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The performance analyses of support vector machine classifiers for examination of the temporal change of land-use/cover in the Beyşehir Basin in Turkey (1984-2018)

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Abstract: *This study aimed to investigate the temporal change in land-use/cover in the Beyşehir-Kaşaklı Subbasin, which is one of the nine subbasins of the Konya Closed Basin and known as the largest closed basin in Turkey, using Remote Sensing and Geographic Information Systems techniques. For this purpose, in the study, Landsat Thematic Mapper, Enhanced Thematic Mapper, and Operational Land Imager digital satellite images obtained in the years 1984, 1990, 1996, 2000, 2006, 2012, and 2018 were used. The Support Vector Machines (SVM) method was applied as the classification method. In order to apply the SVM method, firstly, the kernel function and parameter set, giving the highest accuracy in the classification, were selected. In the study, four different kernel functions and different parameter sets were experienced as different from each other. Seventy-two different models in total were applied using different combinations of parameters. As a result of the trials of seventy-two different parameters, it was concluded that the method and algorithm giving the most accurate result with 83.81% classification accuracy and 0.7949 Kappa statistics were the polynomial function of SVMs. As a result of the classification process examined the period between 1984 and 2018 using the determined algorithm and parameters, it was detected that artificial surfaces increased by 418%, arable agricultural lands and pastures decreased by 14%, forests and semi-natural areas increased by 4%, and coastal wetlands on the coasts increased by 6%. On the other hand, the surface area of the water bodies in the region, which demonstrated a decreasing trend until the year 2003, was determined to increase by 3% with the establishment of Suğla Storage in 2003.*

Keywords: Beyşehir lake, Geographic information systems, Landsat, Support vector machines, Sustainable land management, Remote sensing

Türkiye'deki Beyşehir havzasında arazi kullanım/örtüsündeki zamansal değişimin incelenmesi için destek vektör makine sınıflandırıcılarının performans analizleri (1984-2018)

Öz: *Bu çalışmada, Türkiye'nin en büyük kapalı havzası olarak bilinen Konya Kapalı Havzası'nın dokuz alt havzasından biri olan Beyşehir-Kaşaklı Alt Havzası'nda meydana gelen arazi kullanımındaki/örtüsündeki zamansal değişikliklerin Uzaktan Algılama teknikleriyle incelenmesi amaçlanmıştır. Bu amaçla çalışmada 1984, 1990, 1996, 2000, 2006, 2012 ve 2018 yıllarında elde edilen Landsat Thematic Mapper, Enhanced Thematic Mapper ve Operational Land Imager dijital uydu görüntüleri kullanılmıştır. Çalışmada piksel tabanlı sınıflandırmalar arasından Destek Vektör Makineleri (DVM) yöntemi uygulanmıştır. DVM yönteminin uygulanması için öncelikle sınıflandırmada en yüksek doğruluğu veren kernel fonksiyon ve parametre seti seçimi yapılmıştır. Çalışmada birbirinden farklı olarak 4 farklı kernel fonksiyon ve farklı parametre setleri denenmiştir. Farklı parametre kombinasyonları kullanılarak toplamda 72 farklı model uygulanmıştır. Belirlenen modeller ile algoritma, kernel fonksiyon ve bu kernele ait parametre seçiminin sınıflandırma doğruluğuna etkisi irdelenmiştir. 72 ayrı parametrenin denemesi sonucunda %83.81 sınıflandırma doğruluğu, 0.7949 Kappa istatistiği ile en doğru sonucu veren yöntem ve algoritmanın DVM' lere ait polinomal fonksiyon olduğu sonucuna varılmıştır. Belirlenen algoritma ve parametreler kullanılarak 1984 ve 2018 yılları arası irdelenen sınıflandırma işleminin sonucunda yapay yüzeylerin %418 arttığı, ekilebilir tarım alanlarının ve meraların %14 azaldığı, orman ve yarı doğal alanların %4 arttığı, kıyılarda bulunan kıyısal sulak alanların %6 oranında arttığı ve bölgedeki su yapısının ise 2003 yılına kadar azalan bir trend gösterirken 2003 yılında kurulan Suğla Depolaması ile birlikte su yapısının yüzey alanının %3 arttığı tespit edilmiştir.*

Anahtar Sözcükler: Beyşehir gölü, Coğrafi bilgi sistemleri, Landsat, Destek vektör makineleri, Sürdürülebilir arazi yönetimi, Uzaktan algılama

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1. Introduction

The earth has a dynamic structure due to natural changes such as volcanic activities and unnatural changes such as human activities. The wrong and unconscious use of limited natural resources on the earth causes severe deformations in land cover (Kara & Karatepe, 2012; Rozenstein & Karnieli, 2011). If these deformations exceed the self-renewal balance of nature, irreversible ecological deteriorations occur. Nowadays, the efficient use of rural and urban lands in line with their potential is of global importance in terms of sustainable land management. The destruction experienced in the natural environment due to the increasing population growth and technological advances in our country is the result of unplanned urbanization and wrongly implemented policies. The efficient use of limited natural resources, design and planning sustainably by taking into account the social needs are quite important. In order to preserve the existence of limited natural resources in sustainable land management, it is necessary to record them, examine their temporal changes, determine their potential, and guide decision-makers by continually updating this information (Dengiz & Turan, 2014; Gulersoy, 2008). Remote Sensing (RS) and Geographical Information Systems (GIS), which are used frequently in recent years, are used in examining these changes in land-use/land-cover (LULC) (Acheampong, Yu, Enomah, Anchang, & Eduful, 2018; Banerjee & Srivastava, 2013; Dewan & Yamaguchi, 2009; Dodiya, Goswami, Chauhan, Bhuva, & Parekh, 2019; Geymen & Baz, 2008; Koylu & Geymen, 2016; Kumar, Radhakrishnan, & Mathew, 2019; Mansour, Al-Belushi, & Al-Awadhi, 2020; Zhang & Zhu, 2011). RS technology is one proven strategy to better, faster and more accurate decisions, document, analysis and quantify in LULC (Punia, Joshi, & Porwal, 2011; Wentz, Nelson, Rahman, Stefanov, & Roy, 2008).

In general, the detection of the temporal change in LULC is possible through assigning the reflection and radiation values of the pixels of satellite images to the specified number of classes using the RS techniques (Huang, Davis, & Townshend, 2002; Ustuner, Sanli, & Dixon, 2015). The selection of the number of classes to be used should be assigned in different numbers and features depending on the aim of the study to be conducted and the spatial resolution of the used satellite images. Furthermore, data standards should be provided in terms of the comparison of the determined classes with each other and the protection of their sustainability (Donmez, 2015). For this purpose, classification databases of LULC on different scales were designed in different countries. In the process of determining the number of classes, the Coordination of Information on the Environment (CORINE) project, which is used in the European Union (EU) countries and of which use has accelerated in our country in recent years, is frequently used. The CORINE project is "the management of the same basic data and the formation of a standard database, in line with the criteria and classification system set by the European Environment Agency (EEA), in order to determine environmental changes in the land, manage natural resources rationally, and establish environmental policies in all EEA countries" (CORINE, 2020). The most important aspect of the CORINE project is the use of GIS and RS techniques during application. The classification in the CORINE project is mainly separated into five land-use types at the first level, fifteen land-use types at the second level, and forty-four land-use types at the third level, and they are mapped on a scale of 1/100 000. In this study, the existing CORINE data for the years dedicated were examined, and the classification process was carried out by determining five classes at the first level and ten classes at the second level in the study area.

There are different classification methods used nowadays to examine the temporal change of LULC. In the classification process, low spatial resolutions, the used classification methods, and the assignment of a large number of classes result in pixel complexities and reducing the classification accuracy in large application areas (Ustuner et al., 2015). Among these classification methods, Maximum Likelihood Classification, Neural Network Analysis, Support Vector Machine (SVM) algorithms, and object-based classifications are the most well-known and most practiced supervised classifications in the literature (Otukei & Blaschke, 2010; Srivastava, Han, Rico-Ramirez, Bray, & Islam, 2012; Topaloglu, Sertel, & Musaoglu, 2016; Yu, Lan, Zeng, & Zou, 2019). In the study, in order to determine the kernel function and parameter set giving the highest classification accuracy, four different kernel functions (Radial, Linear, Polynomial, and Sigmoid) and different parameter sets (polynomial degree, error parameter, bias, and Gamma value) were experienced within the SVM method as different from each other, and seventy-two different models in total were applied using different combinations of parameters. As a result of the determined models, the effects of the kernel function and the selection of the parameters belonging to this kernel on the classification accuracy percentage were examined, and the algorithm and parameter set that gave the highest classification accuracy were determined.

This study aimed to investigate temporal changes in LULC occurring in the Beyşehir-Kaşaklı Subbasin over the 35 years between 1984 and 2018 with RS and GIS techniques using the determined algorithm and parameters. When the literature studies were examined, it was determined that the change in LULC was not studied comprehensively using GIS and RS techniques in the previous years in this region. For this reason, it has created the need to prepare a study that will enable the development of sustainable land management in the region. It was intended that this study would be a base inventory study for the purpose of reviewing the local government's existing policies for the protection and management of the existing and limited land resources in the study area and carrying out a more comprehensive planning activity in this sense.

2. Materials and Methods

2.1 Study Area

The Beyşehir-Kaşaklı Subbasin is one of the nine subbasins of the Konya Closed Basin (KCB), which is known as Turkey's largest closed basin, and it is located in the west of the region. It spreads over a wide area of approximately 7.3 km^2, which includes the non-residential areas of Konya, Isparta, and Antalya. The Beyşehir Lake Basin is located between 38° 03'- 37° 26' North latitudes and 31° 46' - 31° 15' East longitudes (Figure 1). There are the Anamas Mountains, Dedegül Mountain, and Kartoz Mountain extending to the east of the Hoyran-Eğirdir runnel in the west of the basin, the Sultan Mountains, Erenkilit Mountain, and Alaca Mountain separating the Lakes section from Central Anatolia in the east, the Şarkikaraağaç Plain located between the Anamas and Sultan Mountains in the north, and the Seyran and Seydişehir Mountains extending in the south east-north west direction in the south.

Lake Beyşehir, which is the third-largest lake in Turkey following Van and Tuz lakes, is located in the "Lakes District" and it is the source of water intended for human consumption and irrigation in Central Anatolia. The area was declared as a National Park under two different names, Lake Beyşehir and Kızıldağ National Park, in 1993 by the Ministry of Agriculture and Forestry. Lake Beyşehir and its surroundings, which are under protection as a first, second, and third-degree natural protected area, represent a quite important region in terms of cultural and historical heritage. In addition to these, the Konya Closed Basin constitutes 14% of our country's land potential in terms of agricultural production (Orhan, 2014). However, due to wild irrigation activities applied in agriculture, the number of arid lands prone to desertification increases as a result of overloading to underground and existing water resources.

The main reasons for choosing this region as the study area could be listed as follows: increased agricultural irrigation activities and unconscious groundwater use; sudden changes in precipitation and temperatures and an increase in aridness as a consequence of this; the drying up of a large part of 27 brooks and streams feeding the lake; the climatic and human-induced changes such as irregular change activities along the shore, and also the absence of a comprehensive study on the Beyşehir-Kaşaklı Subbasin; and the region's inventory data deficiencies to be used as a base.

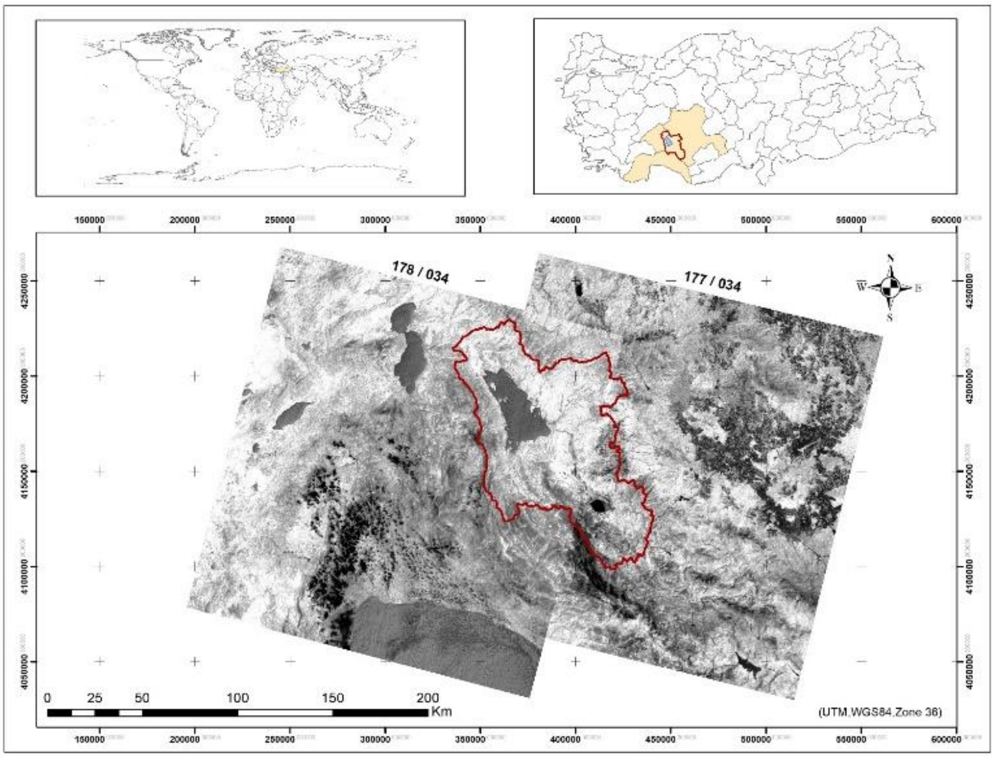

Figure 1: *The study area (Beyşehir-Kaşaklı subbasin boundaries)*

2.2 The Used Data

In this study, Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM), and Operational Land Imager (OLI) digital satellite images obtained in 1984, 1990, 1996, 2000, 2006, 2012, and 2018 were used. Landsat satellite images were used in this study since they have a medium spatial resolution, are often preferred for the detection of environmental changes, provide the sufficient information in a wide range of applications, and are available free of charge. Landsat satellite images were procured from the United States Geological Research Institute (USGS) website (USGS, 2020).

Landsat 5 TM, 7 ETM, and 8 OLI satellites provide images in the visible, near-infrared (infra-red) (VNIR), shortwave infrared (SWIR), and thermal infrared (TIR) ranges and have a medium spatial resolution between 15 to 100 m depending on the spectral range. Swath widths are 183 km for Landsat 5 185 km for Landsat 7-8, and their temporal resolution is 16 days. Spatial resolution of spectral bands is 30 m, their radiometric resolution is 8 bits, and they orbit at an altitude of 705 km. Different from Landsat 5, Landsat 7 has a developed thematic mapper scanner. In addition to the standard seven bands, the panchromatic band (0.50-0.90 µm) with 15 m resolution was added. In addition to these, the resolution of the thermal band was reduced from 120 m to 60 m. Landsat 8, which joined the trajectory of Landsat 7 in 2013, provides scientific data. Besides the common bands, Landsat 8 OLI carries the deep blue band for coastal/aerosol studies, as well as the short wave infrared band for the detection of cirrus clouds. OLI collects data as nine spectral bands (Coastal/Aerosol+VNIR+SWIR+PAN+CIRRUS). Seven of these nine bands have the ranges found in the previous LANDSAT 5 TM and 7 ETM sensors; thus, compatibility with prior Landsat data was ensured. The technical characteristics of the Landsat images used in the study are presented in Table 1.

The CORINE project was utilized in the selection of the class to be used in the classification process. In order to minimize the margin of error in the creation of some education data that cannot be clearly determined from the satellite image in the classification process, the required databases, such as high-resolution Google Earth images, and high-resolution satellite data from the Atlas Globe application, which is open to public access and belongs to the Ministry of Environment and

Urbanization-GIS General Directorate, and high-resolution orthophoto images were procured (Atlas, 2020). The ENVI 5.3 software was used in the digital processing and analysis (classification) stages of satellite data, and the ArcGIS 10.5 software was used in all visualization and mapping stages.

Table 1: *Satellite images and technical characteristics used in the study*

No	Spacecraft_Id	Sensor	Cloud Cover	(177/34) Date_Acquired	(178/34) Date_Acquired	Type
1	Landsat 5	TM	0	1984-08-10	1984-07-16	GeoTiff
2	Landsat 5	TM	0	1990-07-26	1990-08-02	GeoTiff
3	Landsat 5	TM	0	1996-07-26	1996-08-02	GeoTiff
4	Landsat 7	ETM	0	2000-08-14	2000-08-05	GeoTiff
5	Landsat 5	TM	0	2006-08-23	2006-08-30	GeoTiff
6	Landsat 5	TM	0	2011-08.21	2011-08-28	GeoTiff
7	Landsat 8	OLI	0	2018-08-24	2018-08-15	GeoTiff

2.3 Method

2.3.1 Image Preprocessing

Satellite images contain systematic or non-systematic errors in their structure. Therefore, corrections (image preprocessing) must be made before using these images. In the study, firstly, fourteen Landsat images consisting of two full frames belonging to seven years were rectified by performing their atmospheric correction. The FLAASH atmospheric correction module of the ENVI 5.3 software was used for radiometric correction. This module is a very comprehensive atmospheric correction application with the input parameters used. The input parameters used in the system consist of scan center coordinates (center latitude, center longitude), sensor type, sensor height (km), highest point height (km), pixel size (m), flight date, flight time, aerosol model, and multispectral special settings.

2.3.2 Image Mosaicing and Extraction of the Related Boundary

Radiometrically corrected satellite images were mosaiced using the "seamless mosaic module" of ENVI 5.3 software. At this stage, mosaic satellite images belonging to 7 different years were obtained by using two full frames (Path/row: 177/3-178/34) of Landsat TM, ETM, OLI satellite images for each year and then, the arranged satellite images of the study area were obtained by extracting the related boundary.

2.3.3 Investigation of Change in LULC

In the classification process that would be applied in determining the temporal change in LULC, the CORINE project, which is frequently used nowadays in the selection of the number of classes, was used. This project, which is implemented in the EU countries, has also begun to be used actively in Turkey since 1990. The advantage of the CORINE project is that it utilizes RS and GIS (Sari & Ozsahin, 2016). The classification in the CORINE project is mainly separated into five land-use types at the first level, fifteen land-use types at the second level, and forty-four land-use types at the third level (Table 2) (ETC/LC, 1995).

Changes in CORINE LULC cover the years of 1990, 1996, 2000, 2006, 2012, 2018. In the study, the satellite image of 2006 was taken as a reference in order to determine classes belonging to the CORINE project and to compare the results. In CORINE 2006 project, the existing classes were determined and classified separately at the first and second levels. The third level of land type could not be studied. The reason for this is that providing detailed information at the third level is not possible since the spatial resolution of the Landsat satellite image is medium (30 m). The determined classes and levels processed as Region of Interest (ROI) using ENVI 5.3. software are given in Table 3 below.

Table 2: *CORINE Land Class and Codes (ETC/LC, 1995)*

CORINE Land Class and Codes		
1st Level	**2nd Level**	**3rd Level**
1. Artificial surfaces	1.1. Urban fabric	1.1.1. Continuous urban fabric
		1.1.2. Discontinuous urban fabric
	1.2. Industrial, commercial and transport units	1.2.1. Industrial or commercial units
		1.2.2. Road and rail networks and associated land
		1.2.3. Port areas
		1.2.4. Airports
	1.3. Mine, dump and construction sites	1.3.1. Mineral extraction sites
		1.3.2. Dump sites
		1.3.3. Construction sites
	1.4. Artificial, non-agricultural vegetated areas	1.4.1. Green urban areas
		1.4.2. Sport and leisure facilities
2. Agricultural areas	2.1. Arable land	2.1.1. Non-irrigated arable land
		2.1.2. Permanently irrigated land
		2.1.3. Rice fields
	2.2. Permanent crops	2.2.1. Vineyards
		2.2.2. Fruit trees and beryy plantations
		2.2.3. Olive groves
	2.3. Pastures	2.3.1. Pastures
	2.4. Heterogeneous agricultural areas	2.4.2. Complex cultivation patterns
		2.4.3. Land principally occupied by agriculture, with significant areas of natural vegetation
3. Forests and semi natural areas	3.1. Forests	3.1.1. Broad-leaved forests
		3.1.2. Coniferous forests
		3.1.3. Mixed forests
	3.2. Scrub and/or herbaceous vegetation associations	3.2.1. Natural grasslands
		3.2.3. Sclerophyllous vegetation
		3.2.4. Transitional woodland-shrubs
	3.3. Open spaces with little or no vegetation	3.3.1. Beaches, dunes, sands
		3.3.3. Sparsely vegetated areas
4. Wetlands	4.1. Inland wetlands	4.1.1. Inland marshes
5. Water bodies	5.1. Inland waters	5.1.2. Water bodies

Table 3: *The first and second-level classes determined according to the CORINE project*

1. Artificial Surfaces (#ROI-1)
1.1. Urban fabric (#ROI-11)
1.3. Mine, dump, and construction sites (#ROI-13)
2. Agricultural Areas (#ROI-2)
2.1. Arable land (#ROI-21)
2.3. Pastures (#ROI-23)
2.4. Heterogeneous agricultural areas (#ROI-24)
3. Forests and Semi Natural Areas (#ROI-3)
3.1. Forests (#ROI-31)
3.2. Scrub and/or herbaceous vegetation associations (#ROI-32)
3.3. Open spaces with little or no vegetation (#ROI-33)
4. Wetlands (#ROI-4)
4.1. Inland wetlands (#ROI-41)
5. Water Bodies (#ROI-5)
5.1. Inland waters (#ROI-51)

2.3.4 Kernel Function and Parameter Set Selection with Support Vector Machines

In the literature, quite different methods and algorithms have been developed for determining change due to the location, spectral reflection, and temporal differences of satellite images used in the detection of temporal changes in LULC (Ustuner et al., 2015). In the study, SVM algorithms, which are widely used in the literature among pixel-based classifications and give very high classification accuracy with a small amount of education data, were tried. SVM is a method, which has been started to be used frequently in recent years, has been developed for binary classifications, and provides very high accuracy with a smaller amount of education data (Cortes & Vapnik, 1995). SVM is a nonparametric supervised classification algorithm based on the statistical learning theory, in other words, on the Vapnik-Chervonenkis (VC) theory (Li et al., 2009). The algorithm in question is a distribution-independent learning algorithm since it does not need any combined distribution function information related to the data (Ayhan & Erdogmus, 2014; Soman, Loganathan, & Ajay, 2011). The general network structure of the method is given in the Figure 4. The main aim of SVM algorithms is to form two classes that can be precisely separated via a linear boundary line (Sunar, 2017). If a linear line is considered as ax+cy+b=0 in 2-dimensional space and if it is expressed as w=[a c] coefficients and x= [x y]^T feature vector, the linear boundary (w.x+b=0) that will be drawn, should be located at the farthest distance from the features of both classes. Here, the support vectors belong to both classes are expressed as the feature that will define the optimal linear line, and satisfy the condition of w.xi+b=±1 (Sunar, 2017). The method was initially designed for the classification of two-class linear data, later developed for the classification of multi-class and nonlinear data.

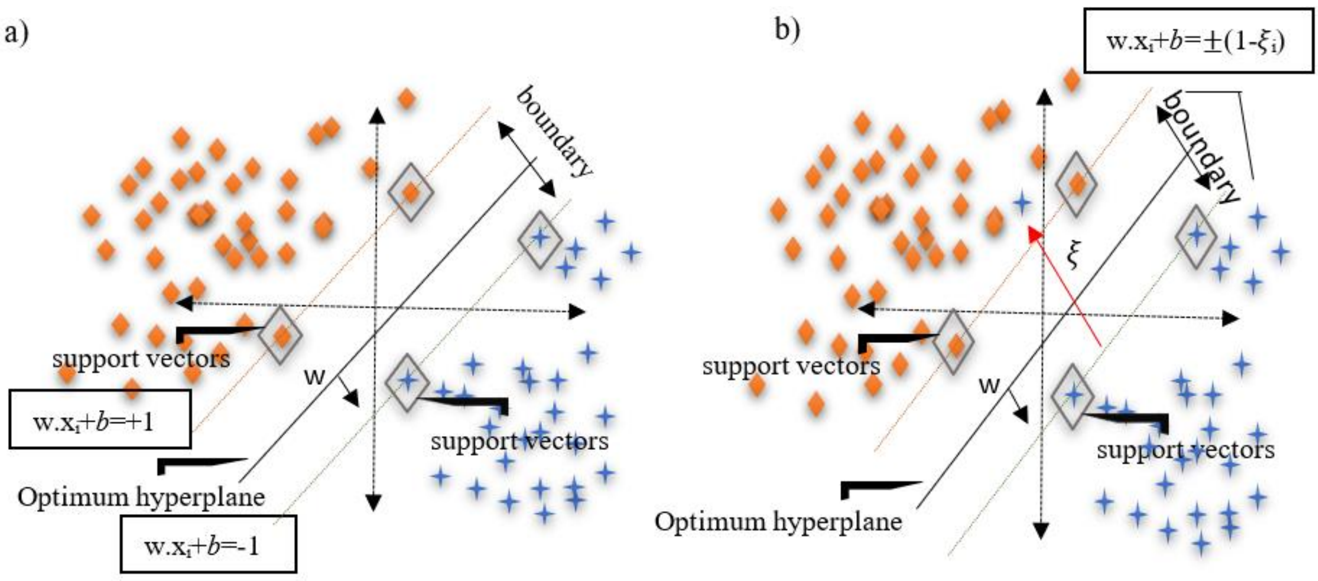

Figure 2: *Linearly separated (a) and non-separated (b) two-dimensional SVM and optimum hyperplane (xi: point on the hyperplane, w: normal of the hyperplane, b: distance of the hyperplane from the origin (Bias), and ξ: distance to the decision limit to which it belongs (slack variable))*

Fundamentally, it is based on the principle of determination of the hyperplane that can separate the two classes from each other (Vapnik, 1995). The results obtained from this method depend on the characteristics of the kernel function and parameters selected (Kavzoglu & Colkesen, 2009). Since SVM can provide high accuracy in classification operations, model complex decision boundaries, work with a large number of independent data, and be applied to both linear and nonlinear data, a large number of studies have been conducted on SVM in the literature (Chen et al., 2019; Dixon & Candade, 2008; Foody & Mathur, 2004).

2.3.5 Accuracy Assessment

Accuracy analysis is a control method, which takes pixel values in regions outside the education areas selected in the classification process as a reference, is based on the principle of statistical comparison with a source that enables achieving precise information about the land (Aslan, 2012). The errors occur due to the fact that pixels cannot be classified correctly. Apart from this, different types of errors, such as the presence of a large number of unclassified pixels, also affect the classification accuracy.

In the accuracy assessment of the classification process, maps that refer to pixel values or ground truth data are used. The accuracies in the classification processes are expressed in Kappa statistics (K). Cohen's Kappa coefficient is a statistical method that measures the reliability of the comparative agreement between two values (Campbell, 1996; Cohen, 1960). The Kappa value is usually between 0-1. The closer the K value is to 1, the closer the classification accuracy is to the actual value. In the Kappa statistical evaluation, results that are better than 0.75 are considered as valid and successful.

3. Results and Discussion

For SVM algorithms, which are nonparametric controlled classification techniques, it is crucial to determine the most appropriate kernel function and parameter set for the study area. In the study, four different kernel functions (Radial, Linear, Polynomial, and Sigmoid) and different parameter sets (polynomial degree, error parameter, bias, and Gamma value) were implemented as different from each other, and seventy-two different models in total were applied. As a result of the determined models, the effects of the kernel function and the selection of the parameters belonging to this kernel on the classification accuracy percentage were examined, and the algorithm and parameter set that gave the highest accuracy was determined (Table 4.1 and Table 4.2).

Table 4.1: *Selection of the most appropriate classification parameter set and comparison of the accuracies*

No	Class Number	Kernel Function	Polynomial Degree	Bias Parameter	Gamma Parameter	Error Parameter	Overall Kappa Index	Overall Accuracy
1	10	Radial	NA	NA	0.167	0	0.669	74.05%
2			NA	NA	0.167	100	0.7613	81.22%
3			NA	NA	0.167	200	0.7679	81.74%
4			NA	NA	0.167	300	0.7706	81.93%
5			NA	NA	0.167	400	0.7703	81.90%
6			NA	NA	0.167	500	0.7708	81.93%
7			NA	NA	0.167	600	0.7724	82.05%
8			NA	NA	0.167	700	0.772	82.02%
9			NA	NA	0.167	800	0.7734	82.12%
10			NA	NA	0.167	900	0.7751	82.26%
11			NA	NA	0.167	1000	0.7752	82.27%
12	10	Linear	NA	NA	0.167	0	0.6646	73.72%
13			NA	NA	0.167	100	0.7357	79.34%
14			NA	NA	0.167	200	0.7375	79.49%
15			NA	NA	0.167	300	0.7381	79.53%
16			NA	NA	0.167	400	0.7387	79.58%
17			NA	NA	0.167	500	0.7389	79.59%
18			NA	NA	0.167	600	0.7396	79.65%
19			NA	NA	0.167	700	0.74	79.68%
20			NA	NA	0.167	800	0.7396	79.65%
21			NA	NA	0.167	900	0.7419	79.84%
22			NA	NA	0.167	1000	0.7426	79.87%

In the model construction stage, since the Gamma value was taken as the inverse of the band number (B-1), error parameter values between 0 and 1000 were tried, and by taking the polynomial degree and bias trend value as between 1 and 6, all probabilities were examined. In the modeling process, the SVM algorithm classification process in Sigmoid functions with seven parameter sets failed, and the related classification process was not realized. Other than these parameters, classification operations were performed in sixty five parameters, and classification accuracy percentages were determined. The algorithm that gave the highest classification accuracy was determined as the Polynomial function of SVM algorithms, and the related parameters, namely Gamma was detected as 0.167, error parameter as 800, the polynomial degree as 6, and the bias value as 5.

Table 4.2: *Selection of the most appropriate classification parameter set and comparison of the accuracies*

No	Class Number	Kernel Function	Polynomial Degree	Bias Parameter	Gamma Parameter	Error Parameter	Overall Kappa Index	Overall Accuracy
23			2	1	0.167	0	0.6676	73.97%
24			2	1	0.167	100	0.7578	80.98%
25			2	1	0.167	200	0.7607	81.19%
26			2	1	0.167	300	0.7645	81.47%
27			2	1	0.167	400	0.7669	81.66%
28			2	1	0.167	500	0.7674	81.69%
29			2	1	0.167	600	0.7686	81.78%
30			2	1	0.167	700	0.7687	81.77%
31			2	1	0.167	800	0.7687	81.77%
32			2	1	0.167	900	0.7695	81.85%
33			2	1	0.167	1000	0.7716	82.00%
34			1	1	0.167	100	0.7306	78.92%
35			3	1	0.167	100	0.7669	81.67%
36			4	1	0.167	100	0.7695	81.85%
37			5	1	0.167	100	0.7718	82.01%
38			6	1	0.167	100	0.7771	82.45%
39	10	Polynomial	2	0	0.167	100	0.7446	79.94%
40			2	2	0.167	100	0.7627	81.36%
41			2	3	0.167	100	0.763	81.38%
42			2	4	0.167	100	0.7578	80.97%
43			2	5	0.167	100	0.7571	80.91%
44			2	6	0.167	100	0.758	80.99%
45			6	5	0.167	0	0.7581	80.99%
46			6	5	0.167	100	0.7892	83.34%
47			6	5	0.167	200	0.7896	83.37%
48			6	5	0.167	300	0.7895	83.38%
49			6	5	0.167	400	0.7922	83.58%
50			6	5	0.167	500	0.7912	83.53%
51			6	5	0.167	600	0.7889	83.33%
52			6	5	0.167	700	0.7927	83.63%
53			6	5	0.167	800	0.7949	83.81%
54			6	5	0.167	900	0.7906	83.46%
55			6	5	0.167	1000	0.7888	83.31%
56								
56			NA	1	0.167	0	No valid result.	
57			NA	1	0.167	100	0.5715	67.01%
58			NA	1	0.167	200	0.5622	66.40%
59			NA	1	0.167	300	0.5604	66.29%
60			NA	1	0.167	400	0.5771	67.88%
61			NA	1	0.167	500	No valid result.	
62			NA	1	0.167	600	0.5582	66.14%
63			NA	1	0.167	700	0.5723	67.51%
64	10	Sigmoid	NA	1	0.167	800	0.5841	68.05%
65			NA	1	0.167	900	0.5824	67.92%
66			NA	1	0.167	1000	0.5906	68.81%
67			NA	0	0.167	800	No valid result.	
68			NA	2	0.167	800	No valid result.	
69			NA	3	0.167	800	No valid result.	
70			NA	4	0.167	800	No valid result.	
71			NA	5	0.167	100	0.637	71.79%
72			NA	6	0.167	800	No valid result.	

The classification process was carried out by applying the algorithm and parameters, which were determined as a result of the modeling in the study and gave the highest classification accuracy, for the years of 1984, 1990, 1996, 2000, 2006, 2012, and 2018 (at approximately five-year intervals) during the 35 years that elapsed between 1985 and 2018. The classification process was carried out in 5 classes at the first level (Figure 3) and in 10 classes at the second level (Figure 4). As a result of the process, the image enrichment and classification techniques were applied to the satellite images, and changes in LULC for each satellite image were determined, and accuracy analyses were performed for seven years for which the classification process was carried out.

A classification accuracy assessment based on 290 random points, defined and placed using a random method with the ENVI 5.3 software in order to represent the classes of different LULC of the basin, was performed in the study. In order to perform the accuracy assessment giving the most successful result, the total of random points produced must be 250 or more. Two hundred ninety points, field control points (ground truth data), Google Earth images, SPOT 5 satellite images, and topographic maps used in our study were used as reference data. The reference data and classification results were compared using error matrices and analyzed statistically.

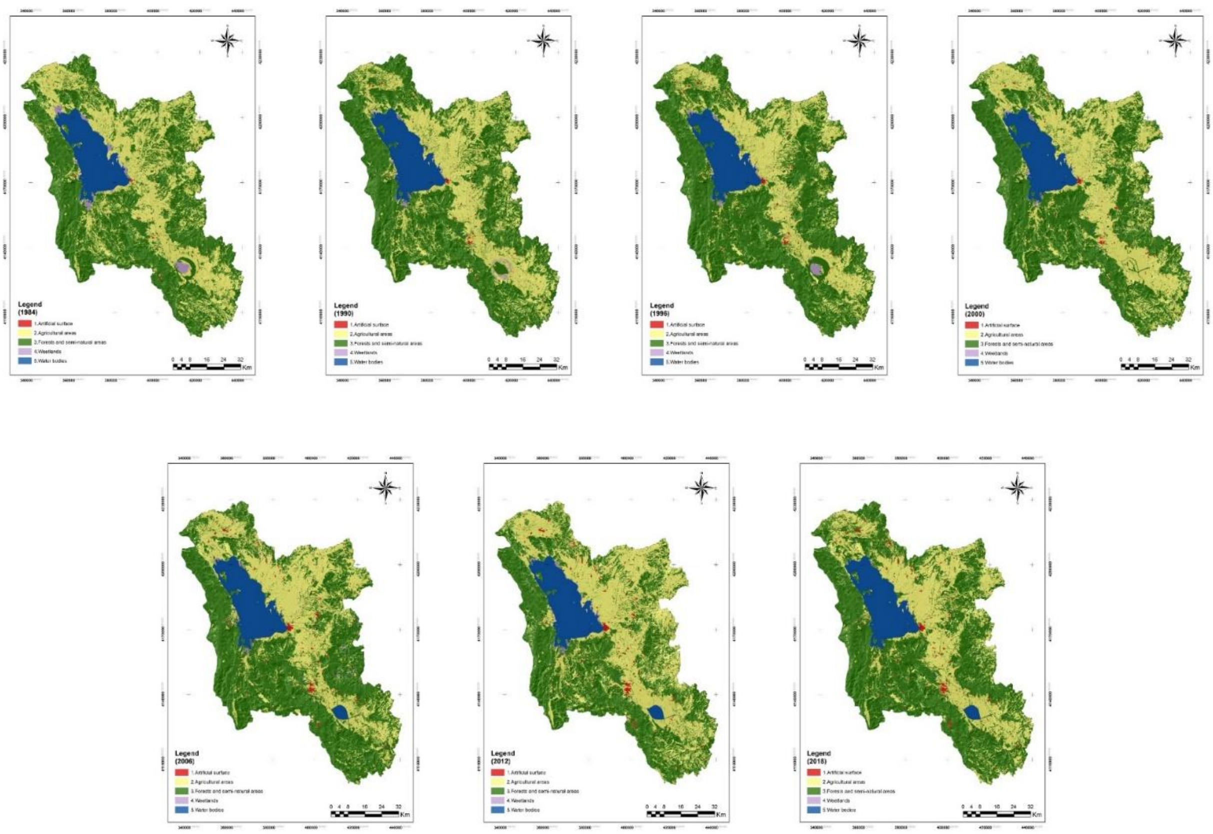

Figure 3: *First level DVM classification image for 1984-2018*

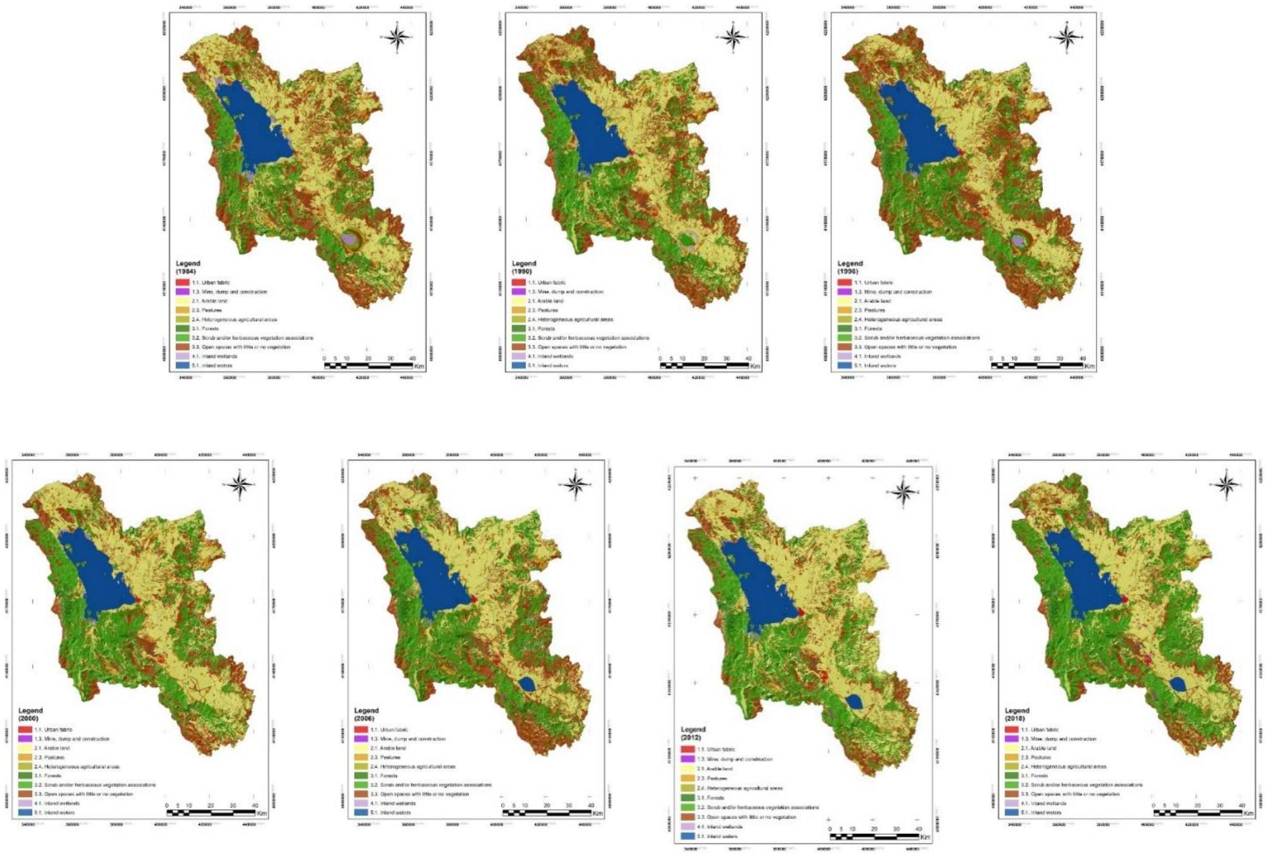

Figure 4: *Second level DVM classification image for 1984-2018*

The overall accuracy percentage in the study was determined to be 91% at the first level and 89% at the second level. Kappa statistics were determined as 0.89 on average at the first level and 0.88 at the second level. The relevant values are presented in Table 5.

Table 5: *The first and second-level classification accuracy analyses*

			First-Level Classification Statistics		Second-Level Classification Statistics	
No	**Sensor**	**Years**	**Overall Accuracy**	**Kappa Coefficient**	**Overall Accuracy**	**Kappa Coefficient**
1	TM	1984	91.29%	0.8873	89.65%	0.8843
2	TM	1990	91.29%	0.8874	88.99%	0.8770
3	TM	1996	92.43%	0.9018	90.04%	0.8887
4	ETM	2000	92.47%	0.9017	89.88%	0.8871
5	TM	2006	92.39%	0.9012	90.10%	0.8893
6	TM	2011	92.20%	0.8989	90.29%	0.8913
7	OLI	2018	91.59%	0.8911	89.81%	0.8861

Furthermore, in the study, the first and second-level classification accuracies were also examined, and the results were compared in percentage (Table 6). In addition to high overall accuracy percentages for each class, the highest first and second-level accuracies were in the water resource class. The accuracy average is 99.97% for both levels. The lowest overall accuracy as percentage was determined as artificial surfaces at the first level (86.81%) and urban structure (83.46%), mines, discharge, and construction areas (75.01%) at the second level. The relevant values are given in Table 6.

Table 6: *First and second-level classification accuracy percentages*

Years	First-Level (%)					Second-Level (%)									
	1	2	3	4	5	1.1	1.2	2.1	2.3	2.4	3.1	3.2	3.3	4.1	5.1
1984	85.3	88.9	92.9	91.4	100	83.0	74.8	89.5	88.3	87.7	90.4	90.4	92.1	91.4	100
1990	85.7	89.1	93.5	88.4	100	79.1	75.4	88.3	89.4	84.4	93.5	90.0	91.3	88.4	100
1996	88.7	90.8	93.0	90.7	100	80.8	79.7	90.3	91.1	88.5	91.3	93.3	89.1	90.7	100
2000	85.2	91.5	94.2	92.2	99.8	79.9	73.2	90.4	93.7	86.0	91.1	89.7	92.0	92.2	99.8
2006	88.0	90.8	93.9	88.1	100	89.7	67.3	92.4	89.0	80.4	91.3	90.7	82.9	87.9	100
2011	88.3	89.6	93.2	91.4	100	88.8	75.4	86.8	92.0	84.4	88.5	91.8	92.6	91.4	100
2018	86.5	91.2	92.2	87.6	100	83.0	79.2	90.3	92.6	88.6	86.7	91.8	90.6	87.6	100

The change statistics and matrix and temporal analysis of LULC are essential to understand the reasons for this rapid change process. The first and second-level spatial changes for the study area are presented in Table 7-8.

Table 7: *First-level spatial change*

Years	Areas (km^2)				
	#ROI-1	#ROI-2	#ROI-3	#ROI-4	#ROI-5
	Artificial Surface	Agricultural Areas	Forest and Semi Natural Areas	Wetlands	Water Bodies
1984	0.158	26.204	39.594	0.873	6.506
1990	0.290	24.383	41.613	0.551	6.434
1996	0.383	24.423	41.510	0.580	6.376
2000	0.426	25.399	40.182	0.443	6.319
2006	0.601	24.348	41.090	0.720	6.621
2011	0.637	23.487	40.721	0.584	6.720
2018	0.817	22.530	41.169	0.927	6.729

Table 8: *Second-level spatial change*

Years	Areas (km^2)									
	#ROI-11	#ROI-13	#ROI-21	#ROI-23	#ROI-24	#ROI-31	#ROI-32	#ROI-33	#ROI-41	#ROI-51
1984	0.134	0.023	22.628	2.238	1.337	3.533	13.222	22.839	0.873	6.506
1990	0.224	0.066	21.233	2.348	0.802	3.501	16.739	21.373	0.551	6.434
1996	0.341	0.041	21.759	2.127	0.536	3.662	17.121	20.726	0.580	6.376
2000	0.382	0.043	22.852	2.093	0.449	3.539	19.332	17.311	0.443	6.319
2006	0.511	0.090	22.210	1.665	0.472	3.544	18.969	18.576	0.720	6.621
2011	0.515	0.122	20.994	1.742	0.750	3.198	19.882	17.640	0.584	6.720
2018	0.539	0.278	20.187	1.569	0.773	2.941	20.669	17.559	0.927	6.729

When the first and second-level spatial changes that occurred in the last 35 years and determined as a result of the classification were examined (Table 7), it was determined that artificial surfaces, forest, and semi-natural areas, wet areas involving swamps in excess, and water resources increased and that losses were experienced in arable agricultural lands, mixed agricultural lands, and pastures. The Seydişehir-Suğla Storage Project, which is of great importance in terms of aquaculture and irrigation in the region, is an important project that came into operation in June 2003 in order to provide water for Lake Beyşehir and Apa Dam regulators and Konya-Çumra projects. Upon examining the spatial change graph in the study, while an increasing reduction was experienced in the water resources in the region year by year until the year 2003, an increase in the surface area was experienced with the formation of the Suğla Storage and with the construction of other dams. While increases were also experienced in agricultural areas during the years between 2000 and 2006, in the following years, losses were experienced again in agricultural areas.

Due to sudden changes experienced in LULC in the region, change detection was performed after classification by using the ENVI 5.3 software in this study, and the results of the analysis are presented in Table 9 below.

Table 9: *1984-2018 percentage change detection analysis*

	Change (%)	1984						
	1984-2018	#ROI-1	#ROI-2	#ROI-3	#ROI-4	#ROI-5	Row Total	Class Total
2018	#ROI-1	**64.587**	0.593	0.578	0.396	0.029	99.996	100
	#ROI-2	14.545	**65.438**	17.36	31.301	0.919	99.987	100
	#ROI-3	20.628	33.07	**80.996**	26.215	1.183	99.982	100
	#ROI-4	0.18	0.428	0.844	**14.992**	1.196	99.449	100
	#ROI-5	0.06	0.459	0.201	27.059	**96.545**	99.972	100
	Class Total	100	100	100	100	100		
	Class Change	35.413	34.562	19.004	85.008	3.455		
	Image Difference	418.2939	-14.0211	3.9765	6.1140	3.4259		

As a result of the analysis, it was determined that 14% of the artificial surface texture was obtained from fertile agricultural areas and 20% from the forest and semi-natural areas in 2018. When all analyses were examined in general, it was detected that in the 35 years covering the period between 1984 and 2018, artificial surfaces increased by 418%, arable agricultural lands and pastures decreased by 14%, forests and semi-natural areas (including bare land) increased by 4%, coastal wetlands on the coasts increased by 6%. On the other hand, the surface area of the water structure in the region, which demonstrated a decreasing statistic until the year 2003, was determined to increase by 3% with the establishment of the Suğla Dam in 2003. In addition to the reason for the 3% increase in the water structure, the regression in the south and east regions that occurred in the coastal change also caused an increase in the surface area of water.

4. Conclusion

Nowadays, the efficient use of rural and urban lands in line with their potential is of global importance in terms of sustainable land management. In Turkey, although there are regulations and zoning plans in urban areas for LULC, planning in line with the potential cannot be realized due to data deficiencies in the planning process and, adequate and comprehensive base inventory deficiencies for sustainable land management (Yakar, 2013).

Thanks to the GIS and RS technologies, it has become quite easy to access reliable information about changes in LULC in recent years and to make comments by conducting analyses on this information. In this study, the temporal change in the LULC of the Beyşehir-Kaşaklı Subbasin, which occurred in the 35 years that elapsed between 1984-2018, was investigated by using the GIS and RS techniques.

In order to observe the actual change in water structure, the volumetric change of water should be examined. Based on the statistics, while urbanization is increasing rapidly, the decrease in lands suitable for agricultural activities adversely affects the ecosystem. Apart from this, it was observed that developing a concrete mechanism for LULC with the Suğla Storage area established for wetlands and agricultural activities had positive results in terms of sustainability in the basin. It was intended that this study would be a base inventory study to review the local government's existing policies for the protection and management of the existing and limited land resources in the study area and carry out a more comprehensive planning activity in this sense.

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Author Contribution

Munevver Gizem Gumus: Literature review, Analysis and interpretation, Data collection, Writing. **Suleyman Savas Durduran:** Conception, Design, Review of article, Supervision.

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