Investigation of The Relationships Between Image Spatial Resolution And Landscape Metrics

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Abstract

Land Use and Land Cover (LULC) maps derived from satellite images are a significant source of geo-information to better understand the current status of landscapes, to analyze the landscape changes, and to develop sustainable decisions for landscape and urban planning. Since the spectral and spatial resolution of satellite images directly impact the LULC classes to be identified and the accuracy of the classification, these will also affect the values of calculated landscape metrics.

This research aims to propose the most appropriate functions and features to obtain highly accurate thematically extensive LULC classification results from multi-resolution satellite images and to investigate how the change in spatial resolution of satellite images would affect the landscape metrics values and landscape pattern analysis

Sentinel-2, SPOT-7, Pleiades, and Worldview-4 images with respective 10 m, 1.5 m, 0.5 m, and 0.3 m spatial resolution were classified using Geographic Object-Based Image Analysis techniques to create multi-scale LULC maps with the overall classification accuracy values of 66.05%, 85.00%, 91.79%, and 95.71%, respectively. Patch Density, Total Area, Largest Patch Index, Shape Index, Euclidian Nearest Neighbor distance, Aggregation Index, and Shannon's Diversity Index metrics were found to be most appropriate metrics to analyze the impact of spatial resolution on landscape metrics calculations considering the ability of these metrics to capture the spatial details, spatial arrangement, spatial distribution and complexity of shapes of landscape and classes.

Landscape metrics results obtained from different LULC maps were compared to analyze the effects of image spatial resolution on different landscape metrics.

Introduction

Land characteristics of the Earth have been changing due to anthropogenic activities and natural processes. The rapid increase in the population, migration, industrialization, and the changes in socioeconomic activities take a vital role in the changes that have been caused by human-induced effects (Mahmood et al.,2010). Therefore, timely, accurate, and reliable mapping of the spatial distribution of land characteristics and its temporal change is out most important for land change-related studies, sustainability research, and global environmental change research (Liu & Yang, 2015). Monitoring and acquiring information on the changes of land use and land cover (LULC) especially for urban areas, is critical for landscape research such as urban expansion, urban planning, and management (Ma et al.,2016).

LULC maps are a significant source of geo-information to better understand the current status of landscapes, to analyze the landscape changes, and to develop sustainable decisions for landscape and urban planning. While representing various kinds of physical and purposeful characteristics of an area of interest, LULC maps also provide important geoinformation for the spatial distribution of different classes and their changes in time. Accurate and timely LULC maps are essential to monitoring land changes in

urban areas and support decision making and resource management processes (Lambin et al., 2001; Turner et al., 2007; Liu & Yang, 2015).).

Remote sensing images are widely used to produce LULC maps and they provide a cost-effective alternative to the ground-based survey (Fenta et al., 2017). With the recent developments in satellite technology, accessibility to high-resolution satellite images have become easier. High and very high spatial resolution satellite images can provide very detailed information about the earth, land biophysical characteristics, and its usage. They are also significantly more advantageous for applications such as urban mapping, analysis of spatial/temporal changes in urban cities (Sertel et al, 2018).

Image analysis techniques have shifted from pixel-based image analysis (PBIA) to geographic object-based image analysis (GEOBIA) because of the increment of finer remote sensing images (Blaschke, 2010; Liu et al.,2020). Generation of LULC maps of urban areas have become quite successful with GEOBA techniques. There are various advantages of the GEOBIA approach, for example having no “salt and pepper” effect, being able to have a large set of features (e.g., image objects), being able to use a large set of features, etc., which leads to a higher classification accuracy (Liu & Xia, 2010). Additionally, it provides the utilization of high degree information, a high degree of data integration, and less manual editing (Gu et al., 2017). On the other hand, GEOBIA makes it easy to integrate satellite and different geospatial information data. Open sources data such as OpenStreetMap, European Environmental Agency Geodata, thematic maps, and Wikimapia, can be implemented to the object-based classification for improved results (Sertel et al., 2018).

One of the most important fields of application of LULC maps is the analysis of patterns in the landscape, which are possible with landscape metrics. Landscape metrics have been acknowledged as an effective tool for analysis and assessment of environmental impacts, landscape changes, and urban planning. Integration of spatial metrics with remote sensing techniques can alleviate the investigation of different structural dimensions and changes on the land (Uuemaa et al., 2009; Peng et al.,2010). Describing spatiotemporal patterns of natural and man-made environments, are possible by using landscape metrics as they quantify distinct spatial features of patches, classes of patches, or a complete landscape mosaic (Liu et al., 2020).

Landscape metrics can be observed at the patch, class (patch type), and landscape level. Landscape metrics are determined for particular patches that represent distinct areas of similar traits. All patches of a particular type, which are LULC classes for this study, are used to calculate the class-level landscape metrics. The combination of all patch and class types in an area of interest is named landscape-level metrics (Turner et al. 2001; McGarigal, 2012). Some of the metrics assess landscape structure, while others quantify landscape configuration at the class and landscape level. It is important to understand each metric and which landscape pattern it quantifies as the landscape composition and configuration have a crucial effect on ecological processes. Thus, the selection of the metric groups that are going to be used in a study is critical (McGarigal, 2012).

Many landscape metrics used to quantify landscape structure are highly sensitive to grain therefore spatial resolution. The selection of the spatial resolution is also important to appropriately represent the ecological phenomenon (Cushman & McGarigal, 2008). Ecological processes occur on different scales. Change in spatial resolution impacts the final LULC maps since identifiable LULC classes, their spatial distribution and land properties change with the spatial resolution resulted in changes in landscape metrics values (Lenchner & Rhodes, 2016).

The increasing spatial resolution resulted in the identification of more land types and this will be useful for ecological perspective and lead to detailed characterization of spatial patterns. Therefore, it is important to estimate the effect of resolution according to the scope of the study to determine the appropriate scale of analysis (McGarigal et al., 2005; Liang et al., 2013).

The main purpose of this study is to investigate the impacts of varying spatial resolution on landscape metrics values. Sentinel-2, SPOT-7, PHR, and WV-4 images with 10 m, 1.5 m, 0.5 m, and 0.3 m spatial resolution, respectively were used to create LULC maps. Four different LULC maps having thematically extensive land classes were created for the selected study area using GEOBIA techniques.

We addressed the below scientific questions in this research:

- Which features and functions are the most appropriate to obtain highly accurate thematically extensive LULC classification results from multi-resolution satellite images?
- How the accuracy and spatial distribution of LULC classes are changing with respect to the image spatial resolution?
- Which landscape metrics are better representing the impact of spatial resolution on the characterization of the landscape?
- How the increase in the spatial resolution of satellite images (from 30 cm to 10 m) is affecting the landscape metrics values and landscape pattern analysis?

Study Area And Data

2.1. Study Area

The study area is located in Izmir metropolitan city, in Turkey (Fig. 1). Izmir is one of the most important metropolitan cities of Turkey with its diverse landscape, hosting various historical and cultural resources and tourism-oriented infrastructure. It is the 3rd most populated city in the country and possesses a variety of transportation, public and industrial infrastructures such as port, airport, exhibition centers, universities, natural parks, and industry areas (URL-1 and URL-2)

The selected study area covers approximately 286 km² and has various kinds of LULC classes such as Urban Fabric, Industrial Areas, Airports, Port Areas, and Agricultural Fields.

2.2. Data

Four different satellite sensor data namely Sentinel, SPOT, PHR, and WV-4 were used in this research to analyze the impact of spatial resolution on LULC mapping accuracy and landscape metrics calculations. Image acquisition times and the main characteristic of the satellites are provided in Table 1.

Table 1
Properties used Satellite images.

Satellite	Image Acquisition Date	Spatial Resolution	Spectral Bands
Sentinel-2A	28.01.2018/07.07.2018	10 m	Aerosol detection, Blue, Green, Red, Vegetation, Near-Infrared, Water vapor, Cirrus, Snow/ice
SPOT-7	08.12.2016/24.04.2017	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)
Pleiades	27.01.2018	Panchromatic: 0.5 m	Panchromatic (0.47–0.83 μ m), Blue (0.43–0.55 μ m), Green (0.50–0.62 μ m), Red, Near-Infrared (= 0.74–0.94 μ m)
Worldview-4	04.03.2019	Panchromatic: 0.3 m	Panchromatic (450–800 nm), Red (655–690 nm), Green (510–580 nm), Blue (450–510 nm), Near-Infrared (780–920 nm)

Multi-temporal Sentinel-2 and SPOT-7 images were used to increase the capacity to detect temporal patterns caused by different seasonal characteristics. Temporal information makes it possible to detect LULC classes such as agricultural lands easier and can be used effectively to separate spectrally similar classes.

Additionally, Wikimapia and Open Street Map (OSM) were used as vector thematic layers to determine road and especially land use classes. Moreover, online maps such as Yandex, Here Maps, etc. were also used for visual interpretation of the study area to assist the classification procedure.

Methods

As the first step, each satellite image obtained from different satellites was pre-processed and then GEOBIA was applied by using several indices and features to create LULC maps. Afterward, an area-based accuracy assessment was carried out to determine the accuracy of different maps. At the last step, landscape metrics were calculated and the results were evaluated.

A classification system determined with Urban Atlas and 2nd level CORINE nomenclatures was used to classify different spatial resolution images covering a pilot district located in Izmir city. High complexity and detail were needed in class definitions to most accurately define the LULC in the study area. Totally 23 classes shown in Fig. 2 are used in this research.

3.1. Image Preprocessing

Firstly, image digital number values were converted into the top of atmosphere (ToA) reflectance values. Then, the geometric correction of the WV-4 image (30 cm spatial resolution) was conducted using highly accurate ground control points obtained from 1/5000 scale ortho-photos. PHR, SPOT, and Sentinel images were geometrically corrected by using ground control points collected from ortho-rectified WV-4 images. All of the satellite images were defined in the same projection system and datum and complied with each other in a sub-pixel scale. As the last step, different dated SPOT and Sentinel images were layer stacked.

3 2. Classification

In this study, the GEOBIA method was performed by following two steps. The first step is segmentation and the widely used multi-resolution segmentation is used to create image objects by using scale, shape, and compactness parameters. It is important to define appropriate scale, shape, color, compactness, and smoothness parameter values for the extraction of different LULC classes (Definiens, 2009; Alganci et al., 2013). The most appropriate multi-resolution segmentation parameters created for different images are given in Figure 3 in dark green boxes with the representative font color of each image such as yellow for Sentinel, green for SPOT, etc.

The second step of the GEOBIA method is the classification and the resulting product of this step is a LULC map which is generated by identifying rule sets (Varga et al., 2014). The suitable indices and functions that were used to create rule sets of each image classification are shown in purple boxes in Figure 3. A detailed description of these features could be found in Sertel & Akay, 2015, Sertel et al., 2018, and eCognition© Developer – Reference Book. Figure 3 illustrates the classification steps, segmentation parameters, features, and functions that were used for the rule set creation of different images and the used vector data for different classes. A similar classification scheme was followed for each image, although some functions, features, and thresholds change according to the different image characteristics. As GEOBIA requires a particular approach when deciding segmentation parameters and values in class identifiers; the thresholds, functions, features vary for each distinct class in every image. Multi-temporal Sentinel-2 and SPOT images were layer-stacked to better identify vegetated and agricultural areas by considering seasonal conditions. Whereas, spatial resolution superiority of VHR images provides enough spatial detail to distinguish unique agricultural and vegetation patterns by using only one date image. Classifications were proceeded class by class starting with water. After the classification of each class or class group, new multiresolution segmentation with different parameters was applied to detect the remaining classes.

For each image, firstly 51000 and 52000 water classes were classified as they could be easily identified based on their spectral patterns by using the Normalized Difference Water Index (NDWI). Area and Coordinate features are also used for water classification (Figure 3). The classes with land use information and that have the support of open-source vector data were classified afterward. By using OSM vector data, road-related classes namely 12210, 12220, and 12230 were classified. Minimum overlap with OSM vectors is used, along with Asymmetry, Length/Width, and Brightness features (Figure

3). Then, after applying segmentation to unclassified areas, natural and impervious surfaces were determined.

As the next step, Wikimapia vector data and Normalized Difference Vegetation Index (NDVI) were used for the identification of natural and man-made LULC classes. Minimum overlap with vector layers, Rectangular Fit, Coordinate, Shape Index, Brightness, and NDVI features were used to recognize some land-use classes which are 12300, 12400, 13300, 14100, and 14200. Urban areas were also masked in this step to prevent the mixing of low-density urban sub-classes with natural vegetation and similar classes such as 32000.

Natural vegetation and agriculture classes were determined by using NDVI, Area, Brightness, Coordinate, Standard Deviation features, and Haralick textures as Grey Level Co-occurrence Matrix (GLCM) Homogeneity, GLCM Dissimilarity, GLCM Contrast, and GLCM mean; agriculture classes that are 21000, 22000, 23000, 24000 were classified (Figure 3). In the next step, Forests, Shrub and/or Herbaceous Vegetation Associations, and Open Spaces with Little or No Vegetation classes were determined with higher scale parameters and classified.

At the last step, Urban areas were classified using different NDVI ranges for different density urban sub-classes (11100, 11210, 11220, 11230, and 11240). After creating LULC maps, accuracy assessment was conducted by using randomly generated 248 grids.

3.3. Landscape Metrics

The purpose of landscape pattern analysis is to characterize the patch mosaic's components and spatial configuration. There are several landscape metrics generated for this purpose. Patches are constituents of thematic maps whereas, in most applications, patches are determined by ignoring the patch heterogeneity (McGarigal, 2002).

Landscape metrics focus on the spatial character and distribution of patches. Although, they have very few basic spatial characteristics, such as size, length, shape. Patch clusters show different aggregation features depending on if the aggregation would happen in single or multiple classes. Usually, landscape metrics are defined in three levels, which are: Patch level, class level, and landscape level. All of the landscape metrics represent some features of landscape patterns. Although, before any of these metrics are taken into account, the user should first define the extent, units, and the whole landscape structure including the patches that generate it. The data format being raster or vector, also the scale and its extent may have effects on many metric values (Aksu, 2012).

In this study, different scale LULC maps of the same region created from multi-resolution satellite images were interpreted using landscape metrics. In this context, we investigated how the change in spatial resolution of satellite images (from 30 cm to 10 m) would affect the landscape metrics values and landscape pattern analysis. The landscape metrics are used to quantify the quality of different LULC

maps. Landscape and class level metrics are selected from the universal and consistent landscape metrics defined by Cushman et al., 2008.

According to McGarigal and Marks, (1995), values of patch size and the number of patches provide significant information about the quality of the landscape and classes, as the patches are the building blocks of landscapes. It is expected to have higher spatial details with the improvement of spatial resolution; therefore, the change in Patch Density (PD) with the relationship to Total Area (CA) and Largest Patch Index (LPI) is investigated. Landscape Shape Index (LSI) is used to define the complexity of shapes of landscape and classes. Euclidian Nearest Neighbor distance (ENN) is one of the simplest yet useful metrics that are used to measure isolation levels of patches (McGarigal, 2015). This metric is closely related to the spatial distribution (Leitao et al., 2006). By using its area-weighted average value (ENN_AM), it was examined how isolated the patches were in the class and landscape, depending on the differences in resolution. Thus, we interpreted how the change in image spatial resolution affects the perception of patches.

A large number of metrics measuring the rate of aggregation of units within the class or landscape are other important metrics that give clues about the spatial organization. The Aggregation Index (AI) was chosen for this research among CLUMPY, PLADJ, and AI, which focuses on the clustering rates of units based on the proposition that the difference in resolution should be reflected in the spatial arrangement the most and determined to be in high correlation with each other (Szabo et al., 2012; Leitao et al., 2006; McGarigal, 2015).

Table 2. List of used landscape metrics (McGarigal et al., 2002; McGarigal et al.2015; Sertel et al., 2018)

Metrics	Descriptions
Total Class Area (CA)	The sum of the class areas.
Patch Density (PD)	The number of patches per unit area.
Number of Patches (NP)	The number of patches of corresponding landscape or class.
Largest Patch Index (LPI)	The area (m ²) of the largest patch in the landscape is 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.
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.
Area-Weighted Mean Patch Size (AREA_AM)	Equals the sum, across all patches in the landscape, of the patch metric values, multiplied by the proportional abundance of the patch.
Shannon's Diversity Index (SHDI)	SHDI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion.
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.

Table 2 presents the definition of each metric used for the study. The landscape metrics are calculated by using FRAGSTAT software applying the 8-cell neighbor rule (McGarigal et al., 2012). Because of the software's inability to compute high file sizes, the LULC maps were rescaled to 1m and the landscape metrics were calculated on rescaled thematic maps.

Results And Discussion

4.1. LULC Maps

The total area of each class obtained after classifications is represented in Fig. 4 and LULC maps are shown in Fig. 5.

According to the PHR LULC map, most of the Urban Fabric consists of 11100 (Fig. 4), the same as in SPOT and Sentinel classification results. On the other hand, the area of 11210 is the highest in the WV-4 classification. With the increase of spatial resolution, a consistency is observed between Urban Fabric class areas. Especially the similarity of the area values of WV-4 and PHR images shows that they can be conveniently used for studies that concern the details of urban fabric classes. Even though the spatial resolution of the Sentinel image is not high enough to identify sub-classes of Urban Fabric and

Agriculture directly, most of the classes were classified by using different functions and spectral indices, and ancillary vector data. When the classification results of SPOT and Sentinel are compared, it is seen the area of the 32000 class in the Sentinel image is almost two times bigger than in the SPOT image.

However, in the Sentinel classification, the 14100 areas are significantly lower than the SPOT classification (Fig. 4) due to its medium spatial resolution. The total area of 32000-class is quite higher in Sentinel illustrating that this class is mixed with other vegetation classes. When all LULC maps from all images are investigated, the Forest, Agriculture subclasses, and LU classes become easier to detect with the increase in spatial resolution (Fig. 4). But even when using high and very high-resolution satellite images, there may be a need to use vector data to correctly obtain detailed LULC classes.

4.2. Accuracy Assessment

In order to define the thematic accuracy, an area-based accuracy analysis is applied. Control points are selected from up-to-date very high-resolution WV-4 images, and open-source high-resolution sources such as Google Earth, Yandex Maps, Here Maps. Totally 248 grids are selected and distributed by the class areas in thematic maps and homogeneously allocated. For the classes with minimum mapping units as 1 ha and 0.5 ha, 100m x 100m and 50m x 50m grids are generated, respectively. The control points are placed inside the homogeneous grids. Then, control grids are generated. After the evaluation of control grids, an error matrix is produced and this procedure is applied for all LULC maps. User's and Producer's Accuracies are calculated. Kappa is calculated for every classification result. The results of the accuracy analysis for all images are given in Fig. 6.

The classification results showed that the highest total accuracy is obtained on the WV-4 image with a value of 95.71 %. Followed by PHR classification with 91.79 %, SPOT with 85 %, Sentinel with 66.05 %. The WV-4 and PHR images having spatial resolution close to each other showed similar accuracy results. The accuracy values of Urban Fabric sub-classes except the 11100 were lower on the Sentinel LULC map compared to others. The classification accuracy of Water areas was not affected by the changing spatial resolution. The classification accuracy value of 51000 is the lowest in the Sentinel LULC map. The 24000 is by definition a complex land cover class. The detection of this class is the poorest on Sentinel-2 images, though the determined areas increased with spatial resolution, resulting in more areas on SPOT, PHR, and WV-4 images. The 12400 was successfully assigned in all images. The use of additional vector data provided an important advantage in determining Airports and Port Areas in all images.

Overall, it was observed that for such a detailed classification, the accuracy is directly proportional to the increase in spatial resolution. After evaluating the classification results, it was seen that classes had different percentages in classified maps produced from different images. Class areas were most similar on the 51000, 31000, and 12400 classes. Other classes are different in terms of total area. These differences are observed in landscape metrics results as well.

The total accuracy of the Sentinel LULC map is the lowest due to the undetectable classes' accuracy values being 0. It was detected that to classify areas correctly, as the complexity of class definitions and

details increase, a higher spatial resolution is needed. The spatial resolution of the image going to be used for a specific purpose should be carefully selected considering the thematic and spatial details of the study.

4.3. Landscape Metrics

Landscape-level and Class-level Landscape Metrics were calculated to evaluate the quality of the classifications by using satellite images with different resolutions. These calculated metrics and results are presented in the following sections.

4.3.1. Landscape Level Landscape Metrics

According to calculated landscape-level metrics, while PD values are usually low, they are especially lower on the Sentinel LULC map (Fig. 7). This is explained by the decrease in the image spatial details and diversity and aggregation indices also support this finding. The AREA_AM value has the highest value on the Sentinel LULC map. Furthermore, the high LPI value of Sentinel image and because of this the low PD value show that the spatial details in the Sentinel image are low and the patches are detected as blocks.

In PHR, the high AI can be explained due to high LPI and PD values indicate that the distance between units is high. In the SPOT, the average distance between the patches is high because of having a high number of relatively small patches. On the other hand, in the WV-4, smaller patches with smaller distances were clustered more since the WV-4 image has more spatial and geometric details. While the values of the SPOT image gave closer values to higher resolution images (PHR and WV-4) on a landscape with this patch structure, the Sentinel image had the lowest performance because of its comparatively lower spatial resolution.

4.3.2. Class Level Landscape Metrics

After the landscape-level evaluation, class-level metrics were analyzed to see the relationship between the lower scale metric values and spatial resolution. Calculated class-level metrics are given in Fig. 8. Classes that have more remarkable metric values were explained in detail. Furthermore, Table 3 indicates that the result of the relationship between classes and resolution according to calculated class-level landscape metrics from produced LULC maps via vector data.

Table 3. The result of the relationship between classes and resolution.

	SENTINEL-2 (10m)	SPOT-7 (1.5m)	PLEIADES (0.5 m)	WORLDVIEW -4 (0.35m)
Class Code				
11100	✓	✓	✓	✓
11210	X	✓	✓	✓
11220	X	X	✓	✓
11230	X	X	✓	✓
11240	X	X	✓	✓
12100	✓	✓	✓	✓
12210	✓	✓	✓	✓
12220	✓	✓	✓	✓
12230	X	✓	✓	✓
12300	X	✓	✓	✓
12400	✓	✓	✓	✓
13300	X	X	✓	✓
14100	X	✓	✓	✓
14200	X	✓	✓	✓
21000	✓	✓	✓	✓
22000	X	X	✓	✓
23000	X	✓	✓	✓
24000	X	X	✓	✓
31000	✓	✓	✓	✓
32000	✓	✓	✓	✓
33000	X	✓	✓	✓
51000	X	✓	✓	✓
52000	✓	✓	✓	✓

Our results show that 11100 is one of the classes that cover up most of the space in the study area. It was seen that with the decrease in spatial resolution, the class area increases. The PD and NP values being too low and LPI and AREA_AM values being too high on the Sentinel compared to other images

show that this image does not perceive class details. In the lower spatial resolution, it is seen that the shape index gets closer to a geometric structure and the details and curves of shapes are eliminated (LSI). On the other hand, AREA_AM values indicate that with the decrease in spatial resolution, patch numbers were declining because of the merge of patches due to the non-differentiated patch nuances. When Aggregation indices are evaluated, it is observed that aggregation decreases directly proportional to the spatial resolution. Usually, this class has many small patches, the difference in resolution is reflected in the literalness of the landscape metrics. Even though the values of the SPOT image seem close to the WV-4 image, the LPI is higher though CA was higher, and ENN_AM value being high while AI was low, shows that the SPOT image falls behind in detecting details.

In 11210, the breakpoint in metric values draws attention, especially in the Sentinel. It can be said that the WV-4 image has reached the highest performance in this class. In response to the highest CA, PD values, LPI, and ENN_AM values were the lowest. This relationship shows that the class details are well perceived. Even though the WV-4 image has the highest CA value, AREA_AM was the lowest compared to other images, which explains that patches with small areas were sensitively distinguished. NP and AI values being high in the WV-4 image also support this finding. Additionally, when metrics of PHR and SPOT images are analyzed, it is seen that those images also show a similar performance. After all, it can be said that excluding Sentinel, 1.5 m, and higher resolution images can be efficient in detecting this class.

In 11220, 11230, and 11240, it was seen that the Sentinel image could not perceive this class sufficiently. In 11220, On the contrary, Sentinel's NP value was found two times higher than the WV-4 image. Nevertheless, ENN_AM and PD being high while LPI is too low show that the patches in this image are scattered and perceived with low precision. For this class, PHR and WV-4 images showed performances close to each other. In SPOT images, especially metrics such as AI, ENN_AM, PD shows that the level of perception is underperformed compared to the other two images.

It is seen in the classified images that this class covers up a quite large area in 12100. The area of this class was perceived less, in the Sentinel image compared to other images. The class areas were found similar in the other three images. The reason why the Sentinel image has a higher value of patch density is that the total area is low, whereas the NP value is too high. When shape indices are investigated, more geometrical forms were represented in SPOT and WV-4 images. On SPOT image, PD was found half lower than WV-4, LPI was also low but ENN_AM was at its peak, also AI value being lower, indicates that on WV-4 image the perception precision of this class is higher. Because of the structure of the class, it was expected to the patches to be shaped more geometrically. The shape index being high on Sentinel might mean that there is a problem with the perception of neighboring relationships that cause the patches to meld together.

In the Sentinel image, PD, AREA_AM, and LPI values were found low, while ENN_AM values were high in 12210. This indicates that this class was not perceived in detail. It can be said that in this class, the SPOT image had high performance. CA value is close to WV-4. Although lower NP, PD, and higher LPI, ENN_AM

values, the finding that AI is close to WV-4, means that the patches of this class can be perceived as integrated and has high precision and this show that SPOT resolution can also be adequate on classes that have linear unit characteristics. Although, it can be seen that the Fast Transit Roads in Urban Fabric areas cannot be detected as clearly as it is on PHR and WV-4 images.

Because 14100 has a structure that was fictionalized on small patches, the Sentinel image with the lowest resolution perceived those areas in the smallest values. AI value is relatively low, LSI value being closest to the geometric form indicates that the resolution of the image is not enough to successfully identify the class. It is seen that the patch densities that were perceived very close to each other in this class on SPOT and WV-4 images are increased on WV-4 images. This situation shows that the patches belonging to this class are perceived more precisely, and the nuances between the patches in the SPOT image are approached in lesser detail. ENN_AM values also support this finding. For this class, it can be said that the landscape metrics differ on PHR image. The highest CA value was perceived in this image. PD and LPI metrics being at their highest values, ENN_AM distances being minimal indicate that the PHR image has the highest performance in perceiving this class.

The highest values in CA and LPI values were perceived on Sentinel image in 21000. Although, LSI value was almost half of the other images and the ENN_AM value being too high, shows that this class was not perceived sensitively in this image. When the metric values of the SPOT image were investigated, it was seen that the precision is not as low as Sentinel, but also not as high as PHR and WV. Patches that were closest to the geometry as shapely and formed in the block are seen in SPOT and low CA, NP, PD but high LPI, ENN_AM value, supports the findings. When the results from PHR and WV images were investigated, similar values draw attention. But the CA, PD, NP, LPI values being even higher shows that the patches were perceived more sensitively. ENN_AM value being lower, and AI value being high also support this finding.

In Sentinel image, PD was found too low and LPI had its highest value, which shows that the patches belonging to 22000 were perceived as integrated parts. LSI value was found prominently lower while ENN_AM was at its highest, which also supports the finding that the integrated patches come closer to the geometric form. It can be seen from the findings of the SPOT image that the patches belonging to this class are perceived more as an integrated and block form. The CA value being highest while PD and NP are low, and LPI is high, support this analysis. The values from PHR and WV-4 images were similar. But, on the WV-4 image, even though CA is low, NP was found high and LPI was low, also ENN_AM distance was shorter, which means that this image has a higher degree of precision.

In the Sentinel image, the CA value was perceived twenty times bigger than the other three images in 23000. Also, PD and LPI values being too different, ENN_AM value being too high, and AI being too low might mean because of the low resolution there is only general sensing done with Sentinel image. For this class, the values obtained from PHR and WV-4 images were found very similar. SPOT image values were different with small nuances.

Even though the 31000 areas are high, the patch densities and patch numbers are low, and ENN_AM is low, which means that this class is represented as big and integrated parts. Only in the WV-4 image, the PD and NP values were found prominently higher. In the Sentinel image, parallel to the decrease in details, patches were closer to geometric shapes, with low patch density, and the distance between patches was found high. With the increasing resolution, the patch number also increased and the distance between the patches got shorter. Even though the patch density is low, the LPI value was found at its highest, and the class area was found largest on the PHR image. This means that the class is represented in blocks and large patches. LSI values being lower than the agricultural fields draws attention to the situation that forest edges are turning into geometric shapes even though they ecologically have organic shapes. Forest areas that are expected to have a more natural form, being close to geometric forms, might show that there is a need to examine the patch neighbor relationships and patch edge characteristics more exhaustively.

In 32000 was perceived approximately three times more in Sentinel image compared to the other three images. On the contrary, the classes that are perceived less than other images were "11210,11220,11230,11240, 12100 and 24000". PD and LPI values were found high on the Sentinel image, which must be because this class has the most area. But, in Sentinel, ENN_AM being high and AI being low, means that there are many numbered but in block form patches that are located far and separated from each other.

4.4. Discussion

Analysis of the classified images shows that the areal distribution of the classes deviates more on the Sentinel image, which indicates that classes with similar spectral properties are mixed. For example, when the values of CA for the 32000 class are examined, it is found that the area is two times larger in the Sentinel image. Thus, it was found that the Sentinel image cannot perceive the nuances between objects with similar reflectance values and that classes may be mixed due to low spatial resolution. This suggests that data with higher spatial resolution than Sentinel should be used for studies that require accurate separation of maquis patches from the forest and urban tissue. This generalization does not seem to be appropriate for studies that require accurate discrimination in neighborhood relationships, as the metrics calculated for the Sentinel image showed lower sensitivity compared to other images.

The SPOT image is sufficient for the classification of 12210, especially in the urban fabric when vector data support is possible. The Sentinel image can also be used to separate 12210 for studies that do not require land cover/use details. It can be seen that the 12220 in urban areas can be distinguished thanks to the use of vector data in the Sentinel image, while forest roads, which cannot always be supported with vector data, cannot be distinguished from the forest texture. For this reason, the Sentinel image is not sufficient for the determination of roads in natural areas. To achieve a higher level of detail for roads, at least an image with a similar resolution as SPOT should be used.

The landscape metrics and accuracy analysis show that the Sentinel image is not able to separate 11210, 11220, 11230,11240 from the 11100. The fact that the CA value is high and the PD value is the

lowest, while the LPI value is high but the area-weighted ENN value is also high, shows that the patches belonging to this class are classified without a sensitive distinction from the similar patches around them. The LSI value is significantly lower than the other images, indicating that the spot shapes lack details at the edges. Sensitive discrimination could not be made in "Urban Fabric" because the patches are small. Therefore, it is recommended that studies requiring discrimination of 11220, 11220, 11230, 11240 details and with very high accurate use at least PHR resolution.

For the determination of land use classes with small patches such as 23000 and 13300 the sentinel image is not worthwhile. Although 14100, 14200, 33000 are classes that are far apart in the landscape, the difference in resolution was effective in perceiving these classes. The small values of PD and LPI also support this statement. The image SPOT showed similar performance to the images PHR and WV-4 in the mentioned classes.

For agricultural fields, the highest performance was obtained with the WV-4 image. The Sentinel and SPOT images roughly detected agricultural fields but have some ambiguities as shown by the high LPI and low LSI values. Therefore, it is concluded that the detail required to distinguish agricultural fields is at least equal to the resolution SPOT. According to the results of "Urban Fabric" and "Agricultural Fields", the discrimination between similar land classes is best achieved with images WV-4 and PHR. The SPOT image was also successful to some extent in determining subclasses, but it is concluded that the resolution of the sentinel image is not suitable for such detailed classification.

Conclusions

The spatial and thematic level of detail, as well as the scale of the study, are important parameters in determining the most appropriate satellite image for a study. When studying the usability of classified data in landscape planning and management, the most important factor to be determined is the scale of analysis.

The issue of proper data selection, which plays an important role in the quality and accuracy of land use planning studies, is examined in detail in this paper. The nuances of features at different resolutions and the tolerance levels of these nuances in small- or large-scale studies are explored, based on the configurations and spatial-formal distributions of different classes located in the landscape. For spatial planning studies, the main elements that should be considered for appropriate data selection are the following:

- **Cost-effectiveness:** the cost of the study,
- **Suitability to the purpose of the study:** Whether the dataset is appropriate for the scale of the study and whether it ensures sufficient information following the expected content and level of detail.
- **Technical and hardware facilities:** Whether there are sufficient suitable hardware and ancillary data for the study, as well as specialists who can carry out the process.

The cost of satellite imagery increases proportionally with improving spatial resolution. Therefore, in some situations, a decision should be made before budgeting whether a low-resolution open-source image is appropriate for a particular study, rather than purchasing an expensive high-resolution satellite image. Knowing the nuances in hierarchical classification systems caused by resolution differences can be critical. This decision will make the planning of the study more realistic by giving the researcher an idea that will save both cost and time. Another important outcome of this work is the multidisciplinary approach. The fact that different disciplines play a role in different parts of the study but share the same common goal makes the study more qualified. Choosing an appropriate dataset and processing it with the right techniques, leading to high thematic accuracy, allows more realistic conclusions about the study area. Especially in landscapes that are going through an intense phase of transformation, it is of great value to have qualified data to make decisions about urban landscapes in a short time.

Declarations

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Availability of data and material: Original satellite images could not be shared because of Copyright issues. We will share our resulting maps.

Code availability: We benefitted from e-cognition software and FRAGSTAT. There are not any codes available for this manuscript.

Ethics approval: Ethics approval is not needed.

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Figures

Figure 1

Study Area.

Figure 2

LULC classes used in this study

Figure 3

The whole flowchart of Classification Step.

Figure 4

Class areas in classified images.

Figure 5

LULC maps of four satellite images.

Figure 6

User's Accuracy (U.A.) and Producer's Accuracy (P.A.) results

Figure 7

Landscape-level landscape metrics results

Figure 8

Class-level landscape metrics results.