelenmesi için gerekli geometrik detay seviyesini sağlayabilmesidir. Kentsel alan yoğunluk seviyelerini en doğru şekilde belirlemek üzere farklı yardımcı veri ve farklı yöntemler sonucunda üretilen sınıflandırma sonuçları birbirleri ile karşılaştırılmıştır. Doğruluk analizinde yine bu görüntü kullanılmış, ek olarak Google Earth, Yandex Maps gibi yüksek çözünürlüklü ve güncel görüntü içeren çevrimiçi kaynaklardan da yararlanılmıştır. Sonuçlar sınıf bazında ve genel doğrulukları ele alınarak değerlendirilmiştir. Doğruluk analizi sonuçlarında genel doğruluk bazında en iyi sonuç%79,09 ile NDVI eşik değerleri kullanılarak elde edilmiştir. Ardından GLDV, GLCM, IMD, Brightness yöntemleri sırasıyla %75,68, %73,64, %68,57, %64,64 genel doğrulukta tespit edilmiştir. Her sınıflandırma için sınıf bazında üretici ve kullanıcı doğrulukları araştırıldığı zaman IMD ile yapılan sınıflandırmada Sürekli Kentse Doku sınıfının en başarılı sınıflandırma yapılan sınıf olduğu görülmektedir. Fakat Süreksiz Yoğun Kentsel Doku sınıfı büyük oranda Sürekli Kentsel Doku sınıfı ile karışmıştır. Süreksiz Orta Yoğunluklu Kentsel Doku sınıfında da Süreksiz Çok Düşük Yoğunluklu Kentsel Doku sınıfı ile karışmalar görülmüştür. Yani, IMD verisinde Süreksiz Çok Düşük Yoğunluklu Kentsel Doku sınıfında olduğundan fazla değer tahminleri bulunmaktadır. Manuel NDVI eşikleri ile yapılan sınıflandırma sonucunda ise Sürekli Kentsel Doku sınıfında tüm kontrol noktalarının doğru sınıflandırılması ile oldukça iyi sonuç elde edilmiştir. Fakat yoğunluk derecesi azaldıkça hatalı nokta sayılarında artış görülmüştür. Parlaklık değerleri ile yapılan sınıflandırmada Sürekli Kentsel Doku sınıfı yüksek doğrulukla sınıflandırılmıştır fakat Süreksiz Yoğun Kentsel Doku sınıfında bir üst sınıf ile parlaklık değerleri yakın olduğundan ve binalar arasındaki dokunun tespiti için uygun bir parametre olmadığı için karışmalar görülmüştür. Çalışmada Haralick doku bilgisinin de kentsel alanların tespitinde kullanılabilirliği araştırılmıştır. Sonuçların gösterdiğine göre GLCM değerleri kentsel alanların tespitinde kullanılmak için uygun olabilir. Bu doku bilgisi en çok Süreksiz Düşük Yoğunluklu Kentsel Doku ve Süreksiz Çok Düşük Yoğunluklu Kentsel Doku sınıfında başarılı sonuç vermiştir. Bunun sebebi belirtilen sınıflarda binalar ile çevresinde fazla bulunan doğal alanların arasında görülen belirgin kontrast farkı olduğu düşünülmektedir. Bu metodun doğruluğu daha yoğun kentsel yoğunluk sınıflarında düşmektedir. Son olarak GLDV değerlerinin de özellikle orta yoğunlukta sınıf için iyi sonuç verdiği görülmüştür. Bu sonuç GLDV değerlerinin genelde sınıf karışan bölgelerde ek bir doğrulama yöntemi olarak kullanılabilirliğini gösterdiği şeklinde yorumlanmıştır. Tüm bu sonuçlar göstermektedir ki yüm yöntemler ayrı ayrı kabul edilebilir genel doğruluk sonuçları verseler de her metodun kendi içinde avantaj ve dezavantajları bulunmaktadır. Bu çalışma bazında sonuçlar özellikle daha yoğun kentsel alanlarda NDVI, Parlaklık ve IMD değerlerinin, daha az yoğun alanlarda ise GLCM ve GLDV yöntemlerinin daha iyi sonuç verdiği yönündedir. Gelecek çalışmalarda tüm metodların birlikte kullanımı ile hem sınıf bazında hem de genel doğruluk sonuçlarının gelişimi gözlemlenebilir.

1. INTRODUCTION, LITERATURE REVIEW and AIM OF THE STUDY

1.1 Introduction

Observation and investigation of the land surface and the activities carried out on it is a crucial aspect to understand the current situation, changes, and developments in a city. With the increasing population and urbanization, correct moves for sustainable development should be made. It is important to visualize and model the earth, especially urban areas to estimate future conditions for people and decision makers. Earth observation data helps researches, related authorities, governments, to make strategies for regional and city planning by providing land cover and land use (LC/LU) information. Investigation of impervious surfaces and their magnitude, location, geometry, and spatial patterns are the key aspect to understand human-environment interactions. Recently, high and very high-resolution optical satellite images are commonly used as earth observation data, for various kinds of applications. They provide up to date, reliable information on the land surface. Especially in urban areas, high resolution images make it easier to detect and analyze very detailed dynamics of impervious surfaces and their relationship with the surrounding environment. Impervious surfaces are defined as features in which water is not able to penetrate into the soil. The degree of imperviousness is also evaluated as a degree of urbanization, and environmental condition (Weng, 2011). By using the spectral features of objects, it is possible to detect the degree of imperviousness with remote sensing. Image classification is used to identify different kinds of objects, different land covers, and areas used for various kinds of activities. After classification, LC/LU maps which provide insight about a study area and the land, can be produced. There are mainly two ways of applying image classification: pixel-based classification and object-based classification. Traditionally, pixel-based classification was a popular method for image classification. The spectral values of pixels are used to differentiate different LC/LU classes. Although, classes having similar spectral characteristics can be mixed, or classes that cannot be determined only by spectral values, such as specific land use classes could not be identified. Sports and leisure facilities class could be an example of this problem. Mixed pixel is another obstacle in pixel-based classification. On the other hand, object-based classification uses image objects, which are clusters of similar pixels, and takes their relationships into consideration. Object to object, object to image relationships can be investigated, and hierarchical models can be used. In addition, remote sensing indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) can be defined and calculated for each image object, instead of the whole image. A variety of object features provided in the software is another advantage of using object-based classification. Features such as length, width, position, border index, rectangular fit, etc., make detecting objects with specific shapes and structures easier. The advantages of object-based classification appear clearer when high or very high spatial resolution images are used. Determination of impervious surfaces has been gaining popularity since the starting of the 21st century, with the developments of better remote sensors with higher and higher resolution and more advanced image processing techniques (Weng, 2011). Although, most of the literature on detection and classification of impervious surfaces are focused on lower resolution images such as LANDSAT MSS, LANDSAT TM, SPOT HRV, etc. which were the best options back in the day but recently, not considered as high resolution and require manual interpretation and processing (Slonecker et al., 2001). Spatial resolution is a combined function of the altitude of the sensor, size of the detector and focal, and system configuration (Jensen, 2005). It refers to the ability to identify small adjacent objects in an image. As the spatial resolution gets higher, to recognize smaller objects is possible. The distance between the centers of two adjacent resolution cells of the same channel is called the ground sampling distance (GSD). Ground resolution cell size and the GSD should ideally be equal; the GSD then particularly defines the spatial resolution of the sensor (Bakker et al., 2001). Although, some features that are smaller than the spatial resolution can be detected by their contrast of reflectance with surrounding pixels, or their unique shapes. Thus, spatial resolution can both include detectability and separability. Generally, the minimum resolution requirement for impervious surfaces is 0.25-0.50 m for buildings, and 1-30 m for roads (Weng, 2011). This can be better seen on the illustration of the relationsip between spatial resolution and object size in Table 1.1. It can be seen that at least approximately 1-meter spatial resolution is needed to extract objects such as buildings, roads, etc. Higher resolution images also work, but it could lead to over segmentation and considered not necessary for this study.

Table 1.1 Relationship between image resolution and planimetric object extraction (The University of Rhode Island, 2019).

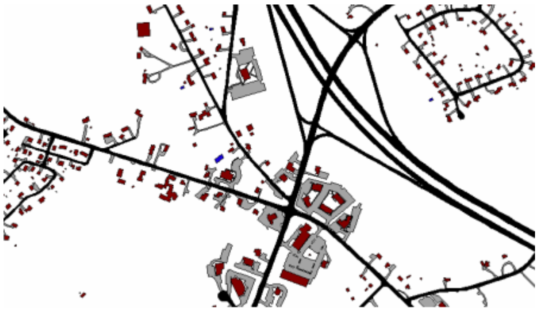
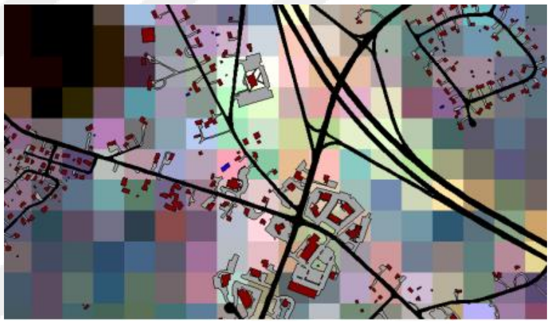
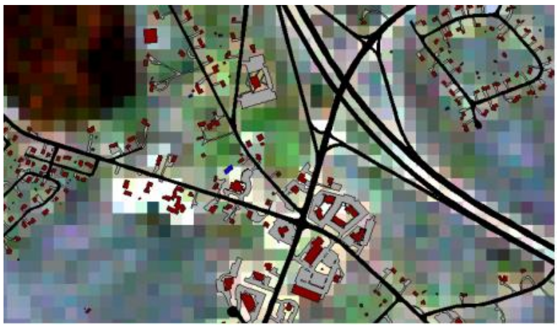
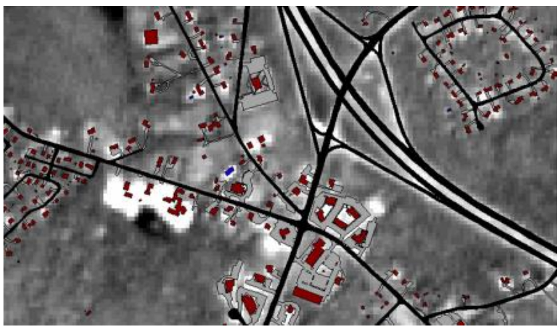
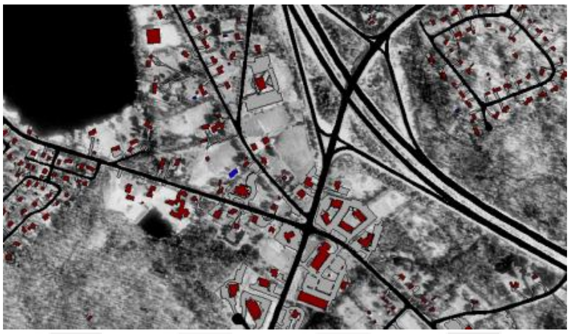
Resolution	Example
Planimetric Data (Roads, buildings, driveways)	
60 meter spatial resolution Landsat MSS with planimetric overlay	
30 meter spatial resolution Landsat TM with planimetric overlay	
10 meter spatial resolution SPOT with planimetric overlay	

Table 1.1 (Continued): Relationship between image resolution and planimetric object extraction (The University of Rhode Island, 2019).

Resolution	Example
1 meter spatial resolution DOQ with planimetric overlay	
Sub-meter data with planimetric overlay	

Thematic vector layers are also one of the key factors to improve the accuracy of the classification. Open source, up to date vector sources such as OpenStreetMap (OSM), Wikimapia, Copernicus high resolution layers provide LC/LU information for various application purposes and can give effective results (Leinenkugel et al., 2019).

1.2 Literature Review

In a recent study, it is observed that using vector layers on object-based classification improves the overall accuracy by a considerable amount, especially on mid resolution images such as Sentinel-2 (Varol et al., 2019). To better understand the geometric features of impervious surfaces are crucial to improving the accuracy of determining those areas. High resolution images from spaceborne and airborne sensors provide effective and efficient extraction of features. Although, shadow and image distortion resulting from acquisition angle can sometimes affect the classification in a negative way because they can cause misclassification and error. Mixing of impervious surfaces with vegetation or, in contrast, to water can happen because of the viewing angle (Van der Linden & Hostert, 2009; Hodgson et al., 2003; Linden and Hostert, 2009). Those problems require additional processes such as Digital Terrain Model (DTM) based orthoimage generation, shadow detection and compensation. In addition to optical satellite images, LiDAR is also used in urban remote sensing applications and shows great potential for building detection, even determining the buildings that are higher than the established boundaries (Varol et al., 2018). There are many methods for determining impervious and urban areas such as object-based image analysis, Artificial Neural Networks (ANN), data and image fusion, knowledge-based expert systems, image texture analysis, and so on. Mostly medium resolution images are used in the previous studies of impervious surfaces. Thus, models, methods and algorithms are focused on such resolution. High resolution images and other sensors such as LiDAR shows great potential and performance on urban remote sensing, although new ways of remote sensing concepts, models and image processing algorithms should be tested and evaluated (Weng, 2011). Huang et al., 2019 addressed the problem of using low or mid resolution images for impervious surface extraction and investigated a method to extract impervious surfaces by using multi source high resolution data, by applying deep learning algorithms. Geiß et al., 2014 extracted seismic structural building types by using multi sensor remote sensing data and machine learning techniques. Lehner et al., 2017 compared Sentinel-1 data with high resolution imperviousness degree layers of Copernicus by using unsupervised classification. Their results showed that with Sentinel-1 data, urban areas could be determined and is in accordance with the high-resolution layers of Copernicus. Kupidura and Uwarowa, 2017, tested the Grey Level Co-occurrence Matrix (GLCM) and granulometry analysis to detect different levels of urban areas by using semi-automatic classification techniques. Their results showed that Haralick Correlation gives efficient results on 10m spatial resolution SPOT 5 images.

1.3 Aim of the Study

By considering the lack of studies on detecting and classifying different types and levels of impervious surfaces by using high resolution optical satellite images, this study focuses on comparing the impacts of different methods, data integrations on object-based classification of impervious surfaces. In the selected test area, various levels of urban fabric and other impervious surfaces are classified. The reason for selecting object-based classification is the wide variability of functions and features that can be integrated into the classification, the advantages in high classification accuracy, computational speed and feasibility of integrating supportive data. The aim is to accurately classify urban classes having different density values by using a high resolution satellite image and object-based classification approach. Different features and functions to be used for the classification of different urban fabric density values are proposed. The detailed explanations of used techniques are written in related sections. In this thesis, firstly the aim of the study and previous related work are explained. Then, pre-classification steps such as determining the satellite image adequate for such work, determining the classification system; which classes are going to be used for defining different levels of urban fabric, are described. Then, object-based classification is introduced, the features and functions are given in detail. The importance of data integration, open source thematic data sources and the methods used to determine and classify impervious surfaces and different levels of urban fabric are described. The study area, used data, and all methods in the application are explained. The results are shown and the accuracy analysis is represented. Lastly, the study is concluded and the results are interpreted.

2. METHODOLOGY

The methodology of this study consists of selection of the study area, selecting and acquiring the satellite image, downloading open source supportive vector data, determining the methods for classification, application of classification and the evaluation of the results. In classification, firstly multiresolution segmentation is applied and object-based features/functions are used to detect image objects related to each class, then thresholds are determined for each urban density level class using statistical averages of each method on the image bands. Image objects are detected according to each urban class characteristics, like area, density, coordinates, brightness, shape, compactness etc. Apart from IMD, all other thresholds for classes are calculated manually by investigating the statistical values on the image bands for image objects, such as minimum, maximum, average etc. For classification with IMD, pre-determined thresholds by Urban Atlas project are used. After, accuracy assessment is done and thematic maps are produced, user's and producer's accuracies are calculated and the results are evaluated. The workflow is briefly illustrated below in Figure 2.1

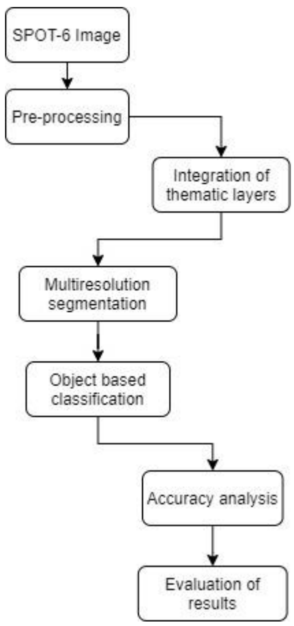


Figure 2.1 : Flowchart of this study.

2.1 Object Based Classification

LC/LU maps can be generated by two methods: pixel-based and object-based classification. Object-based classification is a technique that makes it possible to use the relationships between image objects, which are the smallest elements in object-based classification, and define those relationships by using a set of rules, functions and features, unlike pixel-based classification which only pixel values are used. It is possible to use the topological relationships between image objects. Additionally, vector data could be included to the process. Supportive thematic data can provide the diversity of LC/LU classes and increase the classification accuracy. In order to accurately map the increasing number of LC/LU classes including extensive thematic details, open source geo-information is an important source to be integrated with satellite images during the classification (Blaschke, 2010; Sertel et al., 2018). In eCognition software, there are various kinds of features defined (Figure 2.2). Also, it is possible to add functions manually. (For example: remote sensing indices such as NDVI.)

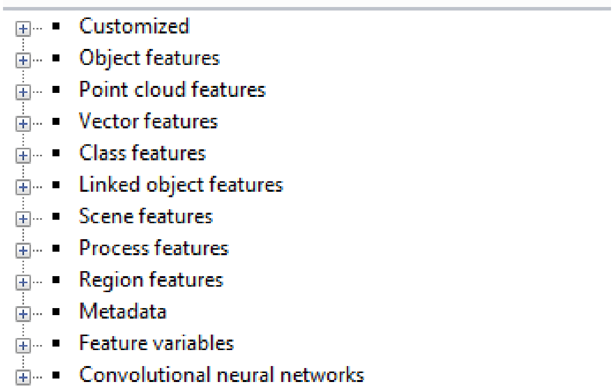


Figure 2.2 : eCognition Developer menu.

Object features are divided into detail, which have information about spectral values, shape, texture, and class relationships of image objects which are smallest elements in object-based classification (Figure 2.3).

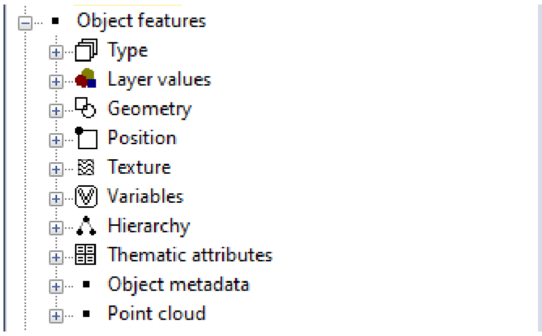


Figure 2.3 : Object features.

Relational functions of layer values are furthermore divided into values such as Mean, Mode, Standard Deviation which contains the spectral statistical values of image bands used (Figure 2.4).

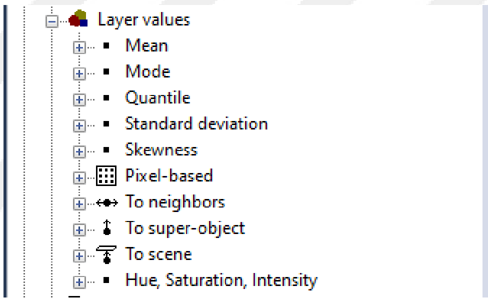


Figure 2.4 : Layer values.

The values can be calculated for all image bands in the project (Figure 2.5). The statistical values are defined for the neighboring classes, as well as objects (Figure 2.6).

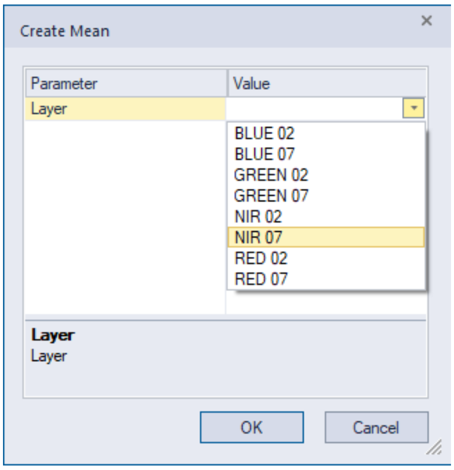


Figure 2.5 : Band values calculation window.

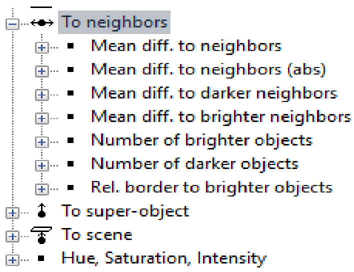


Figure 2.6 : Neighbor object relationship features.

It is also possible to define remote sensing indices in eCognition (Figure 2.7). According to the purpose of application, used image, spectral resolution, different indices can be defined in the project. Although it is also possible in pixel-based classification, the function is calculated within each image object thus more information extraction is possible. They can be used for extracting vegetation, agriculture, water, artificial surfaces etc.

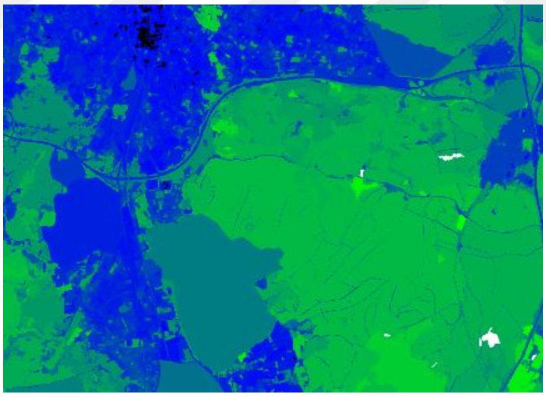


Figure 2.7 : Determination between vegetation and artificial surfaces by using NDVI index.

Some of the most used indices are NDVI (2.1), NDWI (2.2).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2.1}$$

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \tag{2.2}$$

Customized functions can be created (Figure 2.8). Such as NDVI differences of 2 different dates: which can be very helpful for the extraction of Arable Land class.

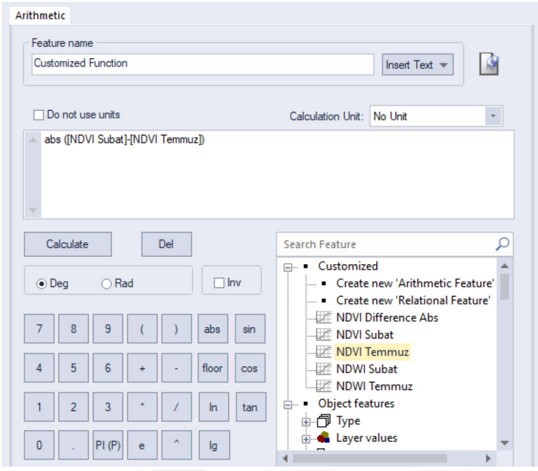


Figure 2.8 : Customized function creation window.

Relational features can be defined by using topological relationships between image objects, classes, neighbors. Geometry features are based on an image object's shape, calculated from the pixels that form it and include features such as Asymmetry, Density, Roundness (Figure 2.9).

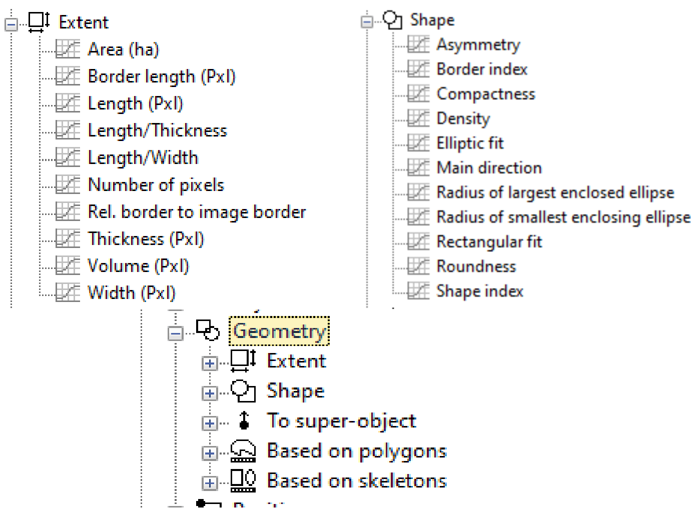


Figure 2.9 : Geometry features.

The geometry of image objects provides crucial information in classification. They provide values such as Area, Length, Width, Volume of image objects. Especially classes like roads, agricultural fields, industrial areas can be detected by using these features, as they have unique and distinguishable shapes. Area, Border, Length functions are number of pixels on those objects. The calculations are based on a geometric shape with the same area as the selected image object (Figure 2.10)(eCognition, 2017). Then they are statistically compared for all the functions listed.

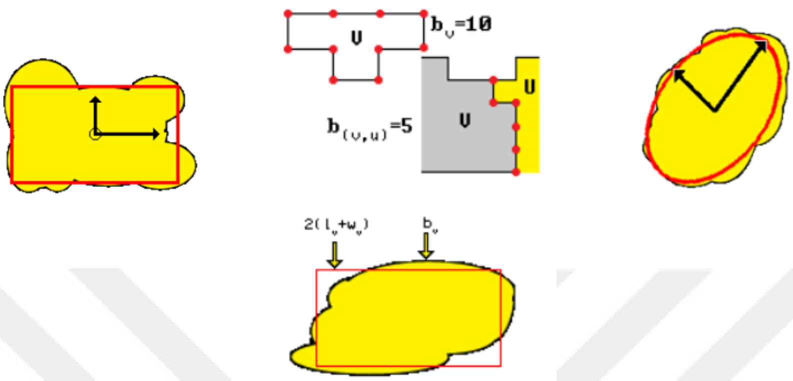


Figure 2.10 : Representation of geometric features.

Position features refer to the position of an image object relative to the entire scene. These features are of special interest when working with geographically referenced data, as an image object can be described by its geographic position. Position features refer to the pixel co-ordinate definition (Figure 2.11).

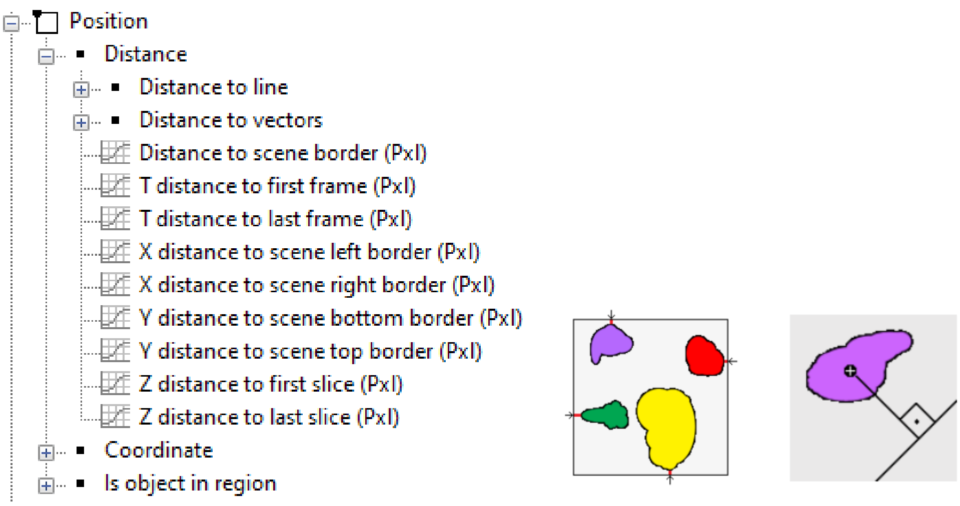


Figure 2.11: Position features and representation of ‘distance to’ feature.

Texture features are used to evaluate the texture of image objects and include features based on an analysis of sub-objects helpful for evaluating

highly textured data. In addition, features based upon the gray level co-occurrence matrix after Haralick are available (Figure 2.12). Texture after Haralick features are based on the GLCM, which is a tabulation of how often different combinations of pixel gray levels occur in an image.

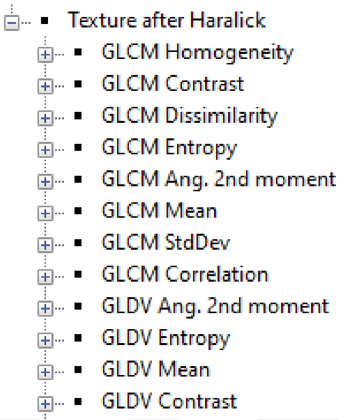


Figure 2.12 : Texture after Haralick features.

Thematic attribute features are used to describe an image object using information provided by thematic layers. If the scene contains a thematic layer, its thematic object's properties, can be used to create thematic attribute features, which can be used for developing rule ware (Figure 2.13). Thematic layers can be used for the extraction of some land cover and land use classes. They are especially useful for land use classes as they cannot be detected on the image only.

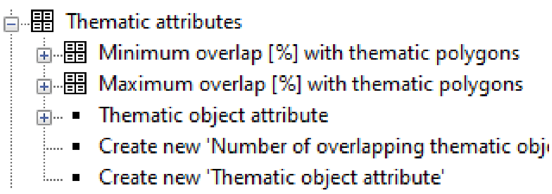


Figure 2.13 : Thematic attributes.

There are different open-source thematic layers available. Some of the most used thematic vector sources in object-based classification are: OpenStreetMap (OSM), Wikimapia, Imperviousness Density Maps (IMD), LC/LU Maps such as CORINE, Urban Atlas and other sources according to the purpose of application; provided by governments, institutions and organizations etc. OpenStreetMap (OSM) Provides vector data for roads, land use and land cover classes (Figure 2.14). Vector data should always be checked for accuracy, coordinate system and overlap with the image. Land use vectors are defined in polygons and has attributes regarding to their purpose of use.

Figure 2.14 : An overview from OpenStreetMap.

Wikimapia is one of the most used open-source vector data. Similar to OSM, it has detailed shape and attributes belonging to cities; roads, buildings, private organizations etc. It has vector data on industrial areas, sport facilities, residence areas, military and public areas (Figure 2.15).

Figure 2.15 : An overview from Wikimapia.

The CORINE Land Cover (CLC) consists of an inventory of land cover in 44 classes. CLC uses a Minimum Mapping Unit (MMU) of 25 hectares (ha) for areal phenomena and a minimum width of 100 m for linear phenomena. CLC has a wide variety of applications, underpinning various Community policies in the domains of environment, but also agriculture, transport, spatial planning and so on. The characteristics of CLC is shown in Figure 2.16, and LC/LU map for Europe and some part of Istanbul is shown in Figure 2.17.

	CLC1990	CLC2000	CLC2006	CLC2012	CLC2018
Satellite data	Landsat-5 MSS/TM single date	Landsat-7 ETM single date	SPOT-4/5 and IRS P6 LISS III dual date	IRS P6 LISS III and RapidEye dual date	Sentinel-2 and Landsat-8 for gap filling
Time consistency	1986-1998	2000 +/- 1 year	2006+/- 1 year	2011-2012	2017-2018
Geometric accuracy, satellite data	≤ 50 m	≤ 25 m	≤ 25 m	≤ 25 m	≤ 10 m (Sentinel-2)
Min. mapping unit/width	25 ha / 100m	25 ha / 100m	25 ha / 100m	25 ha / 100m	25 ha / 100 m

Figure 2.16 : CLC characteristics.

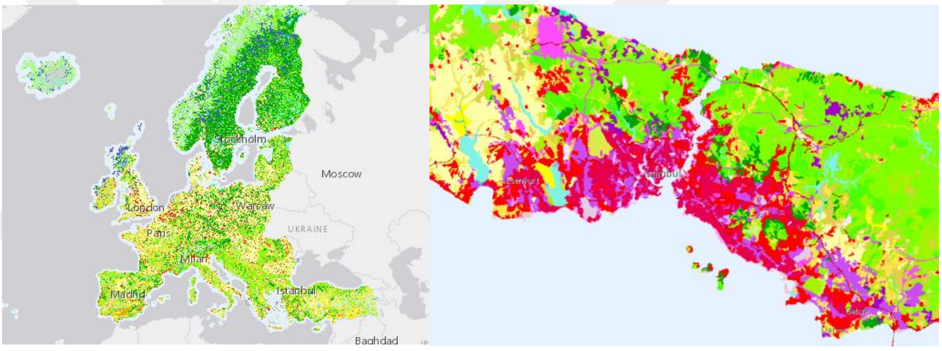


Figure 2.17 : CORINE Land Cover - Europe and Istanbul (2018).

The Urban Atlas provides pan-European comparable land use and land cover data for Urban Areas. The system includes 17 urban classes with MMU 0.25 ha (minor nomenclature changes compared to urban atlas 2006) and 10 Rural Classes with MMU 1ha. Similar to CORINE, Urban Atlas can be used for extracting LC/LU classes. Figure 2.18 shows the LC/LU map of Urban Atlas project for Europe extent and for Istanbul, Turkey.

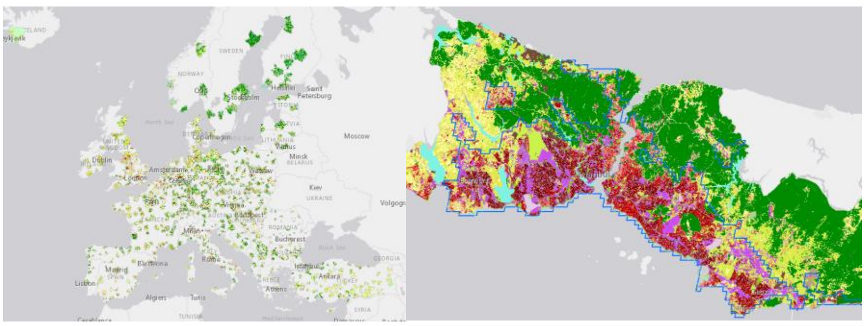


Figure 2.18 : Urban Atlas Land Cover – Europe and Istanbul (2012).

IMD are one of the most important high-resolution layers provided by Copernicus (Figure 2.19). The impervious surfaces are divided into 5 classes by their spectral values and the vector data is provided as 20-meter or 100-meter resolution raster data.

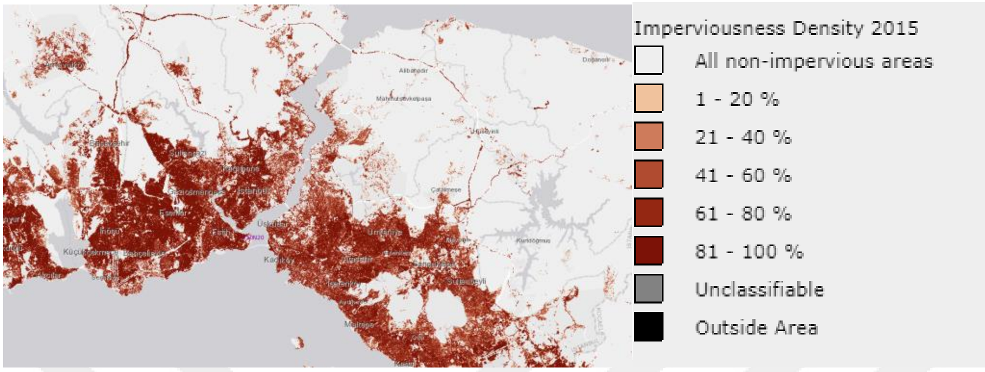


Figure 2.19 : IMD.

2.2 Pre-Classification

In remote sensing applications, the selection of the image is very important. The spatial and spectral resolution, acquisition date, whether or not to use multi-temporal data, and the capacities of satellite sensor should all be considered according to the aim and extent of the study. In this study, accurate determination of impervious surfaces and levels of urban fabric is aimed. Thus, a high-resolution image which make differentiating impervious surfaces like buildings, roads, industrial areas is needed. It is explained in introduction section that close to 1-meter spatial resolution is adequate to extract urban features such as buildings, roads, etc. By considering this, SPOT 6 image is chosen for classification in this study. Additionally, open-source vector data is used for a better segmentation and classification. Before the classification, the geometric correction of the image is done by using the control points provided from the General Command of Mapping. Then, open source vector data is downloaded, cut according to the study area borders and attributes regarding to the application are selected. The geometric transformations are done for the thematic data. Image and all vector data are defined in WGS 84 UTM Zone 35.

2.3 Study Area

The study area is selected as Bursa, located in the southern part of Marmara region in Turkey (Figure 2.20). It is the 4th most populated city in Turkey by having approximately 2 million people. The city has a variety of urban and industrial areas. Bursa is the one of the centers of automotive industry in the country. It has many attractive points for both foreign and local tourists. The test area selected in the city has mostly urban and industrial areas. The reason for this study area to be selected is that the city has different kinds of urban patterns and has all the density levels that this study wants to investigate. The LC/LU variability and general city structure were found ideal and adequate for the purpose of this study.

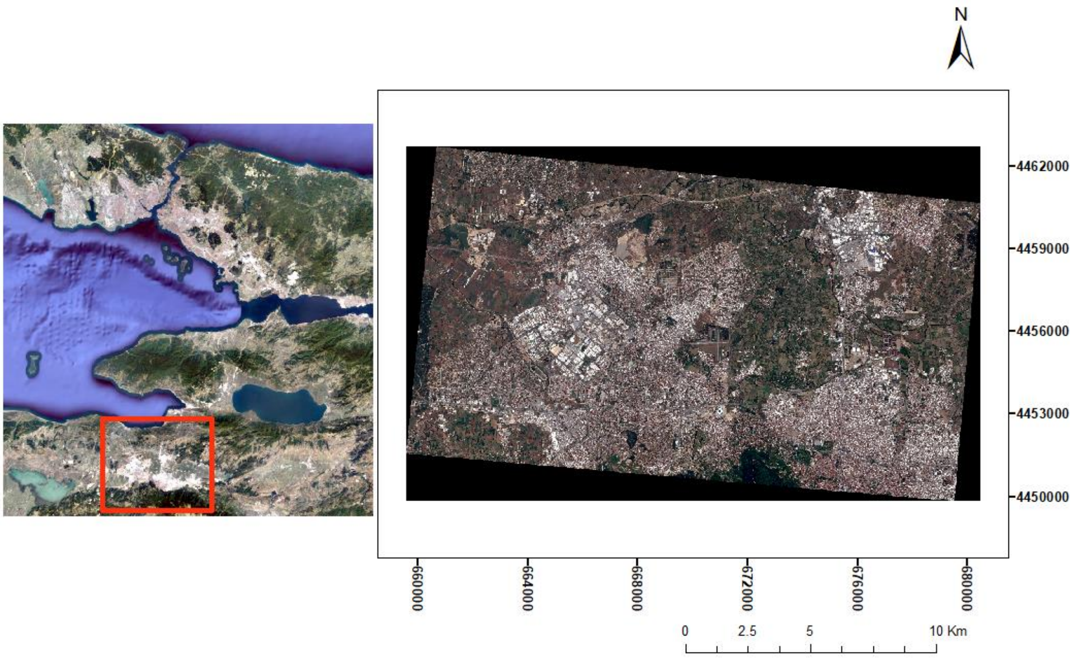


Figure 2.20 : Study area.

2.4 Data Used

In this study, 09/06/2019 dated pan-sharpened SPOT image is used in object-based classification. The spatial resolution of SPOT image is 1,5 meters in panchromatic band. The obtained image was already ortho-rectified and defined in WGS-84 Zone 35 N ellipsoid. Geometric correction was done by using control points obtained from General Command of Mapping. Radiometric correction and atmospheric correction were done already by the data provider. The used image was a GeoTIFF formatted standard ortho product which is a georeferenced image in Earth geometry, corrected from acquisition and terrain off nadir effects. SPOT 6 satellite was launched in 9 September 2012 and designed for a 10-year lifetime. It is a sun-synchronous satellite and it orbits the Earth around 694 km altitude (Astrium, 2013). OpenStreetMap (OSM) thematic vector layers are used in the classification and integrated into the segmentation for better identifying the road classes as well as city block borders. High resolution layers from Copernicus IMD maps are used in classification. To determine industrial fields in the study area, OSM and Wikimapia data are used. For object-based classification eCognition Developer; for image correction, accuracy analysis, data conversion, visualization purposes; ERDAS, Geomatica, ArcGIS, QGIS software are used. For control and verification of vector layers and land use classes, Google Earth, HERE Maps, Yandex Maps open-source imagery are used.

The classification is carried out by pan-sharpened SPOT image acquired in 09/06/2019. The satellite characteristics are represented in Table 2.1. Software and supportive data used for classification, data analysis and data conversion are listed in the table below (Table 2.2).

Table 2.1 : Satellite image used in this study.

Satellite	Image Acquisition Date	Spatial Resolution	Spectral Bands
SPOT-6	09.06.2019	Panchromatic: 1,5 m	Panchromatic (450-745 nm), Blue (450-520 nm), Green (530-590 nm), Red (625-695 nm), Near-Infrared (760-890 nm)

Table 2.2 : Software and supportive data used in this study.

Software/Data	Used for
eCognition	Object-based classification
ERDAS Imagine	Image correction, accuracy analysis, map production
ArcMap, QGIS	Data conversion, accuracy analysis, map production
Open Street Map (OSM)	Road, Industry and some LU class vectors
Wikimapia	LU class vectors
Google Earth Browser	Visual interpretation and LU information
Yandex Maps	Visual interpretation and LU information
Here Maps	Visual interpretation and LU information
CORINE 2018 LC/LU	Visual interpretation and LU information

2.5 Classification

The first step in object-based classification is segmentation. In this study, Multiresolution Segmentation is applied for all classifications. This algorithm starts with pixels and creates image objects by grouping similar pixels in terms of scale, shape and compactness which are the parameters determined by the user. The scale parameter defines the extent of an image object. Shape and compactness is used for determining the impact of shape/color, and compactness/softness. Because object-based classification is highly variable, those parameters are usually determined by trial and error method. For this study, best result for the segmentation is obtained with parameter values 150, 0,5 and 0,5 for scale, shape, compactness respectively. The classification is focused on only impervious and urban areas. So, other LC/LU classes are masked before. This is done by firstly classifying Vegetation, Agriculture and Water areas. Then, those classes were masked and not taken into consideration on the following classifications. Firstly, water areas were masked by using NDWI index. NDWI index gives satisfactory results for classification of water areas. The agricultural fields were masked by using NDVI, GLCM 'Homogeneity' and 'Rectangular Shape' features. Also, some manual editing was done to improve results. Vegetated areas were determined by using NDVI index. After, industrial areas were masked. For this purpose, Wikimapia vector layers, 'Brightness', 'Rectangular Shape', NDVI features are used. Some manual editing is done for defining the areas more complete and small unclassified objects inside the industrial area were merged. Then, left unclassified areas, which are urban areas was segmented again by using multiresolution segmentation with parameters 80, 0,5 and 0,5 for scale, shape and compactness respectively. Classification of levels of urban fabric density was done by defining thresholds for each different feature. For each class, namely, Continuous Urban Fabric, Discontinuous Dense Urban Fabric, Discontinuous Medium Density Urban Fabric, Discontinuous Low Density Urban Fabric and Discontinuous Very Low Density Urban Fabric, control grids are selected and their values were collected into a table. The sizes of the control grids were different, because each class has a different shape and compactness structure and they are selected as the most objective way in the multiresolution segmentation. Meaning that the control grids for each class and each object group in a class represents the specific class, and using smaller or larger reference areas would not be significant. Numerous control grids are selected in accordance with several LC/LU maps, online image sources such as Google Earth, Yandex and HERE Maps etc. to maximize the objectiveness of evaluation. Then mean, median and mode values of features on selected grids are compared. All of these values are grouped for determining adequate minimum and maximum for each class. By using these statistics, the thresholds are determined and used in the classification. Visual examples of the urban fabric classes are shown in Table 2.3. The represented two images of every class are suitable examples of mentioned control grids that are selected for the calculation of average values of each class.

Table 2.3 : Examples of control areas of classes.

Class Name	Control Grids	
Continuous Urban Fabric		
Discontinuous Dense Urban Fabric		
Discontinuous Medium Density Urban Fabric		
Discontinuous Low Density Urban Fabric		

Table 2.3 (Continued): Examples of control areas of classes.

Class Name	Control Grids	
Discontinuous Very Low Density Urban Fabric		

2.5.1 Classification with imperviousness maps

IMD maps were integrated to the image classification. Firstly, the downloaded layers were cut according to the study area borders. Then, translated from raster to vector layers. This is done by using ‘Raster to Polygon’ feature in ArcMap. Then, the projection is changed into WGS-84 ellipsoid by using ‘Project’ function on ArcMap. IMD captures the spatial distribution of artificially sealed areas. The level of sealed soil (imperviousness degree 1-100 %) which is produced by using a semi-automatic classification, based on calibrated NDVI is defined five different Urban Fabric sub-classes (European Union, 2016). It is available in original 20 m and aggregated 100 m spatial resolution. IMD data is intended to be used and works best for satellite images 2.5 m or lower spatial resolution. The 20 m resolution data is used for this study. The data is not revised, but used directly as the provided way. The reason for that is revising the data would take so much manual work and it would be time consuming. Originally, downloaded data has 100 image vector layers that defines all the areas with 0% to 100% imperviousness level. The layers are merged according to the thresholds that are defined by Urban Atlas nomenclature system and shown in Table 2.4.

Table 2.4 : Imperviousness degree thresholds (European Union, 2016).

Class	Threshold (Imperviousness Degree)
Continuous Urban Fabric	> 80 %
Discontinuous Dense Urban Fabric	50 % - 80 %
Discontinuous Middle Density Urban Fabric	30 % - 50 %
Discontinuous Low Density Urban Fabric	10 % - 30 %
Discontinuous Very Low Density Urban Fabric	< 10 %

After integrating the imperviousness degree vector layers into the project, a Multiresolution Segmentation is applied. Because the data has 20 m resolution, over or underestimation of objects are avoided as no calculation for threshold values are done in this step. Only the accuracy of available data is tested. 'Thematic overlap' feature is used for the classification. Each class is classified by using vector attributes. Image objects were classified with the overlapping imperviousness degree layer. This way, all 5 urban fabric density classes are determined.

2.5.2 Classification with NDVI

The NDVI index is used to estimate the density of green areas on a land of interest, by calculating the difference between visible and near-infrared reflectance of the vegetation cover (Weier and Herring, 2000). In urban areas, the spaces are mostly filled with impervious surfaces and green spaces are seen less. Lower density urban fabric areas mostly have trees, parks, and small community gardens. Additionally, villages away from the city there are more activities on farming and gardening, which increases the vegetation cover. By this approach, NDVI index can be used for differentiating between the density levels of urban fabric by assuming the higher NDVI value indicates lower density of urban fabric, and lower value of NDVI indicates the opposite. By using the control grids, threshold values are determined for classification and represented in Table 2.5.

Table 2.5 : NDVI thresholds.

Class	Threshold (NDVI)
Continuous Urban Fabric	< 0.13
Discontinuous Dense Urban Fabric	0.13 – 0.25
Discontinuous Middle Density Urban Fabric	0.25 – 0.32
Discontinuous Low Density Urban Fabric	0.32 – 0.38
Discontinuous Very Low Density Urban Fabric	> 0.38

2.5.3 Classification with brightness

Brightness is the average reflectance value in the ground and represented by digital numbers. In eCogntion, this value is the average of the sum of each, or selected image bands. It can give important information when differentiating man-made objects from natural surfaces as those objects have high reflectance because of their physical properties. The reflectance is higher on artificial surfaces because of their physical properties. Thus, brightness is expected to increase in accordance with increasing imperviousness. For urban areas, more vegetation in a block means less imperviousness and lower degree of urban density. By using this information, ‘brightness’ feature is used for extracting urban fabric densities. By using the control areas, statistical values for brightness values are examined and thresholds to separate levels of urban fabric degrees are determined. The thresholds are shown in Table 2.6. Classification is done by using those values in the conditions of the rule set in the classification.

Table 2.6 : Brightness thresholds.

Class	Threshold (Brightness)
Continuous Urban Fabric	> 930
Discontinuous Dense Urban Fabric	880 - 930
Discontinuous Middle Density Urban Fabric	840 - 880
Discontinuous Low Density Urban Fabric	800 – 840
Discontinuous Very Low Density Urban Fabric	< 800

2.5.4 Classification with haralick texture

Textures in images measure the grey level differences, the decided area of an appeared change, and directionality. Haralick et al. (1973) proposed 14 different texture measures on mathematical pattern analysis. GLCM shows the frequency of different combinations of the pixel brightness values (grey levels) appear in an image. Sometimes, GLDV (Grey Level Difference Vector) is used instead of GLCM, which is actually the sum of the diagonals of the GLCM. Texture information can be used to differentiate particular places in an image by limiting the texture measure calculation to a GLCM, acquired from small parts of different regions on the image. Different texture values belonging to different places in the image can represent the pixel relationships quantitatively on the whole image. Because texture statistic is descriptive, it changes from a part of an image to another part or an image to another image. In this study, sample values are collected from control grids to determine an adequate threshold for different classes. Both GLCM and GLDV measures are calculated and the ones suited best from both measures for the study area are represented. There are totally 12 Haralick features defined in eCognition. All of them are calculated and results were collected into a table. Most of them were not significant results for discriminating urban fabric sub-classes. When the statistical values are investigated, GLCM Contrast and GLDV Mean values were meaningful. Thus, those two are used for classification. Although, in future studies, this can be done with automatic procedures by using more samples from different image sources having various spectral and spatial resolution. In this part of the study, only the feasibility of texture features on classifying urban fabric classes is tested.

2.5.4.1 GLCM contrast

GLCM Contrast is a texture measure from the contrast group of image textures (2.3). Weights related to the distance from the GLCM diagonal are used for this calculation.

$$\sum_{i,j=0}^{N-1} P_{\ i,j}\ (i-j)^2 \qquad (2.3)$$

Where, i and j are pixel values of neighbor pixels in P matrix. The weight increases exponentially as (i-j) increases.

Here, the GLCM values collected from each sample from the control grids, threshold values acquired from taking averages to determine minimum and maximum values of each urban fabric classes to determine them in the classification. The thresholds are shown in Table 2.7. By assigning the values to rule set conditions, classification is done.

Table 2.7 : GLCM Contrast thresholds.

Class	Threshold (GLCM Contrast)
Continuous Urban Fabric	> 480
Discontinuous Dense Urban Fabric	370 - 480
Discontinuous Middle Density Urban Fabric	240 - 370
Discontinuous Low Density Urban Fabric	200 - 240
Discontinuous Very Low Density Urban Fabric	< 200

2.5.4.2 GLDV mean

GLDV Mean values are also calculated as same as other classifications. Average minimum and maximum values are calculated and best suited thresholds are chosen and shown below in Table 2.8. The minimum and maximum threshold values for each class are defined in the classification condition and the image is classified by using them.

Table 2.8 : GLDV Mean thresholds.

Class	Threshold (GLDV Mean)
Continuous Urban Fabric	> 16
Discontinuous Dense Urban Fabric	12 - 16
Discontinuous Middle Density Urban Fabric	10 - 12
Discontinuous Low Density Urban Fabric	6 - 10
Discontinuous Very Low Density Urban Fabric	< 6

3. RESULTS & DISCUSSION

In this study, different levels of urban areas are classified by using various methods and data integrations. The potential of using those methods are tested in terms of general and class-based accuracy. Totally 5 LC/LU maps on urban fabric density levels are produced. All of the results are compared and evaluated according to their performance of representing different levels of urban fabric. The potential of using IMD, NDVI, Brightness, GLCM, and GLDV thresholds for the classification of different densities of the urban fabric is tested. Although all of the results gave acceptable accuracies, the best overall accuracy was obtained with manually defined NDVI thresholds for this specific test area and study. Then, accuracy assessment is applied and the producer's and user's accuracies are calculated. The producer's accuracy defines how often are real features on the ground correctly shown on the classified map. The user's accuracy shows how often the class on the map will be present on the ground. Additionally, online high-resolution image sources such as Google Earth, Yandex Maps, HERE Maps are used for improving the accuracy analysis by double checking the urban fabric with different images and also street view.

3.1 Classification Maps

The classification maps are produced from the classifications with imperviousness maps, manually determined NDVI, Brightness, GLCM, GLDV thresholds and represented in Figure 3.1, Figure 3.2, Figure 3.3, Figure 3.4, Figure 3.5, respectively.

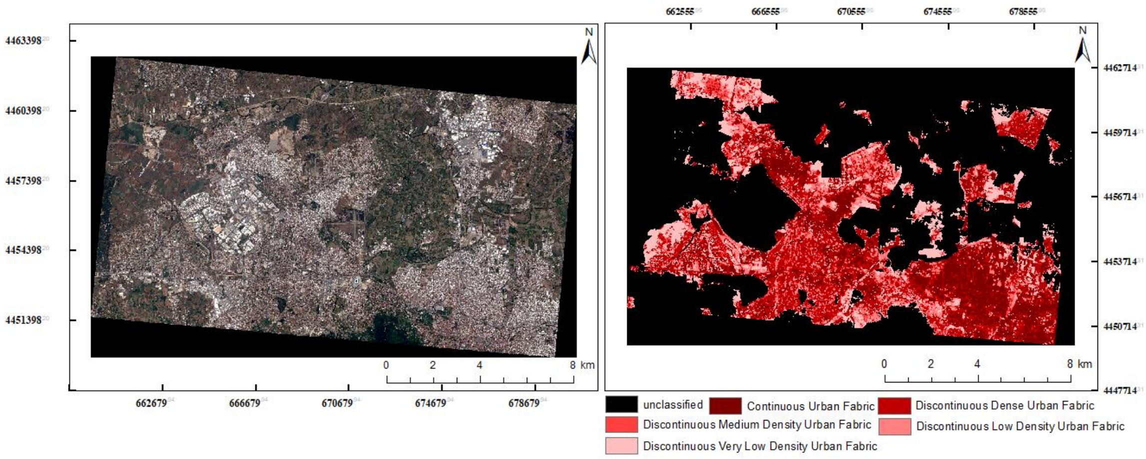


Figure 3.1 : ‘IMD’ classification results.

When class-by-class results are examined, the results showed that the classification with IMD had the most successful in Continuous Urban Fabric class. Although, Discontinuous Dense Urban Fabric class was highly mixed with Continuous Urban Fabric. Discontinuous Medium Density class was mostly mixed with Discontinuous Very Low Density Urban Fabric class. This means that most of the Discontinuous Very Low Density Urban Fabric class was overestimated in the source data.

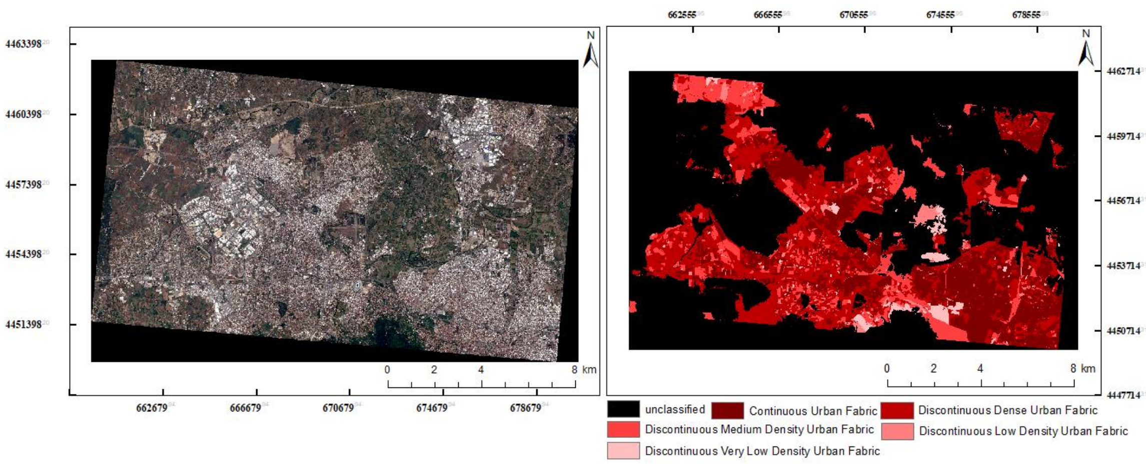


Figure 3.2 : ‘NDVI’ classification results.

The classification with manual NDVI thresholds, gave satisfactory results on Continuous Urban Fabric with no mistaken points but, as the density lowered, the misclassifications were increased.

The classification with Brightness values was also successful on Continuous Urban Fabric class, yet on Discontinuous Dense Urban Fabric, the accuracy was lowered because of the similar roof reflectance and lack of detection of spaces between the buildings.

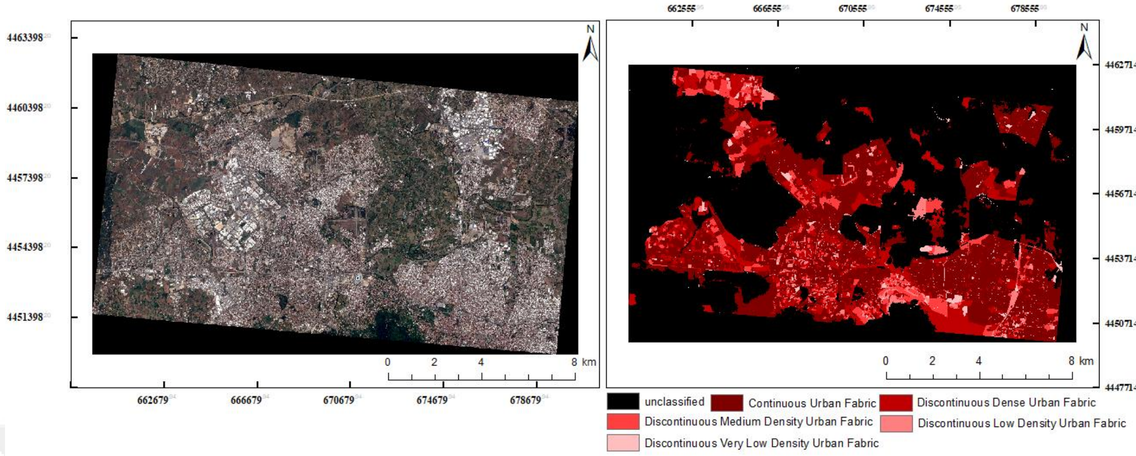


Figure 3.3 : ‘Brightness’ classification results.

Texture information and its potential for classifying urban areas were also tested. The results indicate that GLCM values can also be used for extracting such information. GLCM results were most successful on Discontinuous Low Density Urban Fabric and Discontinuous Very Low Density Urban Fabric. This may be because of the contrast differences seen on those areas. A single building on a green area is easily detected by texture measurements. The performance of this method was not as good as previous ones on the denser urban fabric.

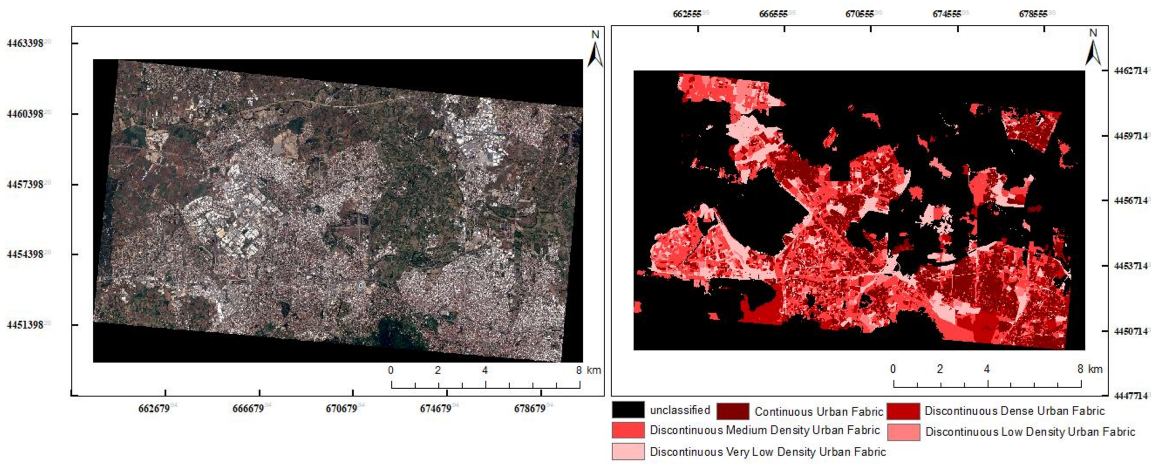


Figure 3.4 : ‘GLCM’ classification results.

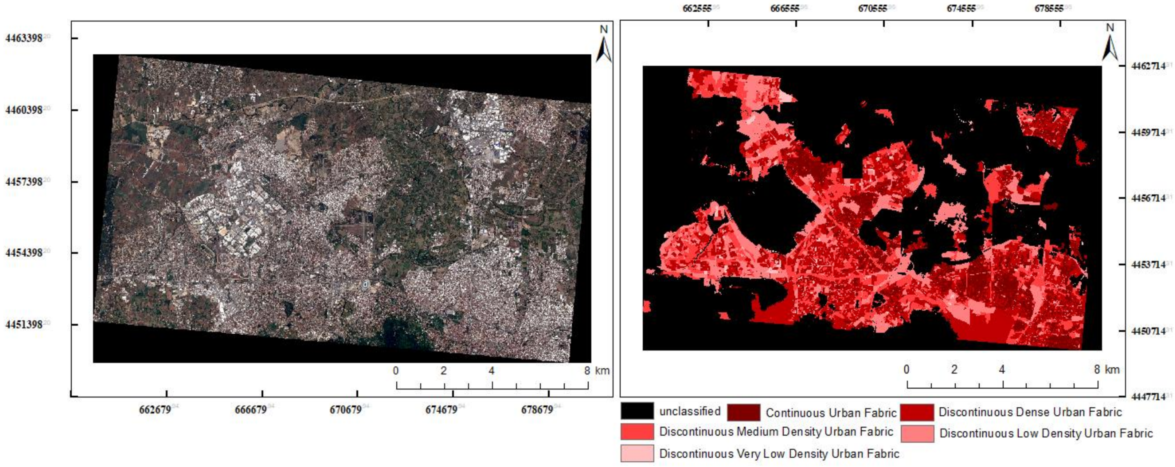


Figure 3.5 : ‘GLDV’ classification results.

Lastly, GLDV values were most suitable on middle classes, and mostly mixed classes on other classifications, such as Discontinuous Low Density Urban Fabric and Discontinuous Dense Urban Fabric. This shows that it could be used as an additional feature for those classes.

3.2 Accuracy Analysis

Accuracy assessment was conducted by using the original SPOT-6 image as a reference image which has multispectral sensors with 6m spatial resolution in RGB and NIR, and has a 1.5 m resolution panchromatic band (AIRBUS, 2018). Additionally, other open-source high resolution satellite images such as Google Earth, Yandex Maps, and HERE Maps and their street views are used when necessary. Randomly and homogeneously selected points that are numbered in accordance with the class areas on the classified image were used. Totally 110 control points are evaluated. According to the class areas, and in order the control points to be homogenically distributed, control points between 15-30 for each class are selected. A total of 110 control points was distributed for accuracy analysis that covers up all the classified image. By using QGIS software, the accuracy assessment is completed and a confusion matrix is produced. For each classification, User’s and Producer’s accuracies are calculated. The results showed that the highest overall accuracy was obtained with NDVI method with 79,09 % overall accuracy, followed by GLDV, GLCM, IMD, Brightness with overall accuracies 75,68%, 73,64%, 68,57%, 66,36%, respectively. The accuracy analysis results are shown in Table 3.1, Table 3.2, Table 3.3, Table 3.4, Table 3.5.

Table 3.1 : Accuracy analysis results of imperviousness maps.

Class	User's Accuracy	Producer's Accuracy
Continuous Urban Fabric	83,33	80
Discont. Dense Urban Fabric	76,19	64
Discont. Med. Dens. Urban Fabric	88,24	60
Discont. Low Dens. Urban Fabric	52,63	66,67
Discont. Very Low Dens. Ur. Fab	45,83	73,33
	Overall	68,57
	Kappa	0,61

Table 3.2 : Accuracy analysis results of NDVI method.

Class	User's Accuracy	Producer's Accuracy
Continuous Urban Fabric	83,33	100
Discont. Dense Urban Fabric	81,82	72
Discont. Med. Dens. Urban Fabric	75	84
Discont. Low Dens. Urban Fabric	73,68	70
Discont. Very Low Dens. Ur. Fab.	81,82	60
	Overall	79,09
	Kappa	0,74

Table 3.3 : Accuracy analysis results of brightness method.

Class	User's Accuracy	Producer's Accuracy
Continuous Urban Fabric	67,57	100
Discont. Dense Urban Fabric	50	52
Discont. Med. Dens. Urban Fabric	62,5	60
Discont. Low Dens. Urban Fabric	80	60
Discont. Very Low Dens. Ur. Fab.	100	53,33
	Overall	66,36
	Kappa	0,57

Table 3.4 : Accuracy analysis results of GLCM method.

Class	User's Accuracy	Producer's Accuracy
Continuous Urban Fabric	100	76
Discont. Dense Urban Fabric	78,95	60
Discont. Med. Dens. Urban Fabric	59,38	76
Discont. Low Dens. Urban Fabric	68,42	65
Discont. Very Low Dens. Ur. Fab.	71,43	100
	Overall	73,64
	Kappa	0,67

Table 3.5 : Accuracy analysis results of GLDV method.

Class	User's Accuracy	Producer's Accuracy
Continuous Urban Fabric	100	72
Discont. Dense Urban Fabric	70	80,77
Discont. Med. Dens. Urban Fabric	78,26	72
Discont. Low Dens. Urban Fabric	59,38	95
Discont. Very Low Dens. Ur. Fab.	100	53,33
	Overall	75,68
	Kappa	0,70

4. CONCLUSION

The objective of this study was to detect impervious surfaces and classify urban density levels by using different methods and data integrations. Object-based classification techniques are used. All of the values mean that even though using just a single one of those methods give adequate results on classification, each method has its advantages and disadvantages. It can be best to use those methods for each different class to increase overall accuracy. According to this study, on selected specific test area and image resolution, while for denser urban fabric, a mixture function of NDVI, Brightness and IMD values can be used; for sparse areas, GLCM and GLDV values can be used for estimation or can be used to provide correction to mixed classes. It is important to remember that in object-based classification, the thresholds can be changed according to the study area, the spectral and spatial resolution of the image, and the purpose of the classification. Although, the results of this study indicate the promising usage of different methods for the classification of urban areas. In future studies, these results should be tested on different test sites to see if the methods and investigation of urban patterns are possible. The methods should also be tested on different topographies, or different kinds of remote sensing data such as very high resolution or hyperspectral images. On the other hand, the effect of pan-sharpening or radiometric and geometric corrections can be investigated to see how those processes affect the classification results. The control areas could be collected from different sources and all of the proposed values from explained methods can be transmitted to, for example an artificial neural network for automatic classification. So that the results can be improved and generalizing the methods could be possible. Urban areas and their correct classification are important, because they can represent both statistical and social factors in a city or even a country. With the correct classification and supportive demographic data, the results may provide insight for both future statistical and socio-economic studies which are crucial for development. More precise thematic maps can be produced and integrated into GIS and other systems or applications, this could help many theoretical or applied studies that concerns urban areas.

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M.Sc., Geomatics Engineering (September 2017 – August 2020)
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WORK EXPERIENCES

ITU Research and Application Center for Satellite Communications and Remote Sensing (CSCRS), (May 2018 -), Istanbul, Turkey

I have been primarily working on object-based image classification for both urban and agricultural remote sensing applications. Recently, I have started getting into deep learning as well.

Istanbul Technical University Computer Center, (March 2015 - November 2016), Istanbul, Turkey

I worked on different projects on Linux system administration, networking and web programming while dealing with the network and computer problems that students and academics are having, via telephone or face-to-face.

Nokia HERE Maps Istanbul Office, (July 2016 – August 2016), Istanbul, Turkey

As an intern, I worked on a project to create the database of the traffic lights and signs' coordinates and orientations in a specific area. I used 3D images with GPS information and a map base to match the data.

PUBLICATIONS

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Varol B., **Yılmaz E. Ö., Maktav D., Bayburt S. & Gürdal S.** "Detection of Illegal Constructions in Urban Cities: Comparing LiDAR Data and Stereo KOMPSAT-3 Images with Development Plans" *European Journal of Remote Sensing*, 2019

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INTERESTS

Besides being an Earth admirer, I am a professional violinist, and a street musician. I also enjoy playing viola, piano, and guitar. I love yoga and running. I like to read novels, and play computer games in my spare time.