International Journal of *Geo-Information*

MDPI

Article

Comparison of Landscape Metrics for Three Different Level Land Cover/Land Use Maps

Elif Sertel [1,2,*], Raziye Hale Topaloğlu [1,3], Betül Şallı [1], Irmak Yay Algan [1] and Gül Aslı Aksu [4]

1 Center for Satellite Communications and Remote Sensing (CSCRS), Istanbul Technical University, Istanbul 34469, Turkey; haletopaloglu@gumushane.edu.tr (R.H.T.); betul@cscrs.itu.edu.tr (B.Ş.); irmaky@cscrs.itu.edu.tr (I.Y.A.)
2 Geomatics Engineering Department, Istanbul Technical University, Istanbul 34469, Turkey
3 Geomatics Engineering Department, Gümüşhane University, Gümüşhane 29000, Turkey
4 Faculty of Architecture and Design, Istanbul Ticaret University, Istanbul 34840, Turkey; aslibozbay@yahoo.de
* Correspondence: sertele@itu.edu.tr; Tel.: +90-212-285-3803

Received: 13 August 2018; Accepted: 9 October 2018; Published: 15 October 2018

check for updates

Abstract: This research aims to investigate how different landscape metrics are affected by the enhancement of the thematic classes in land cover/land use (LC/LU) maps. For this aim, three different LC/LU maps based on three different levels of CORINE (Coordination of Information on The Environment) nomenclature were created for the selected study area using GEOBIA (Geographic Object Based Image Analysis) techniques. First, second and third level LC/LU maps of the study area have five, thirteen and twenty-seven hierarchical thematic classes, respectively. High-resolution Spot 7 images with 1.5 m spatial resolution were used as the main Earth Observation data to create LC/LU maps. Additional geospatial data from open sources (OpenStreetMap and Wikimapia) were also integrated to the classification in order to identify some of the 2nd and 3rd level LC/LU classes. Classification procedure was initially conducted for Level 3 classes in which we developed decision trees to be used in object-based classification. Afterwards, Level 3 classes were merged to create Level 2 LC/LU map and then Level 2 classes were merged to create the Level 1 LC/LU map according to CORINE nomenclature. The accuracy of Level 1, Level 2, Level 3 maps are calculated as; 93.50%, 89.00%, 85.50% respectively. At the last stage, several landscape metrics such as Number of Patch (NP), Edge Density (ED), Largest Patch Index (LPI), Euclidean Nearest Neighbor Distance (ENN), Splitting Index (SPLIT) and Aggregation Index (AI) metrics and others were calculated for different level LC/LU maps and landscape metrics values were compared to analyze the impact of changing thematic details on landscape metrics. Our results show that, increasing the thematic detail allows landscape characteristics to be defined more precisely and ensure comprehensive assessment of cause and effect relationships between classes.

Keywords: object based classification; LCLU maps; SPOT; landscape metrics

1. Introduction

The Earth' surface changes constantly, not only by its natural dynamics, but also due to human activities. These changes, whether they are minor or major, local or global, affect the ecology and the human beings living on that ecosystem. In order to better understand the cause and effect relationships of different changes on the Earth' surface, such as deforestation, urbanization and other processes, some of the most crucial information is up to date spatio-temporal distribution of land cover and land use. Land cover is defined as the physical cover of Earth and land use describes how that land is used by humans. Together, they provide a baseline for many ecological and societal studies such as environmental models, weather and climate studies, hydrological and landscape planning studies, etc. [1–3]. Therefore, mapping land cover/land use (LC/LU) characteristics of the Earth's surface becomes an important topic. There are different standard LC/LU systems developed by different agencies for various scales and needs, such as "National Land Cover Database (NLCD) of United States", "United Nations Land cover maps (LCCS) of Food and Agricultural Organization (FAO)" and CORINE (Coordination of Information on The Environment) project of European Union (EU) [4].

CORINE is a monitoring program that aims to create standardized seamless LC/LU maps throughout the EU and its candidate countries in order to aid environmental policies [5,6]. It is updated every six years and uses satellite imagery as its main data source. CORINE land cover nomenclature provides a conceptual framework for understanding the different types of LC/LU classes and is widely used in related studies [7,8]. It is based on the visual interpretation and on screen digitization of the LC/LU classes according to the defined nomenclature. Five main classes defined for the first level of this nomenclature are; Artificial Surfaces (1), Agricultural Areas (2), Forest and Semi-Natural Areas (3), Wetlands (4) and Water Bodies (5). These five classes become thematically more detailed at the second level with 15 classes and the most detailed thematic classes are defined at the third level with a total number of 44 [9].

Producing the LC/LU maps with on screen digitization could be very time consuming when applied to large areas. Thus, researchers have been exploring ways to include some level of automation into this process by classifying the satellite images [10,11]. However, since the detailed LC/LU systems such as third level of CORINE have complicated class definitions, automatic or semi- automatic classification of these classes becomes a challenging task. Spatial resolution of the satellite images affects the level of detail in classification and accuracy of the final LC/LU map specifically for complex landscapes [11,12]. High and very high resolution satellite images provide significant advantages, especially in urban mapping and analyzing spatial/temporal changes of urban areas, due to their enhanced ability to represent heterogeneous areas and the level of information they provide [13,14]. However, their classification becomes more intricate as their resolution improves.

Geographic Object Based Image Analysis (GEOBIA) is a relatively recent classification approach compared to traditional pixel-based techniques. Pixel-based techniques have some limitations since they only use spectral and textural properties of the pixels [14–16]. Compared to pixel-based classification methods, GEOBIA usually produce higher accuracy values [17–19]. In the first process step of GEOBIA method, segmentation is applied to produce the image objects that are formed by groups of pixels according to a certain criteria set and then the classification is performed on these objects [18,20]. In order to obtain better thematic results from the classification, different features could be added to spectral information such as shape, pattern, tone, texture, context, size, connectivity, proximity of pixels and others. [21]. Geometry of a specific area can be determined by using shape and size information and the pattern can be detected with tone and texture information to improve classification results [21,22]. GEOBIA takes advantage of all these spectral, spatial and contextual information by incorporating them into segmentation and classification process [23]. GEOBIA has proven to be quite successful in creating LC/LU maps of urban areas [13,16,24] and it is quite successful with high and very high resolution satellite images. It provides effective results by producing finer details required for the urban studies, such as creating parcel borders and analyzing adjacent parcels in urban areas [25]. Moreover, GEOBIA is preferred for its ability to easily integrate satellite data and different geospatial information obtained from other geographic data sources such as OpenStreetMap, European Environmental Agency Geodata, thematic maps and Wikimapia.

The LC/LU maps are used in various research areas related to dynamic monitoring of the environment and human interactions with the environment. Since a significant portion of human population are in urban environments, mapping of urban areas and their surroundings with LC/LU systems is one of the most important research topics on this regard. LC/LU maps are also useful to analyze the patterns in a landscape. The landscape metrics, which are the indices developed in order to characterize geometric and spatial properties of map patterns, are used effectively for that purpose [26]. These metrics enable quantitative and objective analysis of the different landscape types.

Thus, they are used to test future scenarios of environmental policies and to monitor environmental goals determined by international conventions and agreements [27].

Landscape is defined by Forman and Gordon as "a heterogeneous land area composed of a cluster of interacting ecosystems that is repeated in similar form throughout" [28]. There are several spatial processes that transform the land by affecting landscape in different ways and cause changes in spatial patterns and ecological processes [29]. Landscape pattern analysis, which studies landscape components and their spatial patterns, is one of the most effective methods defining these spatial processes [30]. In order to analyze the interaction between spatial patterns and ecological processes, first, spatial patterns need to be defined [28,31]. Landscape metrics are useful tools to measure arrangement of landscape components both in time and space and they are used to characterize spatial patterns [32]. More than one metric is needed to define the landscape pattern. The metric group should describe the pattern variety seen throughout the landscape, but should be minimized in use, especially in indexes that are highly related to each other [31].

Previous studies have revealed that selecting the correct approach or combination of different approaches is an important task in landscape investigations. In recent years, Gradient Surface Model (GSM) has arisen as an alternative to Patch Mosaic Model (PMM) and it is becoming widespread. However, this model also has its shortcomings, which are similar to the unaddressed issues of PMM, such as the ecological relevancy of metrics. Therefore, applications of the GSM are also limited [33]. Integration of Gradient surfaces into the ecological analyses is difficult. Additionally, many of the surface metrics might not have patch analogs and might not be ecologically relevant [34]. Considering the above mentioned restrictions of GSM, metrics to be used in this study are chosen according to Patch Mosaic Model approach. Besides, PMM also allows for comparison according to CORINE LU/LC levels.

Landscape metrics can be defined at three levels which are namely; patch level, class level and landscape level. Patch level metrics are calculated for individual patches which represent discrete areas of similar characteristics. Class level metrics are calculated from all patches of a particular type, which, in the context of this study, are LC/LU classes. Landscape level metrics are the combination of all patch and class types in a given area [26]. There are many landscape metrics such as Largest Patch Index (LPI), Euclidean Nearest Neighbor Distance (ENN), Percentage of Landscape (PLAND), Splitting Index (SPLIT) [35–38] that can be used in patch, class and landscape levels.

The main purpose of this study is to investigate how different landscape metrics are affected by changing thematic details of LC/LU maps. This investigation provides clues that can be reflected in the landscape in general, by revealing the causal relationships between different levels. With the aid of CORINE levels, the detailing of classification categories can increase the level of significance of metric interpretations, and also provides a basis for more qualified assessment of the overall landscape. To fulfill this aim, a study area with diverse urban structure is selected in Izmir city of Turkey. Next, two SPOT 7 images of the study area with different dates (winter and spring) are obtained and pre-processed. Object based classification is employed using various features and indexes in order to create the CORINE Level 3 LC/LU map of the area. After that, classes of the Level 3 map were merged according to CORINE nomenclature, in order to create Level 2 and Level 1 maps. Area-based accuracy assessment is performed to determine accuracy of these 3 maps with 200 random areas. For each level LC/LU map, landscape metrics were evaluated and results were compared to objectively evaluate the thematic detail and metric relationship.

2. Study Area and Data

2.1. Study Area

The study area is located in Izmir metropolitan city, which is located in the Aegean region of Turkey (38°24′ N and 27°10′ E). Izmir is the third most populated city of Turkey with the population of 4,279,677 [39]. The city attracts national and international visitors with its long coastline along Aegean

Sea, warm climate and historical sites. Additionally, the Izmir Port is an important transportation hub which contributes to the city's economy. All of these attractions cause a rapid growth in Izmir in recent years and create an urban sprawl.

The study area covers approximately 286 square kilometers. This region has complex landscape characteristics with several LC/LU classes such as water bodies, agricultural areas, forests and urban areas (Figure 1).

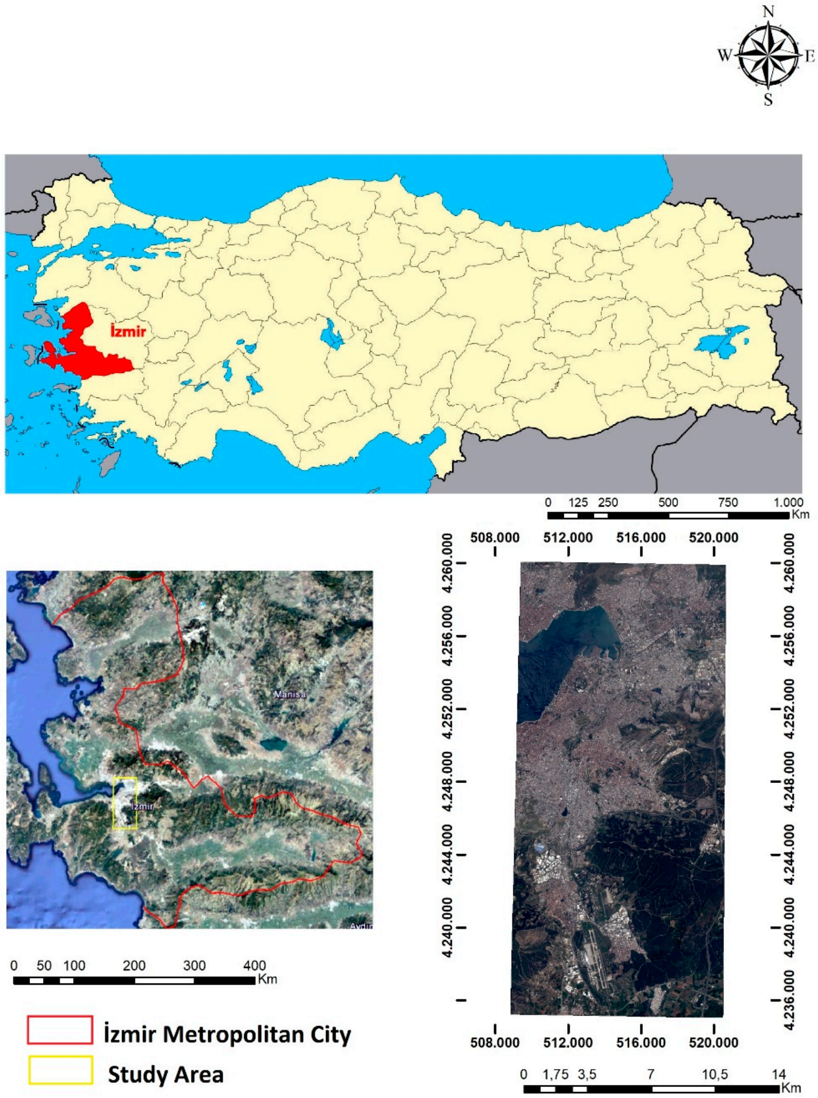

Figure 1. Study area.

2.2. Data

SPOT 6/7 satellites have multispectral sensors with 6 m spatial resolution in Red, Green, Blue and Near-Infrared (NIR) regions of electromagnetic spectrum in addition to 1.5 m resolution Panchromatic sensor [40]. In this study, two SPOT 7 images acquired on 24 April 2017 and 8 December 2016 were used as primary data source for creating LC/LU maps. The main reason for using two images with different dates was to take the advantage of capturing the temporal patterns, in addition to spectral responses for the class definitions. Temporal characteristics provide valuable information to extract the LU classes such as agricultural lands and separating them from spectrally similar classes.

Additionally, Open Street Map (OSM) vector data was used as a thematic layer for road extraction. Wikimapia was also used as a vector thematic layer for some of the artificial classes, which are basically representing the land use. Moreover, online maps such as Google Earth, Google Street Viewer and the

CORINE 2012 dataset were used for visual interpretation of the study area to form the decision trees. Lastly, parcel data obtained from Ministry of Food, Agriculture and Livestock of Turkey is used for accuracy assessment of the classification results.

3. Methods

Figure 2 illustrates the flowchart of the process chain. Firstly, SPOT 7 images (winter and spring) were pre-processed and classified by use of various features and indexes in order to create the CORINE based Level 3 LC/LU map. The reason for choosing winter and spring images was to differentiate between agricultural areas with seasonal crops. In spring time, when crops are in growing stage, vegetation indices such as the Normalized Difference Vegetation Index (NDVI) gives higher results than winter time (after harvest). After that, classes of the Level 3 map were merged according to CORINE nomenclature in order to create Level 2 and Level 1 maps. Area-based accuracy assessment was conducted to determine accuracy of these three maps. Finally, landscape metrics were calculated and evaluated for each LC/LU map.

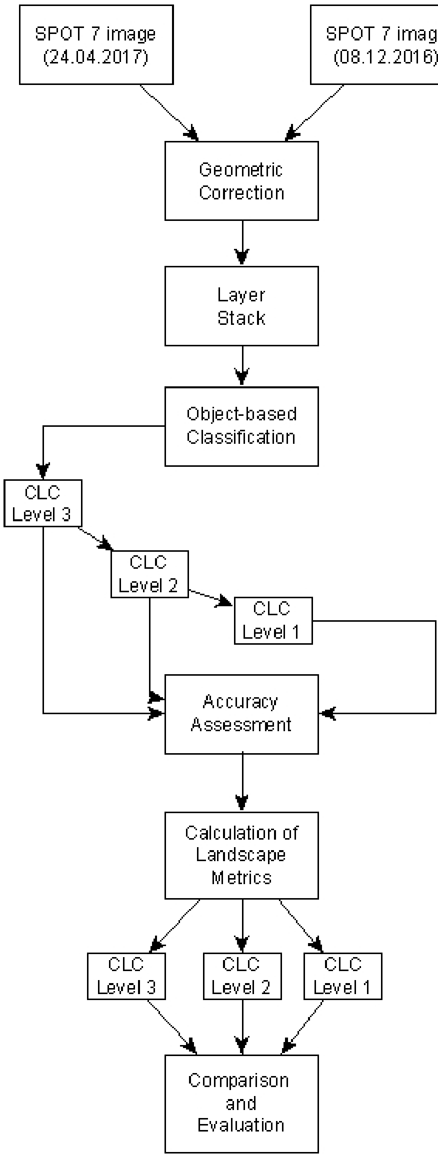

Figure 2. Flowchart of the study.

3.1. Pre-Processing

SPOT 7 images are acquired as ortho-rectified and pan-sharpened products with a 1.5-m spatial resolution. As the first step, image digital number values were converted into top of atmosphere (ToA) reflectance values. Geometric correction was performed for the images with taking the pre-ortho-rectified Pleiades imagery with 1 m locational accuracy as the reference data. Each SPOT 7 image was geometrically corrected using the first order polynomial model and use of homogenously distributed 25 ground control points (GCPs), collected from reference Pleaides imagery. During geometric correction, all RMSE (Root Mean Square Error) values were better than 2 m.

As the last step, different dated SPOT images were layer stacked in order to analyze the impact of different seasons on LC/LU classification simultaneously. Table 1 presents the bands of layer-stacked image.

Table 1. Layer combinations of stacked image.

Layers	SPOT 7 Image Bands
Layer 1	Red band of 2017
Layer 2	Green band of 2017
Layer 3	Blue band of 2017
Layer 4	Near-Infrared band of 2017
Layer 5	Red band of 2016
Layer 6	Green band of 2016
Layer 7	Blue band of 2016
Layer 8	Near-Infrared band of 2016

3.2. Classification

In this study, object-based classification was performed using eCognition Developer© v.9.3 software. Performing GEOBIA on the satellite imagery consists of two steps; segmentation and classification. The purpose of the segmentation is to create image objects by grouping similar pixels. The most popular and widely used segmentation technique is multi-resolution segmentation. In this algorithm, each pixel is considered as an image object at first and homogeneous image objects are created by combining them with their neighbors in an iterative approach [41]. In this process, five parameters called scale, shape, color, compactness and smoothness are defined by the user, based on the spatial resolution and spectral characteristics of the data and desired object size. The most important parameter is scale, which directly affects the size of the object [42]. Using larger scale parameters would create larger objects and vice versa. Shape/color, and compactness/smoothness parameter pairs complement each other to 1, which means decreasing the value of one will increase the value of complementing parameter. Shape parameter is directly related to the geometry; while color, compactness and smoothness parameters are affected by the spectral characteristics of an object [14,42].

In order to obtain the most suitable objects for LC/LU classes with diverse characteristics, several multi resolution segmentations were performed. Parameters used for the segmentation of different classes are presented in Table 2. The reason for using various segmentation scales was the difference between the size and spectral characteristics of classes. For example, the objects belonging to Water Bodies (5) and Sea and Ocean (523) classes covered the biggest area and the objects of Water Courses (511) class were extremely small, compared to 523. Using different shape and compactness parameters changed the composition of objects.

Table 2. Multi-resolution segmentation parameters.

Class Name	Scale	Shape	Compactness
Sea and Ocean	1500	0.6	0.6
Water Bodies	500	0.6	0.5
Water Courses	85	0.7	0.8
Artificial Surfaces sub-classes	250, 85, 200	0.9, 0.8, 0.3	0.5, 0.6, 0.5
Agricultural Areas sub-classes	100, 85	0.7, 0.5	0.5, 0.5
Forest and Semi-natural Areas sub-classes	1000, 500, 100	0.3, 0.4, 0.6	0.6, 0.6, 0.5

During the segmentation and classification processes, 2 thematic layers were used as ancillary vector data in order to obtain better results for some of the LC/LU classes. Table 3 shows the additional vector layers and their purpose in this study. In the classification procedure, using vector layers with related attributes is important to obtain accurate land use (such as schools, hospitals ...) information [13,43]. This information cannot be determined by using only the satellite images, since creating land use information is a much more complex task than creating land cover information. Specifically, for some classes, considering the fact that same representations in satellite image could represent different land use, ancillary data was needed. For example, some vegetated regions located in the Artificial Areas were classified as Green Urban Areas (141) because they had same spectral characteristics as other 141 objects. However, these areas had different purposes, such as being a sport facility, therefore, these objects would be classified as Sport and Leisure Facilities (142). These examples revealed that, in some cases the actual class can only be identified with some ancillary data, which includes land use and management information. As a result, obtaining land use information using only satellite image data was not as easy as determining the land cover. Therefore, additional open source geo-spatial data were used as thematic layers in the GEOBIA procedure to improve the identification of LU classes. However, boundaries of these objects were deducted from satellite images; therefore, compatibility of thematic layers with satellite image was carefully evaluated.

Table 3. Thematic Layers used in segmentation and classification processes.

Thematic Layer	Purpose
OpenStreetMap Road Data	Segmentation/Classification of Road and rail networks and associated land
Wikimapia Open Source Data	Segmentation/Classification of all Agricultural Areas sub-classes (in Level-3)

After image segmentation, image objects were classified with various features and indices, as explained in Table 4 [13,44,45], in order to create the Level 3 LC/LU map of the study area.

Figure 3 shows the general structure of the classification process and features/indices used for the definition of general classes. It is worth noting that, while general classification procedure follows that structure, there are some sub-classes that required refinement in the end, which will be explained in detail further in this section. Additionally, a 0.25 ha minimum mapping unit rule for sub-classes of Artificial Areas (1) and a 1 ha minimum mapping unit rule for all other classes were applied both in classification and segmentation procedures.

Table 4. Features and indices used in this study.

Features/Indices	Explanations
NDVI 2017	Normalized difference vegetation index; NDVI = (Layer 4 − Layer 1)/(Layer 4 + Layer 1)
NDVI2016	Normalized difference vegetation index; NDVI = (Layer 8 − Layer 5)/(Layer 8 + Layer 5)
NDWI2017	Normalized difference water index; NDWI = (Layer 2 − Layer 4)/(Layer 2 + Layer 4)
NDWI2016	Normalized difference water index; NDWI = (Layer 6 − Layer 8)/(Layer 6 + Layer 8)
Ratio of layer 4	The amount that Layer 4 contributes to the total brightness
Ratio of layer 8	The amount that Layer 8 contributes to the total brightness

Table 4. *Cont.*

Features/Indices	Explanations
Mean value of layer 4	Mean intensity values in the NIR 2017 band
Mean value of layer 8	Mean intensity values in the NIR 2016 band
Brightness	Mean of the brightness values in an image
Maximum difference	Calculates the mean difference between the feature value of an image object and its neighbors of a selected class
Standard deviation of layer 4	The standard deviation of the NIR 2017 band derived from intensity values of all pixels in this channel
Skewness of layer 4	The distribution of layer 4 intensity values of all pixels that form an image object
Shape index	Measure of overall shape complexity
Border index	Describes how jagged an image object is; the more jagged, the higher its border index
Asymmetry	Compares an image object with an approximated ellipse around the given image object
Rectangular fit	Describes how well an image object fits into a rectangle of similar size and proportions
Density	The distribution in space of the pixels of an image object
Area	The total number of pixels in the object
Length/Width	The length-to-width ratio of the main line of an object
Coordinate (X, Y Center)	X-position and Y-position of the center of an image object. The calculation is based on the center of gravity (geometric center) of the image object in the internal map.
Related border to	Determines the relative border length an object shares with neighbor objects of a certain class
Distance to	The distance (in pixels) of the image object's center concerned to the closest image object's center assigned to a defined class
Texture after Haralick	Texture features are used to evaluate the texture of image objects. Texture after Haralick features are calculated from gray level co-occurrence matrix.

The classification process was started with the classification of Level 3 classes of Water Bodies (5) which are Water Courses (511), Water Bodies (512), and Sea and Ocean (523). At first, multi-temporal Normalized Difference Water Index (NDWI) indices were used to determine appropriate thresholds. In addition to NDWI, "Ratio" of both Layer 4 and 8 (Near Infrared bands of 2016 and 2017), "Area" and, "Distance to" functions were used for accurate identification of all Water Bodies (5). "Distance to" function was applied to Sea and Ocean (523) class in order to classify Water Courses (511) near Sea and Ocean (523). Classification of these areas were relatively simple, when compared to other classes.

Secondly, Road and Rail Networks and Associated Land (122) class was created with the help of Open Street Map (OSM) vector data. OSM was very beneficial in the segmentation step since it enabled the delineation of highways and crossroads more accurately. "Asymmetry", "Length/Width", "Density", "Border index" functions were used to identify threshold values for (122) due to distinguishing geometries of the members of this class. "Related Border to" function applied to (122) class was useful to assure continuity of the roads.

Normalized Difference Vegetation Index (NDVI) was applied as an arithmetic function to distinguish the vegetated and non-vegetated areas. Then, classification of the remaining Artificial Surfaces (1) conducted with the help of Wikimapia and various features shown in Figure 3. "Coordinate" function applied to "X and Y center", "Shape Index", "Rectangular Fit", "Area" and "Brightness" functions were the best performing features for this process.

Next, classification of Agricultural Areas (2) was performed. The difference between Near Infrared bands of 2016 and 2017 images (Layer 4 − Layer 8) gave the best results to identify Non-Irrigated Arable Land (211) because wheat and other crops cultivated in the study area without irrigation were in the growing stage in April and they were harvested in December. This phenological difference is a key information for the identification of different crop types. NDVI 2016, NDVI 2017 and the difference of these NDVI layers were used to identify Permanent Crops (22), Pastures (231) and Heterogeneous Agricultural Areas (24) classes. NDWI 2016, NDWI 2017, "Maximum difference" and "Mean Layer

Value of Layer 4" supported the classification of cultivated areas. "Texture after Haralick" functions gave best results to differentiate permanent crops from each other and other green areas which are Vineyards (221), Fruit Trees and Berry Plantations (222) and Olive Groves (223). Because, plantation pattern of these crops cause them to have unique texture properties in an image. Texture functions used for this purpose are; Entropy, Homogeneity, Dissimilarity and Contrast in all directions.

In the next step, after applying a bigger scale segmentation to the unclassified areas, classification of the Broad-Leaved Forest (311) and Coniferous Forest (312) were conducted with functions provided in Figure 3. After that, a new segmentation with a finer scale was executed in order to classify sub-classes of Shrub and/or Herbaceous Vegetation Associations (32) and Open Spaces with Little or No Vegetation (33). NDVI data of 2016 and 2017 images, "Coordinate", "Area", "Maximum difference" functions, "Skewness" and "Standard deviation" functions of Layer 4, were used in this step.

After applying these steps, most of the study area was classified into appropriate classes. However, there were two classes that were classified inaccurately during this process, due to their similarities. Some very narrow Water Courses (511) members mixed with Artificial Surfaces because of their similar spectral characteristics. Also, Green Urban Areas (141) were mixed with other vegetated areas were corrected according to their positions. These classes were further analyzed and classified by using geometrical characteristics.

After the segmentation and classification processes, Level 3 LC/LU map was created and classes of Level 3 were combined according to CORINE nomenclature to obtain Level 2 and Level 1 LC/LU maps. Finally, an error matrix was created by using 200 randomly selected reference areas for each level map.

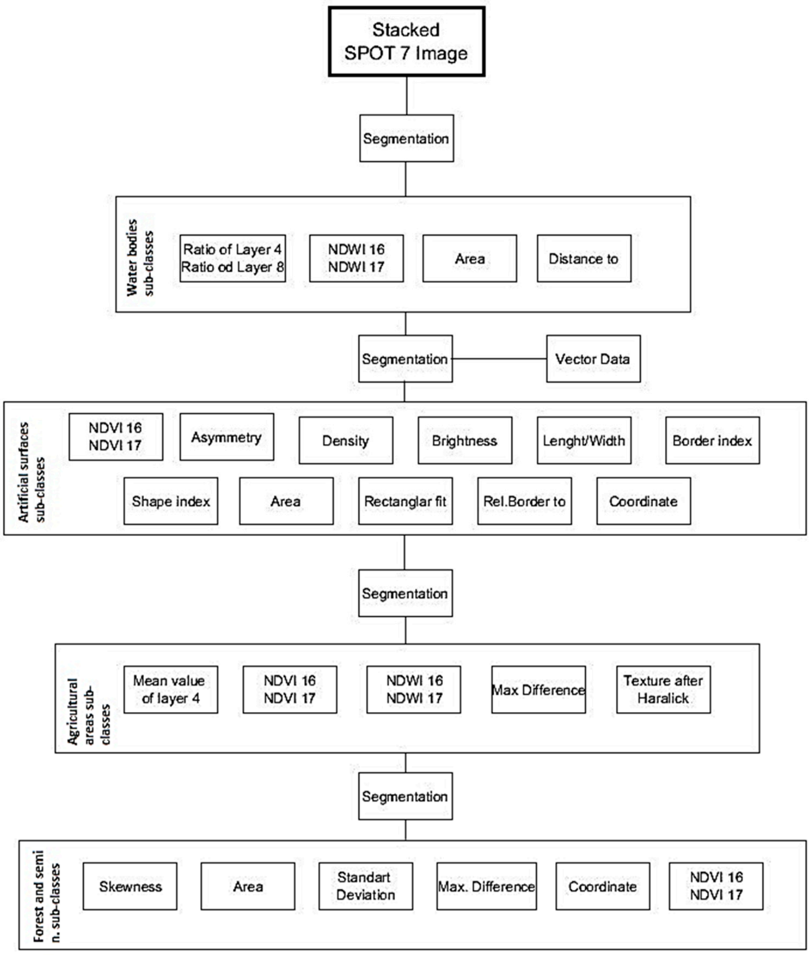

Figure 3. Flowchart of the classification process.

3.3. Landscape Metrics

Turner et al. (1989) states that qualitative and quantitative changes in measurements across spatial scales will differ depending on how scale is defined [46]. There is no single correct or optimal scale to describe spatial heterogeneity. However, since landscape pattern is dependent on the scale, using different scales in analysis could result in different outcomes, which could affect landscape management options. If it is desired to make a comparison between the landscape pattern levels, the data used must have the same spatial resolution [47]. For that purpose, a more qualified landscape assessment by changing the classification level was conducted without changing the spatial resolution. Therefore, universal and consistent class level metrics [48] were used to determine the spatial structure of the study area because information accumulated in class level from patches does not exist at patch level. Landscape level metrics give information about whole region without detailing class relations. Most metrics at the class level are derived from patch level attributes and integrated over all the patches of a particular class [26,49]. The class-level landscape metrics are more effective in defining ecological processes [50]. Additionally, metrics, used in some studies on aggregation and subdivision, were sensitive to the number of classes [51]. In this study, metric values at different levels of classification were interpreted comparatively.

In order to quantify and monitor large databases of landscape characteristics, landscape complexity must be defined and measured [52]. Components that define landscape characteristics have different level of significance depending to classification categories. Thus, metrics to be used in this study are chosen so they could define characteristics in different levels and also be comparatively analyzed in order to assess the complexity in a landscape.

Class metrics used in this study are Percentage of Landscape (PLAND), Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Total Edge (TE), Edge Density (ED), Landscape Shape Index (LSI), Shape Index Area-Weighted Mean (SHAPE_AM), Total Core Area (TCA), Euclidean nearest Neighbor Distance Area-Weighted Mean (ENN_AM), Splitting Index (SPLIT), Aggregation Index (AI). These metrics are described in Table 5 and metrics values were calculated using 8 $\times$ 8 m cell neighborhood rule in FRAGSTAT [26] software for each level CLC map. After that, results are evaluated.

Table 5. Class metrics and descriptions [35,38,53].

Metric	Description
Percentage of Landscape (PLAND)	The percentage of the landscape comprised of a particular patch type
Number of Patches (NP)	Number of patches of corresponding patch type (class)
Patch Density (PD)	Number of patches of corresponding patch type (class) per unit area
Largest Patch Index (LPI)	The area (m^2) of the largest patch in the landscape divided by total landscape area (m^2)
Total Edge (TE)	The sum of the lengths (m) of all edge segments in the landscape
Edge Density (ED)	The sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2)
Landscape Shape Index (LSI)	A standardized measure of patch compactness that adjusts for the size of the patch
Area-Weighted Mean Shape Index (SHAPE_AM)	Weighting patches according to their size, on contrary to LSI in which the total length of edge is compared to a landscape with a standard shape (square) of the same size and without any internal edge
Total Core Area (TCA)	The sum of the core areas of each patch (m^2)
Euclidean Nearest Neighbor Distance Area-Weighted Mean (ENN_AM)	Shortest straight-line distance (m) between a focal patch and its nearest neighbor of the same class
Splitting Index (SPLIT)	The number of patches obtained with subdividing the landscape into equal-sized patches based on the effective mesh size
Aggregation Index (AI)	The ratio of the observed number of like adjacencies to the maximum possible number of like adjacencies given the proportion of the landscape comprised of each patch type, given as a percentage

4. Results and Discussion

4.1. LC/LU Maps

In this study, 3 different levels of LC/LU maps were produced according to CORINE nomenclature by applying GEOBIA technique on multi-temporal SPOT 7 images. Figure 4 illustrates the classification results. In the map of Level 1, Artificial Surfaces (1) cover 167 km^2, Agricultural Areas (2) cover 25 km^2, Forest and Semi-Natural Areas (3) cover 73 km^2, and Water Bodies (5) cover 18 km^2 area. According to classification results, Artificial Surfaces is the dominant land cover type within the study area. A variety of artificial classes could be deducted from Level 2 and Level 3 classifications with more thematic details. As an example for Artificial Surfaces, 4 and 9 different artificial sub-classes were obtained in Level 2 and Level 3, respectively for the study area. These thematic details could provide efficient and precise information on urban, transport, industrial, port areas that could be used as an input for variety of different applications ranging from landscape architecture to environmental studies. Semi-Natural Areas (3) also cover a large proportion when compared to other classes. Evaluation of the generated maps showed that class diversity is quite significant especially at the Level 3 LC/LU map. This suggests the difficulty of keeping the accuracy high during the classification process. In addition, the SPOT 7 image was not enough by itself to determine some LC/LU classes of Level 3 LC/LU map, such as Industrial or Commercial Units (121), and Olive groves (223). Inclusion of different thematic layers shown in Table 3 into the classification improved the results. Considering the different number of patches and classes in different levels, landscape metrics of three different levels provided various information.

Selection of the most appropriate LC/LU classification system is an important step and there are different standardized nomenclatures available for this purpose. For most of the LC/LU systems, hierarchical levels are available in which the 1st Level represents general land cover classes and thematic detail, and complexity in class definition increases in 2nd and 3rd Levels. We used 3 Level hierarchical CORINE-based classes in this research. Although generating 1st Level classes such as Artificial Surfaces, Agricultural Areas, Forest and Semi-natural, Water Bodies are easy and could be automatically done by object based classification approaches in conjunction with some spectral indices, classification of Level 2 and Level 3 thematic classes is a more challenging task to automatize. Specifically, for some Level 3 Artificial Surfaces classes, land use information is crucial, which could not be directly produced from satellite images. In such cases, integration of open source geo-information to segmentation and classification stage improved the accuracy of classifications and lead to identify thematically detailed LC/LU classes. It is important to use multi-temporal data from different seasons to accurately identify agriculture and vegetation related 2nd and 3rd level classes such as Broad-Leaved Forest, Coniferous Forest, Non-irrigated Arable Land and Permanent Crops. Texture based Haralick features are used as an important indicator for the identification of some permanent crops such as Vineyards.

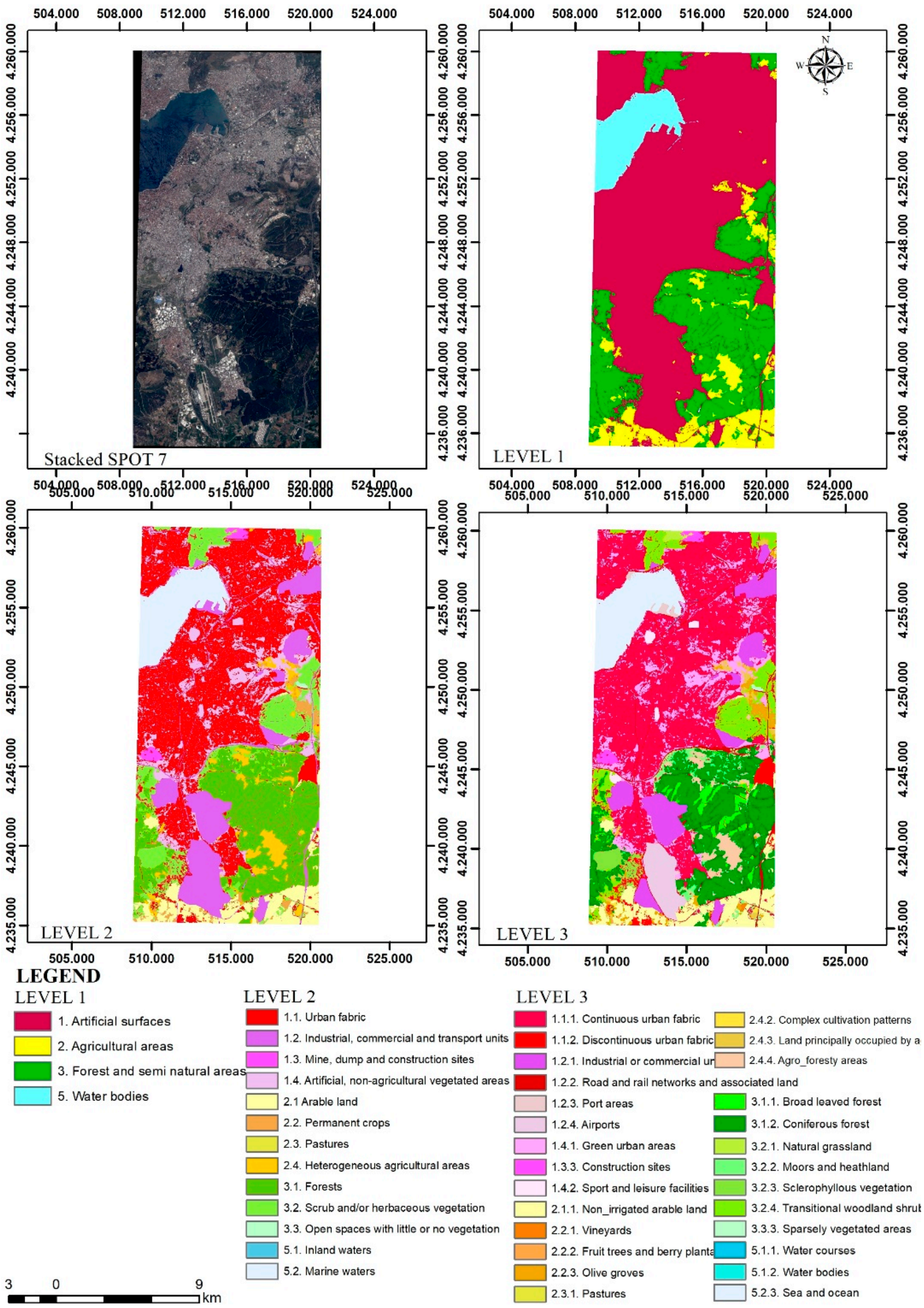

Figure 4. Classification results.

4.2. Accuracy Assessment

An area-based accuracy assessment technique was performed to evaluate thematic accuracies of three LC/LU maps. Very high resolution Pleiades image of the area was used as reference data for ground truth selection. First, whole area was divided grid by grid; each grid having an area of 1 ha (100 m × 100 m). Then, 200 grids with pure LC/LU classes within its borders were randomly selected. Finally, these areas were used for the accuracy assessment of three different level LC/LU maps by visual comparison of Pleiades image. Error matrix of each thematic map was created and accuracy results derived from error matrix are presented in Tables 6–8. Overall accuracy values of Level 1, Level 2 and Level 3 were found as 93.50%, 88.00% and 83.50%, respectively. Reduction of thematic details towards to Level 1 resulted in better accuracy values. Level 3 classes are more complicated and detailed; therefore, obtaining accuracies similar to Level 1 was not possible at this level. Water related classes are the most accurate classes in all three levels. Although Artificial Surfaces (1) could be successfully classified with more than 95% accuracy in Level 1, accuracy values decreased at Level 2 and Level 3 since these classes are more complex in terms of spectral response and geometrical characteristics.

Table 6. Accuracy assessment results of Level 3 classes.

Class Code	Class Name	Producer's Accuracy (%)	User's Accuracy (%)
1.1.1	Continuous urban fabric	91.67	100.00
1.1.2	Discontinuous urban fabric	87.50	100.00
1.2.1	Industrial or commercial units	90.00	81.82
1.2.2	Road and rail networks and associated land	90.00	90.00
1.2.3	Port areas	100.00	100.00
1.2.4	Airports	100.00	100.00
1.3.3	Construction sites	60.00	75.00
1.4.1	Green urban areas	77.78	77.78
1.4.2	Sport and leisure facilities	100.00	100.00
2.1.1	Non-irrigated arable land	77.78	63.64
2.2.1	Vineyards	100.00	71.43
2.2.2	Fruit trees and berry plantations	50.00	100.00
2.2.3	Olive groves	100.00	88.89
2.4.2	Complex cultivation patterns	80.00	57.14
2.4.3	Land principally occupied by agriculture	62.50	100.00
2.4.4	Agro-forestry areas	77.78	87.50
3.1.1	Broad-leaved forest	100.00	75.00
3.1.2	Coniferous forest	73.33	84.62
3.2.1	Natural grassland	100.00	50.00
3.2.2	Moors and heathland	66.67	100.00
3.2.3	Sclerophyllous vegetation	77.78	87.50
3.2.4	Transitional woodland shrub	77.78	87.50
5.1.1	Water courses	100.00	100.00
5.1.2	Water bodies	100.00	100.00
5.2.3	Sea and ocean	100.00	100.00

Table 7. Accuracy assessment results of Level 2 classes.

Class Code	Class Name	Producer's Accuracy (%)	User's Accuracy (%)
1.1	Urban fabric	90.63	100.00
1.2	Industrial, commercial and transport units	96.67	90.63
1.3	Mine, dump and construction sites	60.00	75.00
1.4	Artificial, non-agricultural vegetated areas	85.71	85.71
2.1	Arable land	80.00	80.00
2.2	Permanent crops	82.35	93.33
2.4	Heterogeneous agricultural areas	77.27	77.27
3.1	Forests	95.83	92.00
3.2	Shrub and/or herbaceous vegetation associations	86.21	80.65
5.1	Inland waters	100.00	100.00
5.2	Marine waters	100.00	100.00

Table 8. Accuracy assessment results of Level 1 classes.

Class Code	Class Name	Producer's Accuracy (%)	User's Accuracy (%)
1	Artificial surfaces	95.06	98.72
2	Agricultural areas	91.67	89.80
3	Forest and semi-natural areas	90.57	87.27
5	Water bodies	100.00	100.00

4.3. Landscape Metrics

Landscape metrics such as Number of Patch (NP), Edge Density (ED), Largest Patch Index (LPI), Euclidean Nearest Neighbor Distance (ENN), Splitting Index (SPLIT) and Aggregation Index (AI) metrics are useful indicators to assess the landscape configuration of related regions by using satellite based LC/LU maps. Landscape metric values change with classification levels; therefore, it is important to select the most appropriate classification level for a given area. Most of the studies conducted in the literature are based on Level 1 LC/LU class metrics, which could only provide very general information about the related region. Calculation of landscape metrics for Level 2 and Level 3 classification scheme leads to better understanding of the configuration and composition of the landscape. Tables 9–11 provide the class-level metric calculation results for each of the three different levels LC/LU maps.

Calculated metric values according to Level 1 classification show that Artificial Surfaces (1) is the dominant class in the study area (PLAND = 56.45). Although the NP value of the Artificial Surfaces (1) class is lower than the NP value of the Forest and semi-natural areas (3) class, the LPI, ED, TCA values are higher than the other classes. These values show that compact and related patches are concentrated on this class. ENN_AM, weighted with respect to the patch size, refers to the neighborhood relations of the patches in terms of proximity. According to this metric value, patches that belong to Artificial Surfaces (1) are in a close relation to each other. Also, SPLIT shows that the scattering in Artificial Surfaces (1) is low. Water bodies (5) was identified as the most passive class in terms of PD, NP and PLAND. Patches are too small and too far from each other to develop an edge-core relationship. This relationship is important as it presents the ability of a patch to interpret stability or change in time and it increases the meaning of shape metrics.

Even though it covers half of the surface compared to Artificial Surfaces (1) class, NP and PD values of the Forest and Semi-Natural Areas class (3) are quite high. When considered with the low level of LPI (6.68), these results suggest that this class is undergoing fragmentation over time. It can be also asserted that the Forest and Semi-Natural Areas (3) class, which has the highest LSI value, has a complex structure and formed by natural geometries with relatively natural lines with natural geometries form it. However, in terms of ED and TCA values, it is behind the Artificial Surfaces (1) class. In particular, TCA value is significantly lower (4039.79) when compared to Artificial Surfaces (15,050.68). This shows that patches of Forest and Semi-Natural Areas class (3), have started to lose their core properties and edge relations have been weakened.

Agricultural Areas class (2) was identified as the class with the highest class fragmentation in Level 1. Although value of NP is much higher compared to class Water Bodies (5), which covers the smallest surface in the study area, Agricultural Areas class (2) has the lowest LPI value (1.39). It also has the lowest value for TCA. These values show that the patches in Agricultural Areas (2) are small, undeveloped and according to the values of SPLIT and ENN_AM they are scattered and not connected.

Water bodies class (5), which covers the smallest area in the study region and also is the weakest class in terms of NP and PD has the closest LSI value (3.27) to the geometric form. ED values of patches that belong to this class were found to be particularly low (1.89). Patches are relatively far apart (ENN_AM = 24.96) and scattering level is very high (SPLIT = 266.54) though not as much as the Agricultural Areas class (2).

All of these evaluations of Level 1 class metrics show that, the patches of the Artificial Surfaces (1) in the landscape are compact, big, interrelated and they have mature edge-core relationships. Results conclude that Artificial Surfaces (1) dominate the landscape. Agricultural Areas (2) are scattered in the region as disjointed small units. Forests and Semi-Natural Areas (3) are suppressed by Artificial Surfaces (1) both in area and patch relation. Water Bodies (5) is the weakest class in terms of area, patch density and patch number. Geometry of the water surfaces in the area exhibits unnatural, geometrical forms. These results indicate that water sources in the area are insufficient in terms of ecology.

Table 9. Level 3 landscape metrics results.

Class Code	Class Name	Landscape Metrics											
		PLAND	NP	PD	LPI	TE	ED	LSI	SHAPE_AM	TCA	ENN_AM	SPLIT	AI
1.1.1	Continuous urban fabric	32.20	25,183.00	84.95	0.27	9,054,195.00	305.44	231.70	2.25	195.75	3.60	27,522.07	96.46
1.1.2	Discontinuous urban fabric	1.28	640.00	2.16	0.50	326,466.00	11.01	41.95	2.98	121.82	28.81	39,296.07	96.84
1.2.1	Industrial or commercial units	6.27	51.00	0.17	1.94	84,885.00	2.86	4.92	1.53	1561.90	723.14	1471.41	99.86
1.2.2	Road and rail networks and associated land	4.69	1358.00	4.58	3.95	8,950,512.00	301.94	600.10	515.82	21.32	6.23	638.43	75.89
1.2.3	Port areas	0.29	3.00	0.01	0.23	15,060.00	0.51	4.04	2.81	41.79	1991.98	178,093.85	99.51
1.2.4	Airports	2.56	1.00	0.00	2.56	17,238.00	0.58	1.56	1.56	691.38	-	1528.61	99.97
1.3.3	Construction sites	8.19	1623.00	5.48	0.30	1,909,116.00	64.40	96.88	3.83	278.50	15.23	21,613.86	97.08
1.4.1	Green urban areas	0.54	8.00	0.03	0.29	35,193.00	1.19	6.93	4.70	81.95	7362.11	67,896.71	99.30
1.4.2	Sport and leisure facilities	0.43	4.00	0.01	0.15	11,457.00	0.39	2.54	1.29	84.79	3020.44	201,152.89	99.80
2.1.1	Non-irrigated arable land	4.79	138.00	0.47	1.28	288,921.00	9.75	19.17	5.17	748.22	64.93	3563.10	99.28
2.2.1	Vineyards	0.10	15.00	0.05	0.05	12,297.00	0.41	5.59	2.10	7.52	332.31	3,414,936.14	98.74
2.2.2	Fruit trees and berry plantations	0.12	35.00	0.12	0.02	21,129.00	0.71	8.88	2.58	1.95	1171.44	6,866,804.18	98.01
2.2.3	Olive groves	1.01	50.00	0.17	0.29	125,280.00	4.23	18.11	4.08	58.96	242.77	86,627.64	98.51
2.3.1	Pastures	0.01	10.00	0.03	0.00	2112.00	0.07	3.16	1.47	0.00	50.80	345,408,656.43	98.04
2.4.2	Complex cultivation patterns	0.13	11.00	0.04	0.04	20,487.00	0.69	8.31	2.91	5.78	2971.33	3,923,394.11	98.21
2.4.3	Land principally occupied by agriculture	0.74	56.00	0.19	0.10	90,822.00	3.06	15.29	3.60	41.37	760.56	250,602.11	98.55
2.4.4	Agro-forestry areas	1.76	58.00	0.20	0.69	142,941.00	4.82	15.64	3.64	241.81	126.58	17,331.17	99.04
3.1.1	Broad-leaved forest	1.26	33.00	0.11	0.17	98,382.00	3.32	12.72	2.59	142.88	73.85	111,850.51	99.09
3.1.2	Coniferous forest	14.44	181.00	0.61	3.56	888,384.00	29.97	33.94	6.47	2122.29	5.92	529.59	99.24
3.2.1	Natural grassland	0.27	1.00	0.00	0.27	13,779.00	0.46	3.88	3.88	47.14	-	141,527.10	99.51
3.2.2	Moors and heathland	1.65	523.00	1.76	0.12	411,735.00	13.89	46.48	4.57	52.44	18.37	157,027.38	96.92
3.2.3	Sclerophyllous vegetation	1.23	160.00	0.54	0.68	143,505.00	4.84	18.79	3.41	174.44	3.24	21,037.03	98.60
3.2.4	Transitional woodland shrub	6.00	628.00	2.12	0.71	583,698.00	19.69	34.58	4.04	749.56	16.17	5439.46	98.81
3.3.3	Sparsely vegetated areas	0.10	15.00	0.05	0.06	20,730.00	0.70	9.36	2.67	8.32	269.26	2,485,926.97	97.73
5.1.1	Water courses	0.03	16.00	0.05	0.01	12,402.00	0.42	10.47	3.15	0.00	18.58	113,407,894.57	95.17
5.1.2	Water bodies	0.01	2.00	0.01	0.01	1545.00	0.05	2.15	1.59	0.00	21,949.51	134,859,989.85	99.03
5.2.3	Sea and ocean	6.12	1.00	0.00	6.12	42,405.00	1.43	2.49	2.49	1665.32	-	266.93	99.95

Table 10. Level 2 landscape metrics results.

Class Code	Class Name	Landscape Metrics											
		PLAND	NP	PD	LPI	TE	ED	LSI	SHAPE_AM	TCA	ENN_AM	SPLIT	AI
1.1	Urban fabric	33.47	25,809.00	87.07	0.50	9,378,078.00	316.37	235.36	2.28	317.63	3.65	16,106.63	96.47
1.2	Industrial, commercial and transport units	13.82	1189.00	4.01	13.14	9,011,094.00	303.99	352.03	324.49	2372.95	3.83	57.91	91.77
1.3	Mine, dump and construction sites	0.54	8.00	0.03	0.29	35,193.00	1.19	6.93	4.70	81.95	7362.11	67,896.71	99.30
1.4	Artificial, non-agricultural vegetated areas	8.62	1621.00	5.47	0.30	1,917,036.00	64.67	94.83	3.73	364.24	16.25	19,268.59	97.21
2.1	Arable land	4.79	138.00	0.47	1.28	288,921.00	9.75	19.17	5.17	748.22	64.93	3563.10	99.28
2.2	Permanent crops	1.23	82.00	0.28	0.29	153,711.00	5.19	20.12	3.98	72.96	172.43	79,004.61	98.50
2.3	Pastures	0.01	10.00	0.03	0.00	2112.00	0.07	3.16	1.47	0.00	50.80	345,408,656.43	98.04
2.4	Heterogeneous agricultural areas	2.63	119.00	0.40	0.69	247,434.00	8.35	22.14	3.64	294.39	128.78	15,882.30	98.86
3.1	Forests	15.70	178.00	0.60	4.79	864,522.00	29.16	31.68	6.63	2397.37	5.66	341.21	99.33
3.2	Shrub and/or herbaceous vegetation associations	9.15	1297.00	4.38	0.93	1,133,607.00	38.24	54.40	4.11	1041.76	14.41	3547.41	98.46
3.3	Open spaces with little or no vegetation	0.10	15.00	0.05	0.06	20,730.00	0.70	9.36	2.67	8.32	269.26	2,485,926.97	97.73
5.1	Inland waters	0.04	18.00	0.06	0.01	13,947.00	0.47	10.06	2.73	0.00	3622.90	61,603,568.04	96.05
5.2	Marine waters	6.12	1.00	0.00	6.12	42,405.00	1.43	2.49	2.49	1665.32	-	266.93	99.95

Table 11. Level 1 landscape metrics results.

Class Code	Class Name	Landscape Metrics											
		PLAND	NP	PD	LPI	TE	ED	LSI	SHAPE_AM	TCA	ENN_AM	SPLIT	AI
1	Artificial surfaces	56.45	953.00	3.21	55.43	1,517,148.00	51.18	29.33	19.89	15,050.68	3.31	3.26	99.67
2	Agricultural areas	8.66	138.00	0.47	1.39	537,900.00	18.15	26.54	4.87	1310.37	42.66	1960.96	99.24
3	Forest and seminatural areas	24.96	1148.00	3.87	6.68	1,422,033.00	47.97	41.33	6.20	4039.79	6.53	177.95	99.30
5	Water bodies	6.16	18.00	0.06	6.13	55,929.00	1.89	3.27	2.58	1665.32	24.96	266.54	99.92

Analysis of Level 2 and Level 3 class metrics show that Urban Fabric (11) and Continuous Urban Fabric (111) classes are dominant classes at their respective levels.

At Level 2, Urban Fabric (11) which is dominant in terms of NP, PD, PLAND and ED metrics, is behind Industrial, Commercial, and Transport Unit (12) class in terms of TCA, LSI and LPI metrics. In terms of patch and percentage of landscape Urban Fabric (11), in terms of shape and dominant patch class Commercial, and Transport Unit (12) classes stand out. It had been determined that, the dominant class among the Agricultural Areas classes (21, 22, 23 and 24) is Arable Land (21). The values of PLAND, PD, NP and LPI metrics of this class are relatively higher. Heterogeneous Agricultural Areas (24) and Permanent Crops (22) are the classes that enables the general Agricultural Areas of Level 1 to have a heterogeneous form because of their high LSI values. On the other hand, the most disjointed sub-category in terms of the distance between the patches is Permanent Crops (22), while SPLIT shows that the most scattered is Pastures (23).

Assessment of Level 3 metric results shows that, classes that dominate Level 3 in terms of PLAND and LPI are forest classes (311, 312 . . . , 333). Forest classes are in large units (LPI = 4.79) with centralized area development (TCA = 2397.37). Coniferous Forest (312) leads the forest classes in terms of both PLAND and LPI, and it also has developed edge-core relations (TCA and ED). Transitional Woodland Shrub (324) has the highest patch values (PLAND, PD, NP and LPI). LSI metric of class Moors and Heathland (322) shows that it is the most natural class among others. The interpretation that applies to the whole forest classes at Level 3 is, they have the largest fragmentation (SPLIT = 157,027.38) and the longest average distance between patches (ENN_AM = 18.37). Another notable class at Level 3 is the Olive Grooves class (223), which increases overall LSI value of Permanent Crops. These results revealed that, this class is in a more heterogeneous form than the other sub classes of Permanent Crops.

An overall evaluation of Level 2 and Level 3 metrics shows that, according to PLAND, NP and PD metrics, Level 3 class Continuous Urban Fabric (111) induce the Level 2 class Urban Fabric (11) which means class 111 increases the metric values of class 11. Similarly, Road and Rail Networks and Associated Land class (122) induce Shape Metrics and LPI of Industrial, Commercial and Transport class (12).

It is interesting that the class which causes the patch shape to be more indented (LSI = 600.10) is essentially a linear class. This can be explained by the fact that the Urban Fabric (11) class has a much higher SPLIT ratio than Industrial, Commercial and Transport units (12) classes. A large number of patches of class Urban Fabric (11) are scattered throughout landscape, while class Industrial, Commercial and Transport class (12), which has the lowest SPLIT ratio (57.91), forming more complete and uniform patches (LPI = 13.14) which means that shape irregularities and patch shape has become more heterogeneous. On the other hand, Construction Sites class (131) induces the fragmentation (SPLIT) of class Mine, Dump and Construction Sites class (13) in Level 2. In this class, which stands out with a very low PLAND (0.54), a few patches (NP = 8) are located far away from each other and scattered within the landscape.

Discussion of spatial metrics and their possible contribution to landscape ecology should also address the issue of what these measures are to be compared against [54]. The findings of this research showed that selected metric sets are successful for revealing landscape characteristics at different levels of classification. Using detailed class definitions while keeping the scale level constant, enabled a more comprehensive interpretation of landscape characteristics. Additionally, performing these observations based on quantitative data is a valuable contribution for landscape analysis and evaluation.

5. Conclusions

High-resolution urban LC/LU maps are very important data sources for landscape and city planning, management and decision making progresses, considering the population growth in metropolitan cities, economic and industrial developments and increasing urbanization. Therefore, it is important to create up-to-date, thematically rich LC/LU maps using high-resolution satellite images and geographic object based image analysis.

The bottom-to-top (from Level 3 to Level 1) approach is more feasible than top-to-bottom approach and accurate for the creation of three different level LC/LU maps. Multi-temporal data from different seasons are needed to accurately identify agriculture and vegetation related thematic classes. Texture based Haralick features are useful for the identification of some permanent crops such as Vineyards when these crops have a regular planting pattern such as linear, gridwise. Classification accuracy values of different classes were adequate for this research, however very high spatial resolution (1 m or better) is needed to accurately identify Fruit Trees and Berry Plantations considering their lower accuracy values among all thematic classes. Open source geo-information could be a good data source to enhance the results of GEOBIA; however, accuracy and compliancy of these data sets have to be verified before integrating them to classification procedure.

Evaluation of the same set of landscape metrics calculated for each level LC/LU maps proved that meaningful interpretations based on cause and effect relationships could be achieved with increased thematic detail. Calculation of these metrics (PD, NP, PLAND, LPI, TE, ED, LSI, ...) used in the study has been effective for interpreting the spatial process of each LC/LU class at three different levels. The LPI and PLAND metrics determine the effectiveness of the classes at different levels in the landscape. Fragmentation of the related class could be inferred from the evaluation of NP, PD, ENN, SPLIT and AI indices together. ED, TCA and LSI provided information about the qualifications of the units that make up that class. Interpretations made in this way, with the help of metric groups, provide information on the locations of the classes on the landscape, structure of their quality, and the levels of fragmentation at each level. This interpretation approach can provide a more intensive cause-effect relationship-oriented assessment as the class level increases. It also helps clarify the landscape character more precisely, and to evaluate the spatial processes in the landscape in more detail. The 1st Level classification explanations are usually more general. The possibility of such a detailed Patch Mosaic Model (PMM) based landscape evaluation by using 2nd and 3rd Level classification has become one of the most important outputs of this research. It is important to find methods that will help to reveal the landscape character in landscape analysis and evaluations. Moreover, landscape metrics based evaluations are quantitative analysis and complex structured landscapes could be easily understandable with the aid of these quantitative information.

Author Contributions: Conceptualization, G.A.A.; Formal Analysis, I.Y.A. and G.A.A.; Funding Acquisition, E.S.; Methodology, E.S., R.H.T. and G.A.A.; Project Administration, E.S.; Software, R.H.T., B.S. and I.Y.A.; Supervision, E.S.; Validation, B.S.; Visualization, R.H.T. and B.S.; Writing–Original Draft, E.S., R.H.T., B.S. and I.Y.A.; Writing–Review & Editing, E.S., I.Y.A. and G.A.A.

Funding: This research was founded by the Young Scientists Award Program of Turkish Academy of Sciences [TUBA–GEBIP], Istanbul Technical University Department of Scientific Research Projects (ITU–BAP) for supporting project [MGA-2017-40936].

Acknowledgments: The authors acknowledge the support of "Istanbul Technical University—Application and Research Center for Satellite Communications and Remote Sensing (ITU-CSCRS)" by providing SPOT 7 and Pleiades 1B satellite imagesand General Command of Mapping for providing topographical maps. We would like to thank three anonymous reviewers; their comments have helped us improve our manuscript considerably.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Carlson, T.N.; Arthur, S.T. The impact of land use—Land cover changes due to urbanization on surface microclimate and hydrology: A satellite perspective. *Glob. Planet. Chang.* **2000**, *25*, 49–65. [CrossRef]
2. Pauleit, S.; Duhme, F. Assessing the environmental performance of land cover types for urban planning. *Landsc. Urban Plan.* **2000**, *52*, 1–20. [CrossRef]
3. Pauleit, S.; Ennos, R.; Golding, Y. Modeling the environmental impacts of urban land use and land cover change—A study in Merseyside, UK. *Landsc. Urban Plan.* **2005**, *71*, 295–310. [CrossRef]
4. Giri, C.P. *Remote Sensing of Land Use and Land Cover Principles and Applications*, 1st ed.; CRC Press: Boca Raton, FL, USA, 2012; ISBN 978-1-420-07075-0.

5. Alp, G. Güncel Arazi Örtüsü/Kullanım Haritalarının Doğrudan Ve Dolaylı Yaklaşımlar Ile Üretilmesi. Master's Thesis, Istanbul Technical University, Istanbul, Turkey, 2015.
6. Topaloglu, R.H.; Sertel, E.; Musaoglu, N. Assessment of classification accuracies of Sentinel-2 and Landsat-8 data for land cover/use mapping. In Proceedings of the XXIII ISPRS Congress International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, Prague, Czech Republic, 12–19 July 2016.
7. Goodin, D.G.; Anibas, K.L.; Bezymennyi, M. Mapping land cover and land use from object-based classification: An example from a complex agricultural landscape. *Int. J. Remote Sens.* **2015**, *36*, 4702–4723. [CrossRef]
8. Vizzari, M.; Hilal, M.; Sigura, M.; Antognelli, S.; Joly, D. Urban-rural-natural gradient analysis with CORINE data: An application to the metropolitan France. *Landsc. Urban Plan.* **2018**, *171*, 18–29. [CrossRef]
9. Kosztra, B.; Büttner, G.; Hazeu, G.; Arnold, S. Updated CLC Illustrated Nomenclature Guidelines. Final Report by European Environmental Agency. Available online: https://land.copernicus.eu/ (accessed on 28 March 2018).
10. Brown, N.; Gerard, F.; Fuller, R. Mapping of land use classes within the CORINE land cover map of Great Britain. *Cartogr. J.* **2002**, *39*, 5–14. [CrossRef]
11. Toure, S.; Stow, D.A.; Shih, H.; Weeks, J.; Lopéz-Carr, D. Land cover/land use change analysis using multi-spatial resolution data and object-based image analysis. *Remote Sens. Environ.* **2018**, *210*, 259–268. [CrossRef]
12. Alganci, U.; Sertel, E.; Kaya, S. Determination of the olive trees with object based classification of Pleiades satellite image. *Int. J. Environ. Geoinform.* **2018**, *5*, 132–139. [CrossRef]
13. Sertel, E.; Akay, S.S. High resolution mapping of urban areas using SPOT-5 images and ancillary data. *Int. J. Environ. Geoinform.* **2015**, *2*, 63–76. [CrossRef]
14. Alganci, U.; Sertel, E.; Ozdogan, M.; Ormeci, C. Parcel-level identification of crop types using different classification algorithms and multi-resolution imagery in Southeastern Turkey. *Photogramm. Eng. Remote Sens.* **2013**, *79*, 1053–1065. [CrossRef]
15. Weng, Q. Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. *Remote Sens. Environ.* **2012**, *117*, 34–49. [CrossRef]
16. Blaschke, T. Object based image analysis for remote sensing. *ISPRS J. Photogramm. Remote Sens.* **2010**, *65*, 2–16. [CrossRef]
17. Varga, O.G.; Szabó, S.; Túri, Z. Efficiency assessments of GEOBIA in land cover analysis, NE Hungary. *Bull. Environ. Sci. Res.* **2014**, *3*, 1–9.
18. Myint, S.W.; Gober, P.; Brazel, A.; Grossman-Clarke, S.; Weng, Q. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. *Remote Sens. Environ.* **2011**, *115*, 1145–1161. [CrossRef]
19. Wentz, E.; Zhao, Q. Assessing validation methods for building identification and extraction. In Proceedings of the Joint Urban Remote Sensing Event (JURSE), Lausanne, Switzerland, 30 March–1 April 2015.
20. Ormeci, C.; Alganci, U.; Sertel, E. Identification of crop areas Using SPOT–5 data. In Proceedings of the FIG Congress, Sydney, Australia, 11–16 April 2010.
21. Blaschke, T.; Hay, G.J.; Kelly, M.; Lang, S.; Hofmann, P.; Addink, E.; Feitosa, R.Q.; van der Meer, F.; van der Werff, H.; van Coillie, F.; et al. Geographic object-based image analysis—Towards a new paradigm. *ISPRS J. Photogramm. Remote Sens.* **2014**, *87*, 180–191. [CrossRef] [PubMed]
22. Lillesand, T.M.; Kiefer, R.W.; Chipman, J.W. *Remote Sensing and Image Interpretation*, 7th ed.; John Wiley & Sons: New York, NY, USA, 2008; ISBN 978-1-118-34328-9.
23. Sertel, E.; Alganci, U. Comparison of pixel and object-based classification for burned area mapping using SPOT-6 images. *Geomat. Nat. Hazards Risk* **2016**, *7*, 1198–1206. [CrossRef]
24. Zhou, W. An object-based approach for urban land cover classification: Integrating LIDAR height and intensity data. *IEEE Geosci. Remote Sens. Lett.* **2013**, *10*, 928–931. [CrossRef]
25. Li, X.; Myint, S.W.; Zhang, Y.; Galletti, C.; Zhang, X.; Turner, B.L. Object-based land-cover classification for metropolitan Phoenix, Arizona, using aerial photography. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *33*, 321–330. [CrossRef]
26. McGarigal, K. Landscape pattern metrics. In *Encyclopedia of Environmetrics*, 2nd ed.; El-Shaarawi, A.H., Piegorsch, W.W., Eds.; Wiley: Chichester, UK, 2012; Volume 6, ISBN 978-0-470-05733-9.

27. Uuemaa, E.; Mander, Ü.; Marja, R. Trends in the use of landscape spatial metrics as landscape indicators: A review. *Ecol. Indic.* **2013**, *28*, 100–106. [CrossRef]
28. Forman, R.; Godron, M. *Landscape Ecology*; John Wiley and Sons: New York, NY, USA, 1986; ISBN 0471870374.
29. Forman, R.T.T. *Land Mosaics: The Ecology of Landscapes and Regions*, 1st ed.; Cambridge University Press: Cambridge, UK, 1995; ISBN 978-0-521-479980-6 (PB).
30. Jaeger, J.A.G. Landscape division, splitting index, and effective mesh size: New measures of landscape fragmentation. *Landsc. Ecol.* **2000**, *15*, 115–130. [CrossRef]
31. Turner, M.G.; Gardner, R.H.; O'Neill, R.V. *Landscape Ecology in Theory and Practice: Pattern and Process*; Springer: New York, NY, USA, 2001; ISBN 978-0387951225.
32. Leitão, H.C.G.; Stolfi, J. A multiscale method for the reassembly of two-dimensional fragmented objects. *IEEE Trans. Pattern Anal. Mach. Intell.* **2002**, *24*, 1239–1251. [CrossRef]
33. Frazier, A.E. Landscape metrics: Past progress and future directions. *Curr. Landsc. Ecol. Rep.* **2017**, *2*, 63–72. [CrossRef]
34. Kedron, P.J.; Frazier, A.E.; Ovando-Montejo, G.A.; Wang, J. Surface metrics for landscape ecology: A comparison of landscape models across ecoregions and scales. *Landsc. Ecol.* **2018**, 1–16. [CrossRef]
35. McGarigal, K.; Cushman, S.A.; Neel, M.C.; Ene, E. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst, USA. 2002. Available online: http://www.umass.edu/landeco/research/fragstats/fragstats.html (accessed on 16 April 2018).
36. Cushman, S.A.; McGarigal, K.; McKelvey, K.S.; Vojta, C.D.; Regan, C.M. Chapter 6. Landscape Analysis for Habitat Monitoring. In *A Technical Guide for Monitoring Wildlife Habitat*; U.S. Department of Agriculture, Forest Service: Washington, DC, USA, 2013. Available online: https://www.fs.usda.gov/treesearch/pubs/45223 (accessed on 24 April 2018).
37. McGarigal, K.; Tagil, S.; Cushman, S.A. Surface metrics: An alternative to patch metrics for the quantification of landscape structure. *Landsc. Ecol.* **2009**, *24*, 433–450. [CrossRef]
38. Plexida, S.G.; Sfougaris, A.I.; Ispikoudis, I.P.; Papanastasis, V.P. Selecting landscape metrics as indicators of spatial heterogeneity—A comparison among Greek landscapes. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *26*, 26–35. [CrossRef]
39. Turkish Statistical Institute (TUIK). Available online: www.tuik.gov.tr (accessed on 2 April 2018).
40. AIRBUS Defence and Space. Available online: https://www.intelligence-airbusds.com/en/147-spot-6-7-satellite-imagery (accessed on 10 April 2018).
41. Definiens. *Definiens© Developer 8 Reference Book*; Definiens AG: Munich, Germany, 2009.
42. Belgiu, M.; Drauţ, L.; Strobl, J. Quantitative evaluation of variations in rule-based classifications of land cover in urban neighborhoods using WorldView-2 imagery. *ISPRS J. Photogramm. Remote Sens.* **2014**, *87*, 205–215. [CrossRef] [PubMed]
43. Hecht, R.; Kunze, C.; Hahmann, S. Measuring completeness of building footprints in OpenStreetMap over space and time. *ISPRS Int. J. Geo-Inf.* **2013**, *2*, 1066–1091. [CrossRef]
44. eCognition. *Trimble eCognition© Developer 9.3 for Windows Operating System Reference Book*; Trimble: Germany GmbH: Munich, Germany, 2017.
45. Mcfeeters, S.K. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *Int. J. Remote Sens.* **1996**, *17*, 1425–1432. [CrossRef]
46. Turner, M.G.; O'Neill, R.V.; Gardner, R.H.; Milne, B.T. Effects of changing spatial scale on the analysis of landscape pattern. *Landsc. Ecol.* **1989**, *3*, 153–162. [CrossRef]
47. Cushman, S.A.; McGarigal, K.; Neel, M.C. Parsimony in landscape metrics: Strength, universality, and consistency. *Ecol. Indic.* **2008**, *8*, 691–703. [CrossRef]
48. Wu, J. Effects of changing scale on landscape pattern analysis: Scaling relations. *Landsc. Ecol.* **2004**, *19*, 125–138. [CrossRef]
49. Brady, M.; Kellermann, K. *Methodology for Assessing the Regional Environmental Impacts of Decoupling: A Focus on Landscape Values*; SLI-Working Paper; Swedish Institute for Food and Agricultural Economics: Lund, Sweden, 2005; Volume 2.
50. Tischendorf, L. Can landscape indices predict ecological processes consistently? *Landsc. Ecol.* **2001**, *16*, 235–254. [CrossRef]

51. Szabó, S.; Csorba, P.; Szilassi, P. Tools for landscape ecological planning-scale, and aggregation sensitivity of the contagion type landscape metric indices. *Carpathian J. Earth Environ. Sci.* **2012**, *7*, 127–136.
52. Papadimitriou, F. Modelling spatial landscape complexity using the Levenshtein Algorithm. *Ecol. Inform.* **2009**, *4*, 48–55. [CrossRef]
53. McGarigal, K.; Marks, B.J. *FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure*; General Technical Report; U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: Portland, OR, USA, 1995.
54. Dramstad, W.E. Spatial metrics—Useful indicators for society or mainly fun tools for landscape ecologists? *Norsk Geografisk Tidsskrift* **2009**, *63*, 246–254. [CrossRef]