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LAND COVER CHANGE ANALYSIS BETWEEN 1990 AND 2021 USING LANDSAT IMAGES AND OBJECT-BASED CLASSIFICATION: A CASE STUDY IN BODRUM PENINSULA, AEGEAN REGION, TURKEY

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Abstract

Bodrum Peninsula is one of the most important tourism centers of Turkey with its geographical location, coastal and marine tourism, natural and cultural features. It has been determined that the winter population has also increased in Bodrum in recent years, and it is thought that this may cause an increasing permanent resident population and urbanization. The objective of this study is to determine the changes in land cover due to the rapid increase in urbanization in Bodrum Peninsula. For this purpose, object-based classification analysis was applied to Landsat 4-5 TM 1990, 2000, 2010 and Landsat 8 OLI 2021 multispectral satellite images. Within the scope of the analysis, the objects were created by applying the segmentation process to satellite images. Secondly, land cover classes were determined according to the Corine land cover classification with levels 1-2-3. Thirdly, the classification process based on a decision tree was carried out with the classes defined using the threshold values determined for spectral and texture properties of the objects using multiresolution segmentation. In the last stage, accuracy assessment analysis was applied to the classification results. According to the results, it is obtained that while Urban Fabric and Burnt Areas are increased in 32 years, Forest and semi-natural areas are decreased. As a result of population pressure due to tourism, Urban Fabric areas have moved closer to Forests and Semi-Natural Areas. Wildfires with the effect of heatwaves were increased, biodiversity has been endangered in the study area located in the Mediterranean basin, where human-related climate change is most clearly detected. Significantly, there has been a wildfire in Bodrum in August 2021, which lasted for days and caused severe degradation on the land cover. For this, sustainable land cover management is recommended to protect the natural ecosystem by minimizing the risks that cause land degradation in the Bodrum peninsula.

Keywords: Remote sensing, Object-based classification, land cover change, Bodrum Peninsula, Turkey

1. INTRODUCTION

Rapid and uncontrolled land use/land cover (LULC) changes can seriously affect climate, biodiversity, soil quality, water bodies, urbanization rate, and population pressure and many other environmental systems (Lambin, Turner, & Geist, 2001; Thuiller, Lavorel, & Araujo, 2015; Cürebal, Efe, & Soykan, 2019; Ustaoğlu, İkiel, & Dutucu, 2021; Topaloğlu, Aksu, & Ghale, 2021; Firatlı, Dervisoglu, & Yagmur, 2022). The Eastern Mediterranean Basin is one of the most sensitive and vulnerable areas in the world in terms of climate change (Koc, Biltekin, & Ustaoğlu, 2021). According to the latest, Six Assessment Report of the IPCC (The Intergovernmental Panel on Climate Change), the Mediterranean Basin is stated as one of the regions where climate change and its effects (drought, forest fire, etc.) are seen most effectively (IPCC, 2021). In recent years, frequency, extent, and severity of wildfires have increased in the Mediterranean Basin due to land use change and global warming (Mitri & Gitas, 2006). Particularly drought, heat waves, wind speed and Pinus bruita Ten., which is the climax type of the Mediterranean Phytogeographical Region, increase the possibility of fire (Atalay, Sezer & Çukur, 1998; Atalay, 2015; Baylan & Ustaoğlu, 2020). According to the recent studies, frequency and extent of large wildfires will increase throughout the Mediterranean Basin 14% by the end of the century

(2071–2100) under the RCP4.5 scenario, and by 30% under the RCP8.5 (Ruffault, Curt, & Moron, 2020). Determining the LULC classes and examining their spatial distributions is an important data source for analyzing the effects for different problems using actual and accurate geographical information. Satellite images provide the opportunity to determine the spatial distribution or transformation of each LULC class with different resolution data in monitoring the current conditions of large areas or their changes over time (Sertel, Musaoğlu, & Alp, 2018; Mishra & Rai, 2021).

There are many studies that determine LULC with opensource Landsat images effect on forest cover (Yavaşlı, Masek, & Franks, 2013), water resources (Cüceloğlu, Şeker, & Tanık, 2021), vegetation (İkiel & Koç, 2015), geomorphology (Ölgen, 2004) and soil salinity (Aksoy, Yıldırım, & Gorji, 2022). In recent years, there are a lot of studies in which Object-based classification is used in determining the LULC (Sertel & Akay, 2015; Alganci, Sertel, & Kaya 2018; Esetlili, Bektas Balcik, & Balik Sanli, 2018; Karabulut, Ceylan, & Bahar, 2021).

Object-based classification method gives higher accuracy values specifically for the classification of high-resolution satellite images and selected as the classification approach for this study. In this method, homogeneous image objects consisting of pixels with similar spectral properties are created. The images are classified by considering the spectral, statistical, texture and geometric properties defined for the objects. Bodrum is one of the coastal tourism centers located in the Aegean Region, in the Mediterranean Basin. Coastal tourism benefits significantly from the sea with a wide variety of recreational activities and provides services such as accommodation depending on the coast. Coastal tourism primarily chooses sparsely populated coasts with natural beauty, mild climate, and natural vegetation as far as the shore (Doğaner, 2001). Bodrum Peninsula, with various cultural features and transport facilities and the suitability of the natural environment, have become one of Turkey's most important tourism centers in recent years. In addition to touristic facilities, the demand for summer residences are increased. A rapid urbanization has been observed in Bodrum harbor and its surroundings and on the coasts of Turgutreis, Gündoğan, Akyarlar, Torba, Yalıkavak, Göltürkbükü and Ortakent. In the Bodrum peninsula, which has a rich history dating back to ancient times, the people's main economic activities in the early 20th century were fishing, sponge fishing, and agriculture. Population growth is the most important factor in the development and sprawl of settlements (Bhatta, 2010). Tourism has started to develop since the mid-1960s in Bodrum. International Bodrum-Milas airport, marinas such as the Milta Bodrum Marina, D-Marin Turgutreis Marina and Palmarina have been effective in the transportation of domestic and foreign tourists after the 1990s with the development of tourism.

The population has shown an increasing trend in the last 15 years in Bodrum (URL 2). The most important factor in the increase of the population is the increase of summer houses, and second houses and the residents of these sites continue to live not only in summer but also in winter. According to the population projections, it has been stated that the population growth will continue to increase in the next ten years and will reveal the problem of drinking and usage of water (Bakış & Arı, 2010). Human factors such as population, tourism, etc., and natural disasters such as forest fire, drought, etc. and their effects caused by climate change and its effects have caused significant changes in land cover in recent years. According to this the purpose of this study is to determine the changes in land cover by using Landsat 4-5 TM and Landsat 8 OLI satellite images and object based classification method in the Bodrum Peninsula between 1990- 2000- 2010- 2021 for 32 years.

1.1. Study area

Bodrum peninsula is located in the south-west of Turkey with coordinates of the 36°57′N - 37°17′N, 27°13′E - 27°58′E (Figure 1). The peninsula is surrounded by the Aegean Sea in the north, south, and west directions and is connected to Anatolia from the east. Volcanic rocks are located in the west of this area, with a hilly morphology of medium slopes, while limestone rocks are common in the east. There are many large and small karstic holes on the limestone rocks, and the streamline is weak. While there are many bays on the western and northern coasts of the peninsula, the southern coasts have flat terrains. Bodrum harbor and settlement are located in the southwest of the study area, protected by Karaada (İkiel, 2004). Mediterranean climate characteristics, Csa in the Köppen-Geiger Classification, are observed in Bodrum Peninsula. The summer season is hot and dry, the winter season and the spring is rainy. Annual mean temperature is 20 °C. The average temperature between May and October is above 20 °C. Average annual precipitation is 710 mm. This precipitation mostly occurs in winter, spring and autumn seasons. Snowfall is rare. The annual average wind speed is 3.9 m/s and northerly winds are dominant. Wind speeds increase in the afternoon during the day (İkiel, 2005). The research area is located in the Mediterranean Phytogeography region depending on the climatic conditions. Due to the destruction of the Pinus brutia

Ten. forests that constitute the natural vegetation, maquis vegetation is generally seen in the coastal areas and around the settlement areas. Garig vegetation has developed in areas where maquis vegetation has been destroyed. There are local Pinus brutia Ten. communities in high areas (İkiel, 2004). The 7 month period between May and October offers ideal conditions for coastal and marine tourism, depending on the temperature, relative humidity, average wind speed, and sea surface temperatures in the study area (İkiel, 2005). Yacht tourism has developed since the bays suitable for yacht tourism are close to each other in terms of climate conditions and coastal geomorphology, there are winds suitable for yachting, and this coast is close to the islands of Kos, Patmos, and Rhodes, where yachts are most visited (Doğaner, 2001). The population of the Bodrum peninsula, which was 16,387 in 1904 and 15,694 in 1927 (Kodal, 2008) reached 25,811 in 1965, 97,826 in 2000, 124,820 in 2010, and 175,435 in 2019 (Figure 2). In addition to the population increase, the number of tourists visiting Bodrum and its surroundings has increased year by year (URL 3). In addition to these, Bodrum and its surroundings have turned into an area that accommodates and serves a population well above the population with those on yachts and boats, those who come for a day, those who stay in summer houses.

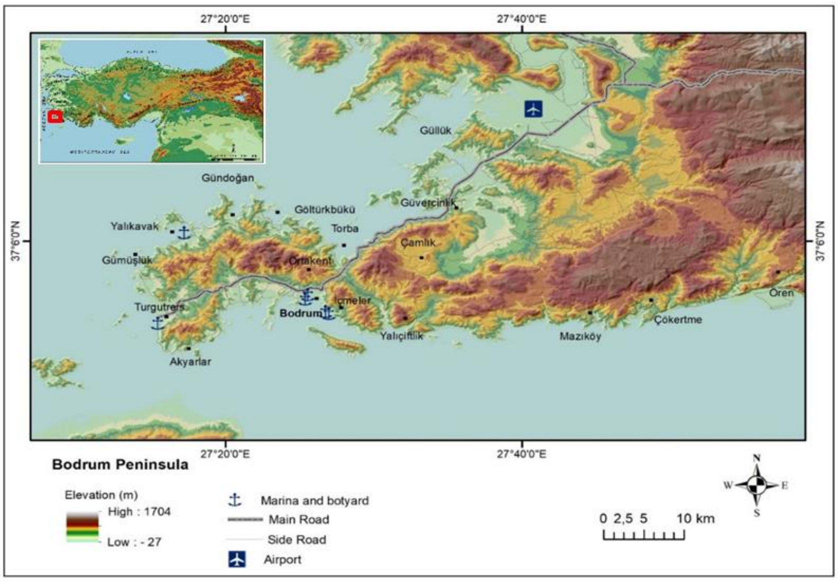

Figure 1- Location Map of Bodrum Peninsula

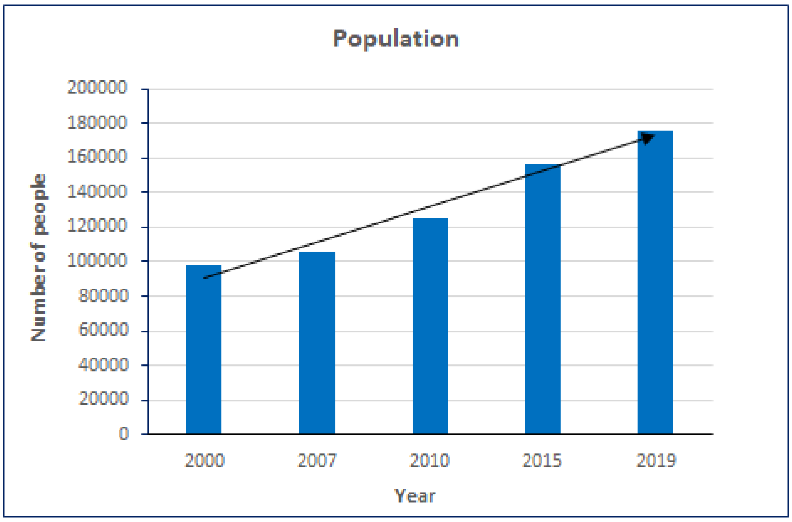

Figure 2- Population change in Bodrum

2. MATERIAL AND METHOD

In this study 30 m. spatial resolution multispectral Landsat 4-5 TM 1990 (16.08.1990), 2000 (26.07.2000), 2010 (06.07.2010) and 15 m. spatial resolution panchromatic image and Landsat 8 OLI (21.08.2021) image (URL 4) used with Trimble eCognition Developer software. Fieldwork was carried out in July 2019 and 2020. Images were prepared using the Bodrum Peninsula boundary vector data, and pre-processing was completed. Corine land cover classification was used for determining land cover classes. CORINE (Coordination of Information on the Environment) is the LULC data produced by computer-aided visual interpretation method over satellite images according to the LULC Classification defined by the European Environment Agency (URL 5). There are different classification systems (Anderson, Ernest, & John, 1976; URL 6) besides Corine, in all member countries of the European Environment Agency, including Turkey, an accessible Corine database has been created, and Corine classes are used to make comparisons in studies on Turkey (URL 7).

In this study, 9 main and subclasses were determined using Level 1, Level 2 and Level 3. The land cover classes determined for this study are Level 1.1 Urban Fabric, Level 1.3: Mine, Dump and Construction Sites, Level 1.2.3: Port areas, Level 1.2.4: Airports; Level 2: Agricultural Areas, Level 3: Forests and Semi-Natural Areas, Level 3.3.4 Burnt Areas, Level 4: Wetlands, Level 5: Water Bodies. The workflow chart prepared for the study is given in Figure 3.

2.1 Object-Based Classification

Image classification is the most commonly used method to extract information about remotely sensed images. The classification is separating pixels into user-defined classes by using the reflection and brightness values of each pixel on the image. In general, pixel-based and object-based classification methods are used in the classification process. In recent years, the object-based classification method has been used instead of the traditional pixel-based classification method. The most important reason for this can be shown that the rich information content available with the increase in the spatial resolution of satellite image data and aerial photographs in recent years cannot be fully reflected in the products obtained from the pixel-based approach (Navulur, 2007). Object-based classification uses both spectral and spatial patterns for image classification. This is a two-step process involving dividing and classifying the image into separate objects. Object-based classification is the opposite approach of traditional pixel and sub-pixel-based classification processes. It is based on the grouping of pixels with similar spectral characteristics on the image, not with individual pixels, to create image objects representing these pixels and classifying the objects in question instead of pixels (Blaschke, 2010; Myint, Gober, & Brazel, 2011; Esetlili, Bektaş, & Balık, 2018; Kavak, 2018). Instead of millions of pixels on the image, the objects representing them are classified with this process. In the object-based classification approach, structure, texture, spectral information, and sizes of objects are taken into account in the classification process (Avashia, Parihar, & Garg, 2020), and a lot of additional information can be extracted from image objects.

Pixel-based approaches work on each pixel and extract information from remotely sensed data based on spectral information (Gupta & Bhadauria 2014). The main purpose of this method is to automatically combine each pixel in the image according to the terrain attributes. The problems encountered by pixel-based approaches are overcome by object-based image classification. Object-based information interprets an image not only according to a single pixel, but also in meaningful image objects and interrelationships.

Object-based information extraction depends not only on spectrum character but also on geometry and structure information (Wei, Chen, & Ma, 2005). In addition, the object-based approach gives more meaningful and positive results for the thematic class than the pixel-based approach since it uses many properties of these segments such as color, frequency, and neighborhood by grouping pixels in the segmentation stage. At the same time, object-based classification process has a structure that can be updated continuously with the decision set or fuzzy logic algorithms it uses. eCognition Developer software, which is the most used object-based image analysis software, offers a similar approach to pixel-based approach with its nearest neighbor classification method and gives the same meaningful results in a more practical way (Hofmann, 2001; Kalkan & Maktav 2010). It is seen in the literature that pixel-based classification algorithms are frequently used to determine the current state of land cover (Efe, Soykan, & Cürebal, 2012; İkiel, Ustaoğlu, & Kılıç, 2013; Dutucu & İkiel 2016; Alevkayalı & Tağıl 2018; Sekertekin, Marangoz, & Akcin, 2017; İkiel, Ustaoğlu, & Dutucu, 2019; Mishra, Rai, & Rai, 2020). On the other hand, object based classification, is a classification algorithm that is used extensively after the widespread use of very high resolution satellite images, and its use in medium spatial resolution data such as Landsat has also become widespread (Sertel & Algancı, 2016; Algancı, 2018; Aahlaad, Mozumder, & Tripathi, 2021; Sang, Guo, & Wu, 2021). In recent years, there have been many studies in which pixel-based and object-based classifications have been made comparatively. The results obtained from these studies show that; the accuracy analysis results obtained from Object Based classification, which is based on both classification and segmentation principles, are higher than the accuracy analysis results obtained from pixel-based classification (Tampubolon, Abdullah, & Hwee, 2013; Phiri & Morgenroth 2017; Avashia, Parihar, & Garg, 2020). Object-based classification process consists of two stages. In the first step, the segmentation of a multi-layered data set represents a meaningful earth object alone or in groups. Scale, color, shape, and texture parameters are taken into consideration in the segmentation process. In the second stage, the segments are classified within hierarchical or relational definitions, taking into account their reflection, shape, and texture characteristics. In this study, eCognition Developer v.10.0 software was used for object-based classification process (Algancı, 2018).

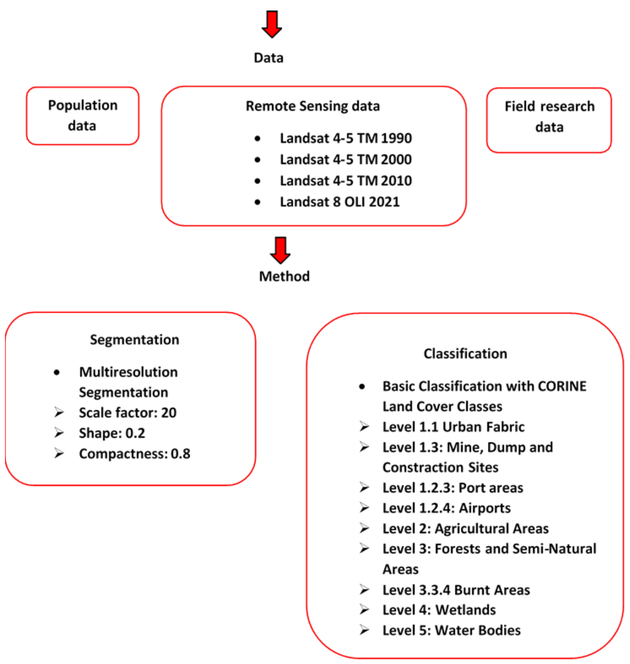

Figure 3- The flowchart of the methodology

2.2 Segmentation

The segmentation process works in two different methods: top-down and bottom-up. The basis of the top-down method is the process of breaking the whole into the smallest pieces. There are other top-down segmentation methods. These; chessboard segmentation, quadtree-based segmentation, and contrast segmentation algorithms. The second strategy of the segmentation process is bottom-up segmentation. In this approach, small pieces are obtained as large pieces by taking specific criteria into account. The most important method used for bottom-up strategy is the "Multiresolution Segmentation" method (Baatz & Schape 2000; Benz, Hofmann, & Willhauck, 2004; Witharana & Civco 2014). With the multi-resolution segmentation algorithm, three parameters given as scale, shape and density in segmentation are determined by the user. The most important of these three parameters is the scale parameter. In the multi-resolution segmentation phase, the scale parameter, color / shape parameter and softness / density parameters should be determined as close to reality as possible. Color / shape and softness / density parameters complement each other to 1. After the segmentation step, different parameters are set for the image data used, classification is made, and the desired detail extraction is performed.

2.3 Classification

At this stage, it is aimed to assign objects with similar characteristics from the image objects obtained by the segmentation process by evaluating them with different parameters such as homogeneity, size, texture and color. eCognition software provides two basic classifiers, namely the nearest neighbor classifier and fuzzy membership functions. While the closest neighbor classifier defines the classes that will emerge with the help of sample objects determined according to the class hierarchy through the segments formed, fuzzy membership functions are based on the definition of a decision set to be created for the related classes of the properties of the objects and their equivalent values (Kavzaoğlu & Yıldız 2014).

2.4 Accuracy Assessment

Classification accuracy in remote sensing is obtained by investigating the compatibility between the actual class of objects assigned to several classes in the post-classification image. This research is performed visually by comparing it with reference data and/or statistically. For this purpose, the compatibility of these pixels / segments with the reference data is examined by selecting the pixels / segments during the classification or over the classified data. As reference data, data obtained from aerial photographs, existing maps and plans or GPS measurements can be used.

The most common way to describe the degree of accuracy is to create an error matrix. Error matrix is a quadratic pattern of numbers arranged in rows and columns of the number of pixels/segments assigned to a particular land cover type according to the actual land cover. The classification results of this table are shown with rows and columns; rows represent class data, representing location facts based on sample points (Sertel & Yay 2014; Algancı, Besol, & Sertel, 2018). Many criteria for the correctness of the classification can be derived from the error matrix. The most common of these is the calculation of the percentage of correctly separated categories. The ratio of individual accuracies of classes, the sum of pixels/segments correctly assigned to a class, to the sum of all pixels/segments belonging to that class can be found by deriving from the error matrix (Foody, 2002). User and producer accuracy and kappa statistics are derived from these matrices. The number of random control points in each class was determined by considering the class priority, the area covered by the class, and the homogeneity of the class (Cohen, 1960; Story & Congalton 1986; Van Deusen, 1996; Foody, 2020).

3. RESULTS AND DISCUSSIONS

The multi-resolution segmentation algorithm was used for the segmentation process, which is the first step of the analysis. The algorithm aims to determine the most suitable scale parameter for the land, based on the necessity of expressing different objects in different scales according to their size and texture characteristics, especially in working areas with heterogeneous cover types (Li & Shao 2012; Kavzaoğlu & Yıldız 2015). The scale parameter controls the spectral variation of the group of pixels that will create the object and the resulting segment size. The first of the two complementary parameter sets in the segmentation process is the shape - color component. The shape and color are defined so that they complement the other to the value 1. It is determined according to this weighting which parameter will be more important in determining the object boundaries. The shape properties are also determined by the compactness and softness sub-parameters. In the second stage, determining the threshold values of the classes and defining the class relationships by using the spectral and texture parameters of the pixels that make up the segments was initiated. In this context, the most suitable segmentation is provided with the parameter set defined by a scale factor: 20, shape: 0.2, and compactness: 0.8.

After the segmentation process, the classification stage was started. Following the purpose of the study, first of all, the settlement class was defined. The classification process has been made with the nearest neighborhood. The nearest neighborhood algorithm primarily calculates the mean value vectors representing the classes within the training set. Then, spectral distances between the estimated class average vectors of the candidate pixel to be classified are calculated. According to the calculated spectral distances, the pixel is assigned to the sample class at the closest distance (Lillesand, Kiefer, & Chipman, 2007). Afterward, open areas with shrub, forest ,and water bodies were defined, respectively. Object-based classification results were transformed into vector data with the "export" menu in the Trimble eCognition software and saved as a file with the extension of "* .shp". The saved file was opened with Arc Map 10.5 software as a "*. shp" extension file, and maps were created (Figure 4-5). For the accuracy analysis on the classification results, a total of 365 randomly selected control points were taken from the Landsat 4-5 TM August 1990 image, 70 in Urban Fabric, 80 in Agricultural Areas, 80 in Forests and Semi-Natural Areas, 30 in Wetlands, 25 in Water Bodies, 65 in Mine, Dump and Construction Sites, 5 in Port areas, 10 in Burnt Areas. There was no airport level class in 1990 because Milas Bodrum Intenational Airport was built after 1990. In the Landsat 4-5 TM August 2000 image, a total of 390 randomly selected control points were taken. 80 in Urban Fabric, 80 in Agricultural Areas, 80 in Forests and Semi-Natural Areas, 40 in Wetlands, 20 in Water Bodies, 70 in Mine, Dump and Constraction Sites, 10 in Port areas, 10 in Airport. There was no burnt area level class in 2000. Because there have been no forest fires in this year. A total of 420 randomly selected control points were taken from the Landsat 4-5 TM August 2010 image, 90 in Urban Fabric, 80 in Agricultural Areas, 80 in Forests and Semi-Natural Areas, 40 in Wetlands, 20 in Water Bodies, 70 in Mine, Dump and Construction Sites, 10 in Port areas, 10 in Airrport, 20 in Burnt Areas. In the Landsat 8 OLI 2021 image, a total of 450 randomly selected control points were taken. 90 in Urban Fabric, 80 in Agricultural Areas, 80 in Forests and Semi-Natural Areas, 40 in Wetlands, 20 in Water Bodies, 70 in Mine, Dump and Construction Sites, 10 in Port areas, 10 in Airport and 50 in Burnt Areas (Table 1-2-3-4).

Error matrices have been created with the class labels of these points and their corresponding control references (Table 1-2-3-4). Within the scope of the study, Google Earth web map service was used because it provides high-resolution satellite data for all the years mentioned as verification reference data. User accuracy for the year 1990, respectively; 78,6% in Urban Fabric, 75% in Agricultural Areas, 87.5% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 84,6% in Mine, Dump and Constraction Sites, 100% in Port areas, 100% in Burnt areas. Producer accuracy has been calculated as respectively; 78,6% in Urban Fabric, 80% in

Agricultural Areas, 87.5% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 78,6% in Mine, Dump and Construction Sites, 100% in Port areas, 100% in Burnt areas. According to accuracy assessment results, overall accuracy of the classification is 84.9 % with a kappa value of 0.82 (Table 1). User accuracy for the year 2010, respectively; 87,5% in Urban Fabric, 76,3% in

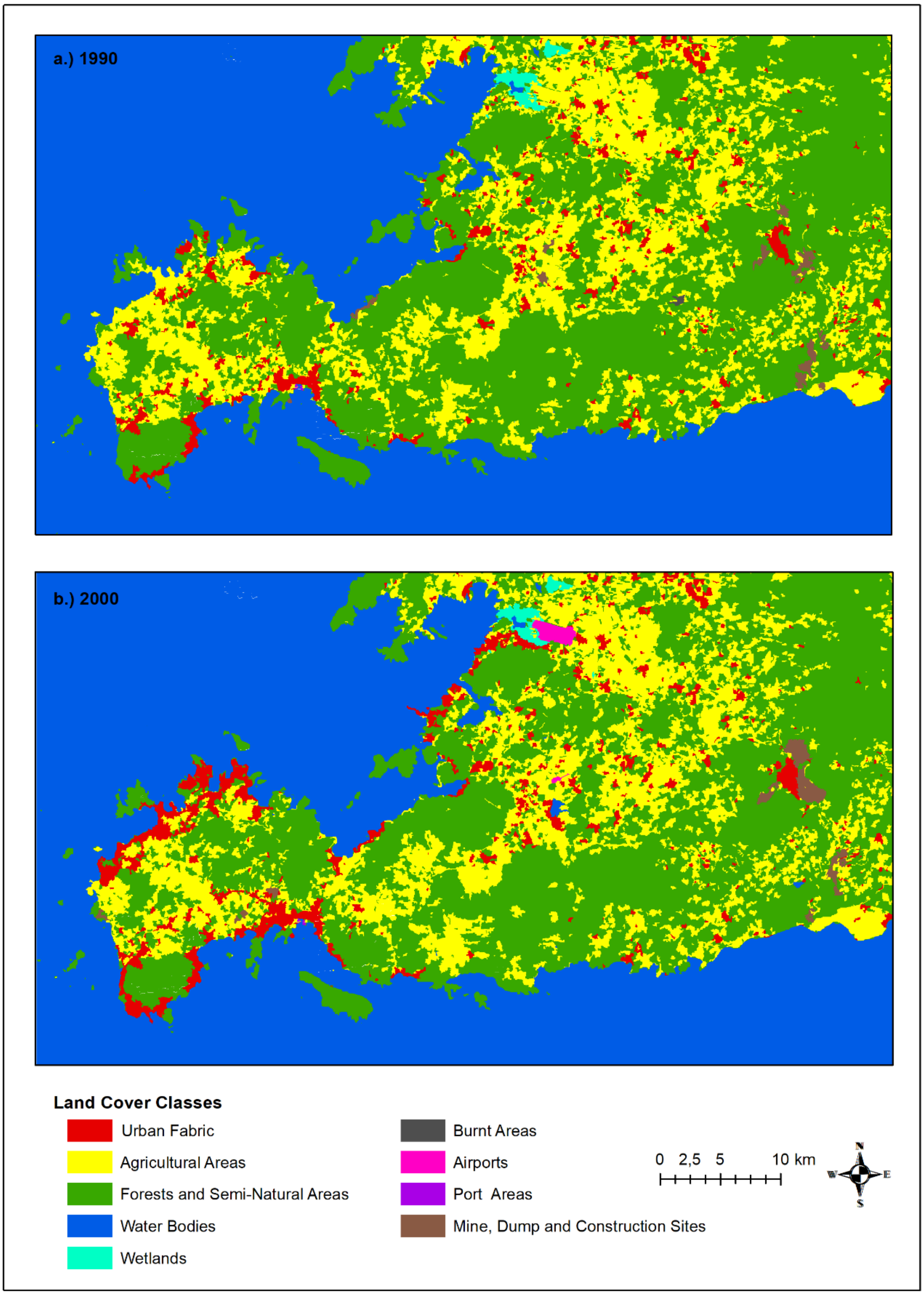

Figure 4- Land Cover Map of Bodrum Peninsula, Landsat 4-5 TM 1990-2000

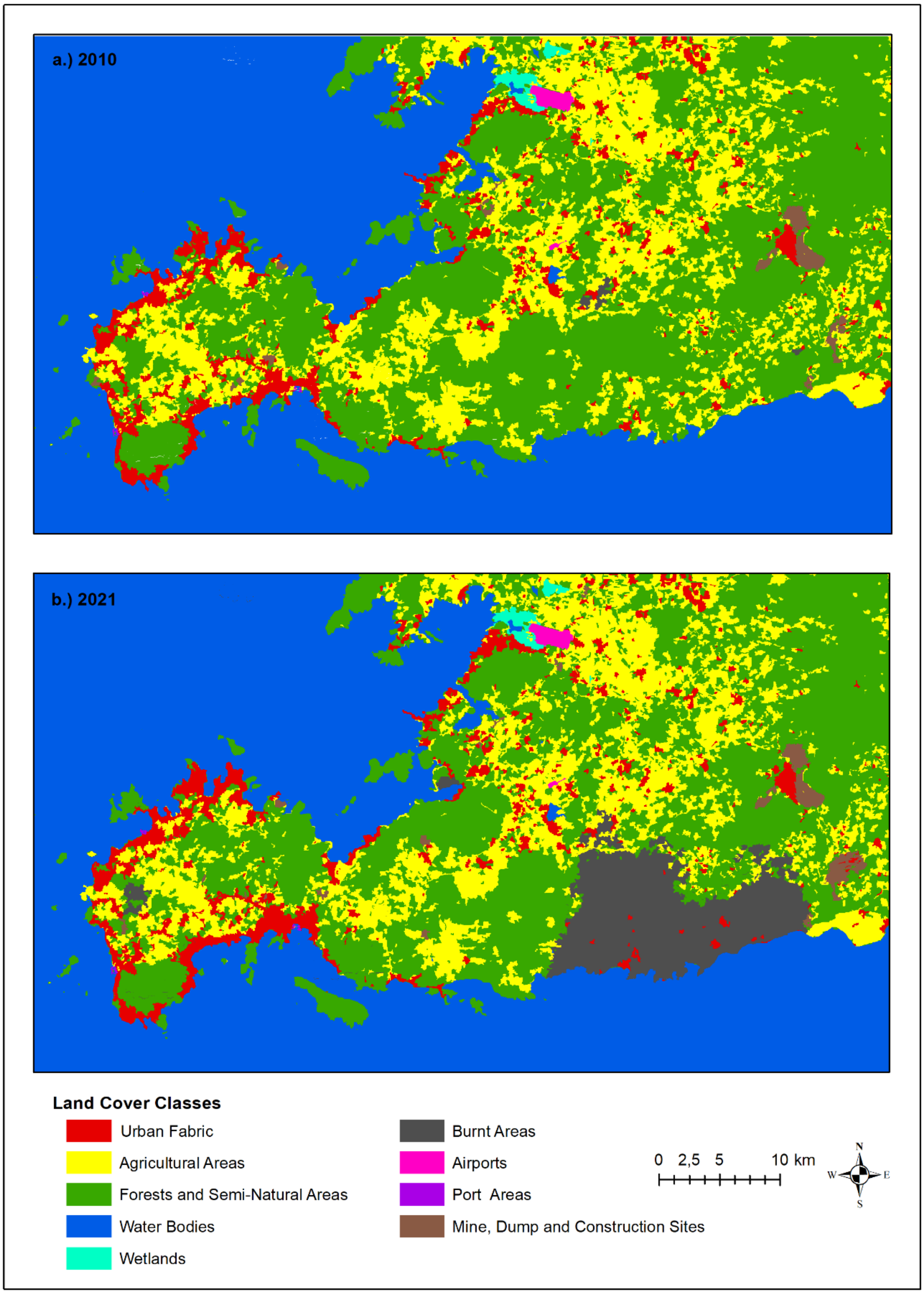

Figure 5- Land Cover Map of Bodrum Peninsula, Landsat 4-5 TM 2010- Landsat 8 OLI 2021

Table 1- Accuracy Assessment Results of Landsat 4-5 TM 1990

Land Cover Classes 1990	Urban Fabric	Agricultural Areas	Forests and Semi-Natural Areas	Wet lands	Water Bodies	Mine, Dump and Constraction Sites	Port Areas	Air ports	Burnt Areas	Total	User Accuracy (%)
Urban Fabric	55	10	0	0	0	5	0	0	0	70	78,6
Agricultural Areas		60	10			10			0	80	75,0
Forests and Semi-Natural Areas	5	5	70	0	0	0	0	0	0	80	87,5
Wetlands	0	0	0	30	0	0	0	0	0	30	100,0
Water Bodies	0	0	0	0	25	0	0	0	0	25	100,0
Mine, Dump and Construction Sites	10	0	0	0	0	55	0	0	0	65	84,6
Port Areas	0	0	0	0	0	0	5	0	0	5	100,0
Airports	0	0	0	0	0	0	0	0	0	0	0,0
Burnt Areas	0	0	0	0	0	0	0	0	10	10	100,0
Total	70	75	80	30	25	70	5	0	0	365	100,0
Producer Accuracy (%)	78,6	80,0	87,5	100,0	100,0	78,6	100,0	0,0	100,0	100,0	100,0
Overal Classification Accuracy: 84.9 %			*Kappa Statistics: 0.82*								

Table 2- Accuracy Assessment Results of Landsat 4-5 TM 2000

Land Cover Classes 2000	Urban Fabric	Agricultural Areas	Forests and Semi-Natural Areas	Wet lands	Water Bodies	Mine, Dump and Constraction Sites	Port Areas	Air ports	Burnt Areas	Total	User Accuracy (%)
Urban Fabric	70	2	0	0	0	8	0	0	0	80	87,5
Agricultural Areas		61	10			9			0	80	76,3
Forests and Semi-Natural Areas	5	3	72	0	0	0	0	0	0	80	90,0
Wetlands	0	0	0	40	0	0	0	0	0	40	100,0
Water Bodies	0	0	0	0	20	0	0	0	0	20	100,0
Mine, Dump and Construction Sites	10	0	0	0	0	60	0	0	0	70	85,7
Port Areas	0	0	0	0	0	0	10	0	0	10	100,0
Airports	0	0	0	0	0	0	0	10	0	10	100,0
Burnt Areas	0	0	0	0	0	0	0	0	0	0	0,0
Total	85	66	82	40	20	77	10	10	0	390	100,0
Producer Accuracy (%)	82,4	92,4	87,8	100,0	100,0	77,9	100,0	100,0	0,0	100,0	100,0
Overal Classification Accuracy: 87.9 %			*Kappa Statistics: 0.85*								

Agricultural Areas, 90% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 85,7% in Mine, Dump and Construction Sites, 100% in Port areas, 100% in Airports. Producer accuracy has been calculated as respectively; 82,4% in Urban Fabric, 92,4% in Agricultural Areas, 87.8% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 77,9% in Mine, Dump and Construction Sites, 100% in Port areas, 100% in Airports. According to accuracy assessment results, overall accuracy of the classification is 87.9 % with a kappa value of 0.85 (Table 2). User accuracy for the year 2010, respectively; 88,9% in Urban Fabric, 83,8% in Agricultural Areas, 90% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 84,3% in Mine, Dump and Constraction Sites, 100% in Port areas, 100% in Airports, . Producer accuracy has been calculated as respectively; 82,4% in Urban Fabric, 92,4% in Agricultural Areas, 87.8% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 77,9% in Mine, Dump and Construction Sites, 100% in Port areas, 100% in Airports and 65%

in Burnt areas. According to accuracy assessment results, overall accuracy of the classification is 88.3 % with a kappa value of 0.86 (Table 3). User accuracy for the year 2021, respectively; 91,9% in Urban Fabric, 85 % in Agricultural Areas, 87,5% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 85,7% in Mine, Dump and Construction Sites, 100% in Port areas, 100% in Airports, 88% in Burnt areas. Producer accuracy has been calculated as respectively; 89,1% in Urban Fabric, 91,9% in Agricultural Areas, 84.3% in Forests and Semi-Natural Areas, 100% in Wetlands, 100% in Water Bodies, 89,6% in Mine, Dump and Construction Sites, 100% in Port areas, 100% in Airports and 81,5 % in Burnt areas. According to accuracy assessment results, overall accuracy of the classification is 89.8 % with a kappa value of 0.88 (Table 4).

Table 3- Accuracy Assessment Results of Landsat 4-5 TM 2010

Land Cover Classes 2010	Urban Fabric	Agricultural Areas	Forests and Semi-Natural Areas	Wet lands	Water Bodies	Mine, Dump and Constraction Sites	Port Areas	Air ports	Burnt Areas	Total	User Accuracy (%)
Urban Fabric	80	2	0	0	0	8	0	0		90	88,9
Agricultural Areas		67	10						3	80	83,8
Forests and Semi-Natural Areas	0	3	72	0	0	0	0	0	5	80	90,0
Wetlands	0	0	0	40	0	0	0	0	0	40	100,0
Water Bodies	0	0	0	0	20	0	0	0	0	20	100,0
Mine, Dump and Construction Sites	11	0	0	0	0	59	0	0	0	70	84,3
Port Areas	0	0	0	0	0	0	10	0	0	10	100,0
Airports	0	0	0	0	0	0	0	10	0	10	100,0
Burnt Areas	0	4	3	0	0	0	0	0	13	20	65,0
Total	91	76	85	40	20	67	10	10	21	420	100,0
Producer Accuracy (%)	87,9	88,2	84,7	100	100	88,1	100	100	61,9	100	100,0
Overal Classification Accuracy: 88.3 %			*Kappa Statistics: 0.86*								

Table 4- Accuracy Assessment Results of Landsat 8 OLI 2021

Land Cover Classes 2021	Urban Fabric	Agricultural Areas	Forests and Semi-Natural Areas	Wet lands	Water Bodies	Mine, Dump and Constraction Sites	Port Areas	Air ports	Burnt Areas	Total	User Accuracy (%)
Urban Fabric	82	1	0	0	0	7	0	0		90	91,1
Agricultural Areas		68	9						3	80	85,0
Forests and Semi-Natural Areas	0	3	70	0	0	0	0	0	7	80	87,5
Wetlands	0	0	0	40	0	0	0	0	0	40	100,0
Water Bodies	0	0	0	0	20	0	0	0	0	20	100,0
Mine, Dump and Construction Sites	10	0	0	0	0	60	0	0	0	70	85,7
Port Areas	0	0	0	0	0	0	10	0	0	10	100,0
Airports	0	0	0	0	0	0	0	10	0	10	100,0
Burnt Areas	0	2	4	0	0	0	0	0	44	50	88,0
Total	92	74	83	40	20	67	10	10	54	450	100,0
Producer Accuracy (%)	89,1	91,9	84,3	100	100	89,6	100	100	81,5	100,	100,0
Overal Classification Accuracy: 89.8 %			*Kappa Statistics: 0.88*								

Table 5- Results of land cover change from 1990 to 2021

	1990		2000		2010		2021		1990-2021
Land Cover Classes	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)
Urban Fabric	7387,2	2,5	11127,3	3,8	12232,4	4,2	13421,3	4,6	6034,1
Agricultural Areas	48178,2	16,4	46883,1	15,9	46245,4	15,7	42446,3	14,4	-5731,8
Forests and Semi-Natural Areas	103292,8	35,1	99985,0	34,0	99102,4	33,7	86021,3	29,3	-17271,5
Wetlands	791,3	0,3	773,2	0,3	773,2	0,3	768,1	0,3	-23,2
Water Bodies	133335,1	45,3	133482,2	45,4	133430,9	45,4	133430,9	45,4	95,9
Mine, Dump and Construction Sites	989,9	0,3	1283,8	0,4	1447,4	0,5	1833,6	0,6	843,7
Port Areas	17,0	0,0	17,0	0,0	53,9	0,0	53,9	0,0	36,9
Airports	0,0	0,0	500,0	0,2	500,0	0,2	500,0	0,2	500,0
Burnt Areas	59,9	0,0	0,0	0,0	265,8	0,1	15576,1	5,3	15516,2
Total	*294051,4*	*100,0*	*294051,4*	*100,0*	*294051,4*	*100,0*	*294051,4*	*100,0*	*0,0*

The most significant change between 1990 and 2021 occurred in Urban Fabric, Forests and Semi-Natural Areas, and Burnt areas (Table 5). IPCC Sixth Assessment Report 2021 clearly states that human activities have a direct impact on climate change. In recent years, in which the effects of climate change have been clearly seen, the number of forest fires has increased all over the world, in the Mediterranean Basin and in Turkey, together with the heat waves. In particular, 2021 has been the year with the most fire incidents of the last 40 years and spread over large areas. In the study area, where the Mediterranean climate and vegetation are typical, the land cover has been destroyed, and the biodiversity is endangered. The main reason for the increase in Urban Fabric areas is the population pressure caused by tourism activities (Figure 6). As a matter of fact, depending on the demands in tourism, an airport was built in the study area after 1990 (Fig 7), and the number of marinas gradually increased after the 2000s. While there was only the Marina in Bodrum city center before, Turgutreis D Marin Port and Yalikavak Palmarina Port were built after the 2000s (Figure 8). Population growth in the last 15-20 years after 2010 was also reflected in the statistics. This situation has caused the settlements to move from the city center to natural areas (Figure 6). As a matter of fact, while the number of forest fires was negligible during the study period, a wide range of forest fires occurred in 2021 due to natural and human activities, a decrease in forest areas and an increase in burned areas. It was observed that there were fires especially in the northeast (Figure 9) and southeast (Figure 10) of the study area.

4. CONCLUSION

In this study, land cover change due to the development of tourism activities in Bodrum Peninsula, where fishing, sponge fishing, and agricultural activities were common in the early 20th century, has been analyzed. Medium resolution satellite images were analyzed as data in the study. These data were analyzed using object-based classification method in eCognition Developer software, and high accuracy segments were produced. It is thought that the results and the proposed method of the study can be useful in the periodic provision of spatial base data that can be used in the administrative activities of decision-makers, owing to the capacity to quick and reliable detection of time-dependent changes.

According to the satellite image analysis results in the period studied (1990-2021), it was determined that while the Urban Fabric and Burnt areas increased in the research area where marine and coastal tourism developed, Forests and Semi-Natural Areas, are decreased. Significant spatial changes occurred along the shores of the study area, especially with the urbanization in the western part of the peninsula. As a result of the urbanization along the coast, when the land to be built decreases, it moves towards the back slope terrains.

As a result of population pressure due to tourism, Urban Fabric areas have moved closer to Forests and Semi-Natural Areas. Forest fires with the effect of heat waves were increased, biodiversity has been endangered, forest areas have decreased, and burning areas have increased in the study area located in the Mediterranean basin, where human-related climate change is most clearly detected.

According to obtained results, climate change has caused forest fires in the region with the effect of heatwaves. In the following years, again with the effect of heatwaves, it will mainly affect human health, thermal comfort, water resources, drinking and utility water, agricultural areas and food safety.

Within the framework of the United Nations Convention to Combat Desertification and Sustainable Development Goals, the issue of balancing land degradation is considered to become a global aim. In this context, the outputs obtained from the study for sustainable land management in the study area located in the Mediterranean Basin, which is one of the most vulnerable hot and sensitive points to land degradation are to be shared with decision-makers.

Figure 6- Land Cover Change in Urban Fabric, Bodrum city center from 1990 to 2021

Figure 7- Land Cover Change in Airport, Milas Bodrum International Airport, Bodrum 1990 to 2021

Figure 8- Land Cover Change in Port areas, Turgutreis D-Marin Port and Yalıkavak Palmarina Port from 1990 to 2021

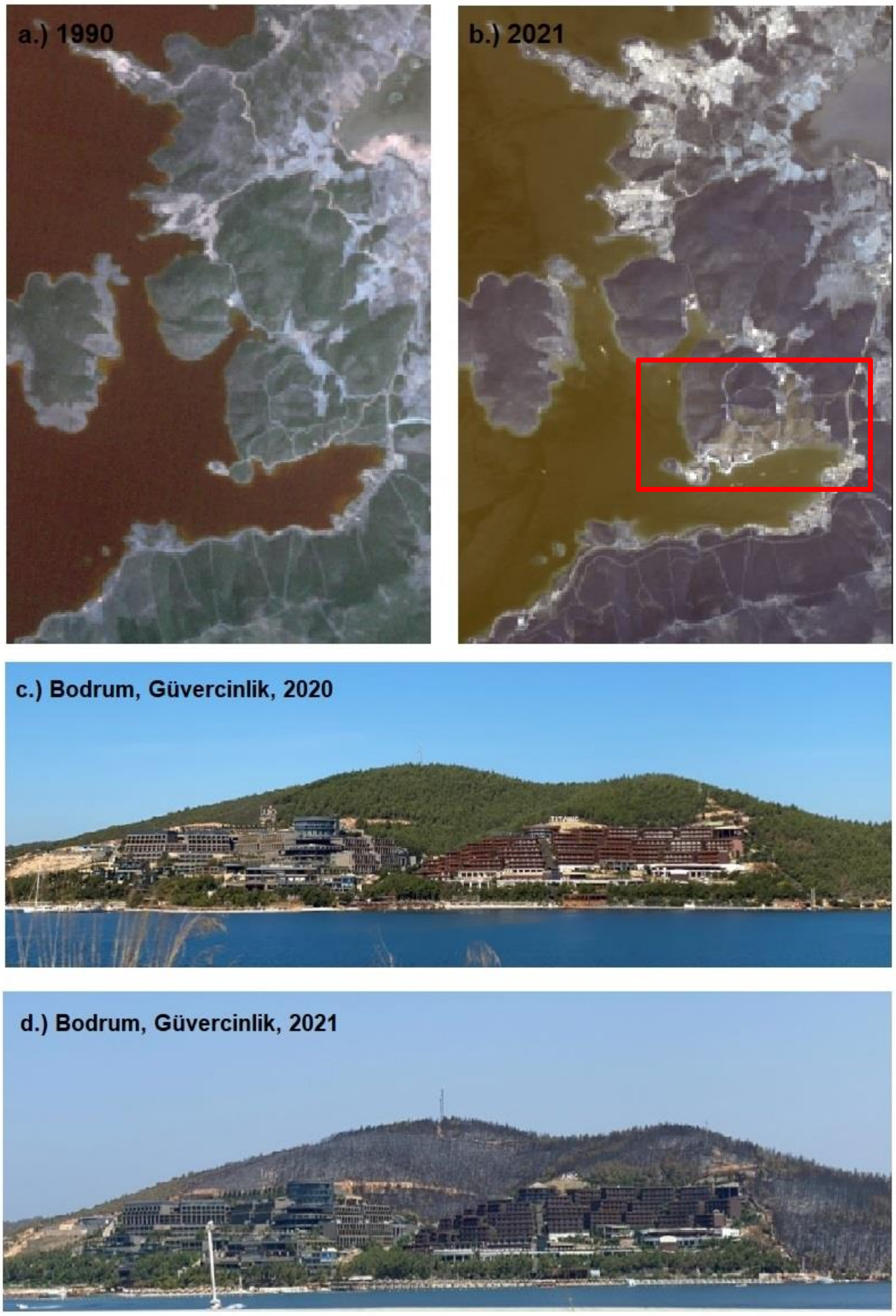

Figure 9- Land Cover Change in Burnt Area, Güvercinlik from 1990 to 2020 and 2021

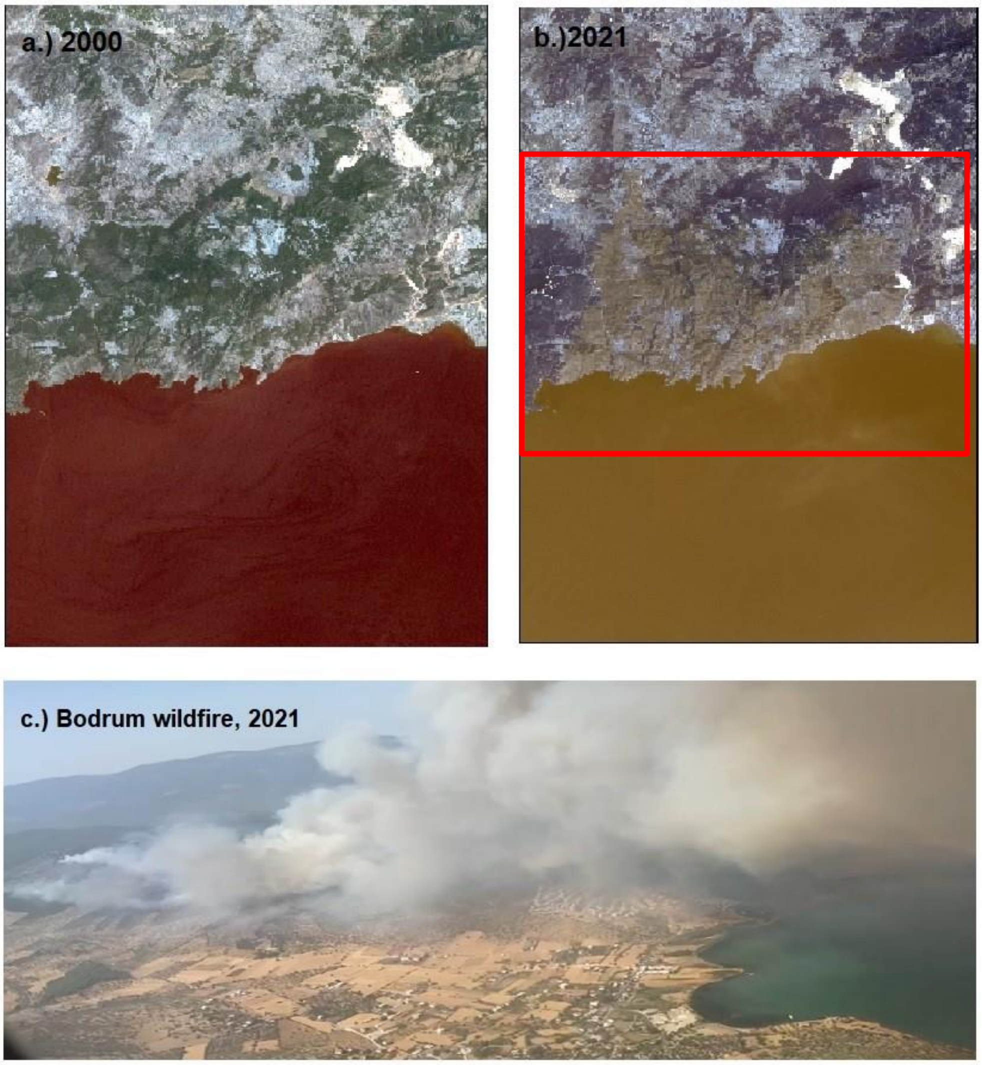

Figure 10- Land Cover Change in Burnt Area, Bodrum Wildfire from 2000 to 2021

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