JOURNAL OF DESIGN FOR RESILIENCE
IN ARCHITECTURE & PLANNING

Research Article
Online: www.drarch.org
Volume 3, Issue 2, (224-236), 2022
DOI: 10.47818/DRArch.2022.v3i2055

Assessing the performance of machine learning algorithms in Google Earth Engine for land use and land cover analysis: A case study of Muğla province, Türkiye

Hazal Yalçın-Bayrakdar[a]
Mehtap Özenen-Kavlak[b*]
Burcu Yılmazel[c]
Alper Çabuk[d]

Abstract

Regions with high tourism density are very sensitive to human activities. Ensuring sustainability by preserving the cultural characteristics and natural structure of these regions is of critical importance in order to transfer these assets to the future world heritage. Detecting and mapping changes in land use and land cover (LULC) using innovative methods within short time intervals are of great importance for both monitoring the regional change and making administrative planning by taking necessary measures in a timely manner. In this context, this study focuses on the creation of a 4-class LULC map of Muğla province over the Google Earth Engine (GEE) platform by utilizing three different machine learning algorithms, namely, Support Vector Machines (SVM), Random Forest (RF), and Classification and Regression Tree (CART), and on comparison of their accuracy assessments. For improved classification accuracy, as well with the Sentinel-2 and Landsat-8 satellite images, the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) are also derived and used in classification of the major land use classes, which are 'built-up area & barren land', 'dense vegetation', 'water surface', and 'shrub, grassland & sparse vegetation'. Experimental results show that the most relevant algorithm is RF with 0.97 overall accuracy and 0.96 Kappa value, followed by SVM and CART algorithms, respectively. These results indicate that the RF classifier outperforms both SVM and CART classifiers in terms of accuracy. Moreover, based on the results of the RF classifier, 19% (2,429 km^2) of the study region is classified as built-up area & barren land, 48% (6,135 km^2) as dense vegetation, 2% (301 km^2) as water surface and 30% (3,832 km^2) as shrub, grassland & sparse vegetation class.

Keywords: Google Earth Engine (GEE), land use/land cover (LULC) maps, machine learning, remote sensing.

1. Introduction

Due to globalization and rapid population growth, while the world's resources are rapidly depleting, an ever-increasing energy need has emerged. Analysis and evaluation of land use are crucial now more than ever to fulfill the needs of developing cities and growing populations (Avtar, Tripathi, Aggarwal, & Kumar, 2019; Long, Qu, Tu, Zhang, & Jiang, 2020). One of the main parameters

[a]*MSc., Eskisehir Technical University, Turkey,* hazalyalcin@eskisehir.edu.tr, **(Corresponding author),* [b]*Ph.D., Eskisehir Technical University, Turkey,* mehtapozenen@eskisehir.edu.tr, [c]*Assist Prof. Dr., Eskisehir Technical University, Turkey,* byurekli@eskisehir.edu.tr, [d]*Prof. Dr., Eskisehir Technical University, Turkey,* acabuk@eskisehir.edu.tr
Article history: Received 14 July 2022, Accepted 15 August 2022, Published 31 August 2022,

in protecting natural resources by ensuring sustainable development and combating climate change is the creation of regional and global land use and land cover (LULC) maps (Borrelli et al., 2017; Rajbongshi, Das, & Adhikari, 2018; Feizizadeh, Omarzadeh, Kazemi Garajeh, Lakes, & Blaschke, 2021). LULC maps, which can be produced with high-resolution satellite images and remote sensing (RS) techniques (Dou, Shen, Li, & Guan, 2021; Fonseca et al., 2021), play a critical role in the determination and effective management of land use (Harper et al., 2018; Shirmohammadi et al., 2020). For instance, the planning of actions such as monitoring and guiding urbanization, agricultural activities, and conservation of natural resources by decision-makers, taking into consideration the economic benefit, is directly related to the efficient production of LULC maps (Y. Qu & Long, 2018; Stehfest et al., 2019). For this reason, improving classification accuracy in RS applications has long drawn the interest of researchers. (Richards, Landgrebe, & Swain, 1982; Khatami, Mountrakis, & Stehman, 2016; Phiri & Morgenroth, 2017).

With its strong capacities to access, handle, and analyze huge volumes of multi-source, multi-temporal, and multi-scale earth observation data through a cloud platform, Google Earth Engine (GEE) has been recognized as a significant geospatial analysis platform for RS applications (Sazib, Mladenova, & Bolten, 2018). GEE provides more than 40 years' worth of remotely-sensed data from satellites like Landsat, MODIS, Sentinel 1, 2, 3, and 5-P, National Oceanographic and Atmospheric Administration Advanced Very High Resolution Radiometer (NOAA AVHRR), and Advanced Land Observing Satellite (ALOS), as well as demographic, geophysical, climate, and weather datasets (GEE, 2022). In this regard, GEE offers fascinating possibilities for a wide range of studies, such as those involving climate change, urban mapping, crop mapping, forest mapping, water surface investigations, soil moisture, and soil carbon sequestration (Tamiminia et al., 2020; GEE, 2022). Moreover, GEE is considered to be a promising tool for the production of LULC maps with the abilities of evaluating changes in forest and water areas, land and agricultural areas (Huang et al., 2017; Sidhu, Pebesma, & Câmara, 2018; Carrasco, O'Neil, Morton, & Rowland, 2019; Qiu, Schmitt, Geiß, Chen, & Zhu, 2020). However, it is often challenging to scale-up these findings globally because most of the existing studies in the literature concentrate on the production of LULC maps for certain regions (Loukika, Keesara, & Sridhar, 2021). A more wide-ranging application area would be provided if further studies are conducted on improving the accuracy of the machine learning algorithms used to generate these maps. For example, Li, Qiu, Ma, Schmitt, and Zhu (2020) proposed a framework for African land cover mapping at 10 m resolution, and the effectiveness of GEE for large-scale areas was evaluated. In a study conducted by Aghlmand, Kalkan, Onur, Öztürk, and Ulutak (2021), the feasibility of creating land use maps over GEE with RS methods in Eskişehir/Türkiye was investigated. Farda (2017), in the study conducted in Segara Anakan lake/Indonesia, aimed to determine the accuracy level for multi-time land use mapping of coastal wetlands with ten different machine learning algorithms in GEE. The obtained results showed that machine learning in GEE is very useful for multi-temporal land use mapping, where CART being the most successful method with an overall accuracy of 96.98% among the others. The oil palm distribution in Malaysia was mapped by Shaharum et al. (2020) with a variety of machine learning techniques using RS and GEE. The results investigated that the SVM algorithm with an accuracy of 93.16% was the most effective one. L. a. Qu, Chen, Li, Zhi, and Wang (2021) examined the effect of six ancillary features in GEE on accuracy improvements in the classification of LULC maps in the Yangtze River Delta/China region.

Understanding machine learning techniques and how they work in popular cloud-based systems like GEE is crucial given the rising need for trustworthy LULC maps derived from satellite images. The aim of this study is to produce LULC maps of Muğla province in Türkiye using machine learning algorithms in the GEE platform and to compare the performance of the algorithms for LULC classification task. In this context, three different machine learning methods - namely, Support Vector Machines (SVM), Random Forest (RF), and Classification and Regression Tree (CART), are utilized in the classification of four major land use classes which are 'built-up area & barren land', 'dense vegetation', 'water surface', and 'shrub, grassland & sparse vegetation'. Multispectral satellite images from Landsat-8 and Sentinel-2, as well with two indexes (Normalized Difference

Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI)) are used in producing the LULC maps. The selected study area, Muğla, is significant in terms of its natural resources and tourism potential, but also has high fire activity rates continuously increasing due to climate change (Sari, 2021). The original aspect of this study is the production of the 4-class LULC map of the Muğla province, with Sentinel-2 and Landsat-8 image collections and two supplementary indexes over the GEE platform. Another aspect of the study is the accuracy assessment of these machine learning algorithms with standard metrics and comparison with each other in LULC classification task. The study contributes to the literature in producing the LULC maps of the Muğla province at the regional level and in improving the classification accuracy.

2. Materials and Methods

The study area and the material and methodology utilized in the study are described in this section.

2.1. Study area

The study area is Muğla province, located between 37.928 N - 35.93 N and 27.045 E - 29.87 E in southwestern Türkiye, with a surface land area of 13,338 km^2 (Muğla Valiliği, 2022). The province, which consists of 13 districts and 14 municipalities, has a population of 1,021,141 according to 2021 records (Muğla Valiliği, 2022). In terms of climate, it has a rather humid Mediterranean climate, where summers are hot and dry, and winters are warm and rainy (Atmaca et al., 2022). Located at the intersection of the Aegean and the Mediterranean, the province has the longest coastline in Türkiye, with a total of 1124 km. It is one of Türkiye's leading provinces in the tourism sector, world-famous gulfs and bays, forested areas covering 67% of its land area, and a wealth of cultural treasures. (Bahar, 2008). At the same time, significant economic activities are carried out in the province in agriculture, animal husbandry, and industry sectors (T.C. KTB, 2022).

After İstanbul and Antalya, Muğla is the third-most-visited city in Türkiye. Due to the city's tourism-driven growth and the activities experienced in the coastal regions, both the continuation of conservation efforts and the preservation of the city's cultural traits must be handled with care (Yücel & Ertin, 2019). In this context, the Muğla Governorship Provincial Culture and Tourism Directorate (Bingöl, 2022), Muğla Metropolitan Municipality (Muğla Büyükşehir Belediyesi, 2022b), Department of Reconstruction and Urbanization (Muğla Büyükşehir Belediyesi, 2022a), and related institutions conduct various studies and legislative arrangements. The province of Muğla is selected as the study region to support this legislative structure and assure the adoption of innovative methodologies in the construction of a LULC map that can be utilized by decision makers. The location of the study area is illustrated in Figure 1.

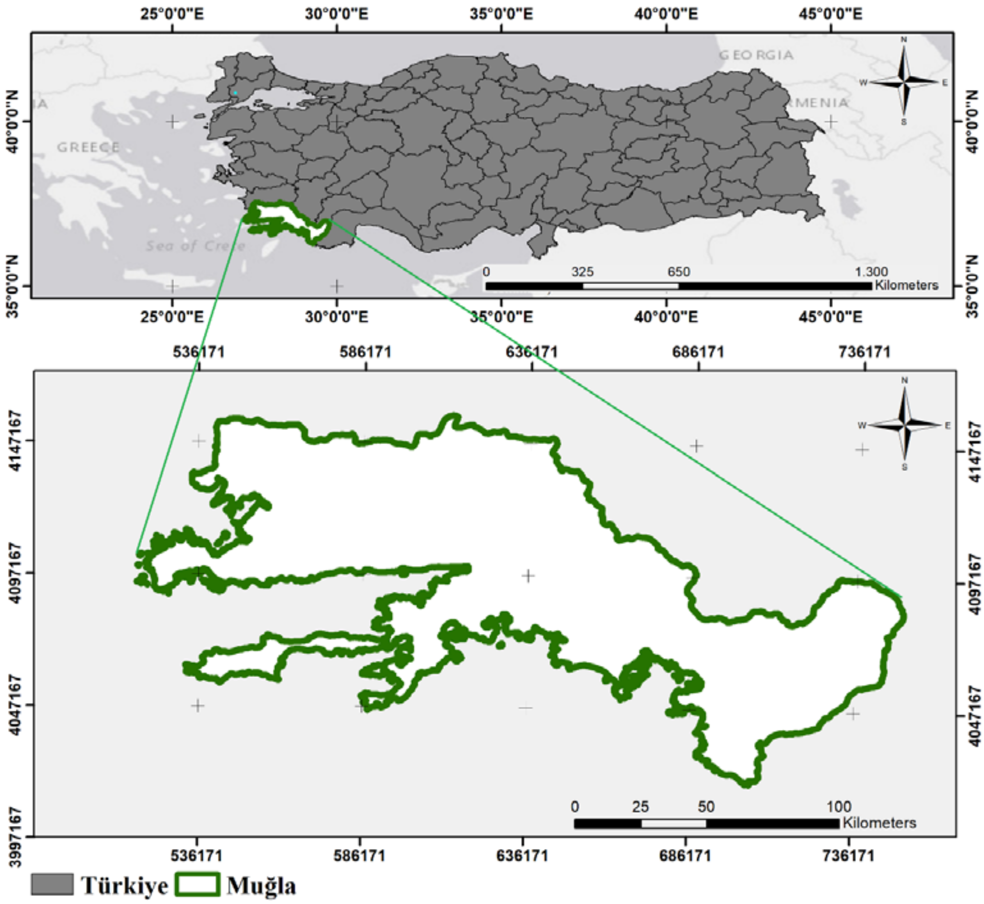

Figure 1 Location of the study area: Muğla Türkiye

2.2. Material and Method

The main material of the study is the satellite imageries. Two different spatial resolution satellite data, Landsat-8 satellite images at 30 m resolution and Sentinel-2 satellite images at 10 m resolution, are utilized that are retrieved through GEE searches. The search results are filtered with "5% cloudiness" for the period "2020-05-01 to 2020-08-11" and image collections are compiled between these dates. By adding a cloud cover percentage filter on the images, it is aimed to minimize the noise sources. Then the median values of the obtained images are calculated. For this study, Bands 2, 3, 4, 5, 6, 7 of Landsat-8 satellite images, and Bands 2, 3, 4, 5, 6, 7, 8 of Sentinel-2 satellite images of Muğla province are used in the classification stage, as well with the auxiliary data (NDVI and NDWI) generated from these bands. The resulting maps are visualized with the ArcGIS-ArcMap 10.7.1 program.

The method of this study is to perform four-class supervised classification process in Muğla province by utilizing three different machine learning algorithms over GEE and to compare the performance of the algorithms using standard metrics. In this context, SVM, RF, and CART machine learning algorithms are trained with the band features, as well with NDVI and NDWI indexes.

In the first stage of the study, the auxiliary data that have the ability to extract certain information more effectively, are generated, which are used together with the band features as input in the classification. Within the scope of the study, as auxiliary data NDVI and NDWI are produced both to provide input to machine learning algorithms in supervised classification task and improve the accuracy of classification analyses. This way, a more comprehensive determination of the vegetation and water surfaces in the study area is aimed.

NDVI is one of the most preferred data for monitoring vegetation (Julien & Sobrino, 2009; Ozyavuz, Bilgili, & Salici, 2015; Mutti, Lúcio, Dubreuil, & Bezerra, 2020). NDVI analysis, which is performed using various bands of satellite imagery, is often used in many studies such as monitoring drought, determining the health of plants, the productivity of agricultural lands, and the effects of forest fires (Ozenen Kavlak, Cabuk, & Cetin, 2021; Dikici, 2022). On the other hand, NDWI developed by McFeeters (1996) and Gao (1996) is relevant in identifying water components from satellite images. Water components can be determined by sieving soil and above-ground vegetation using near-infrared (NIR) and visible green (Green) bands. The values obtained as a result of NDVI and NDWI analysis are between -1 and 1. For higher chlorophyll density, the NDVI value is expected to be 1 or close to 1, and for higher water density, the NDWI value is expected to be positive (Bhandari, Kumar, & Singh, 2015). The formulas used in the calculation of these indices are given in Table 1.

Table 1 The formulas of NDVI and NDWI (Hayati, Hestrio, Cendiana, & Kustiyo, 2021)

Name of the index	Index	Formula
Normalized Difference Vegetation Index	NDVI	$\frac{NIR - Red}{NIR + Red}$
Normalized Difference Water Index	NDWI	$\frac{Green - NIR}{Green + NIR}$

The second stage of the study is to reveal the LULC map of the Muğla province including four different land use classes as

- built up area & barren land,
- dense vegetation,
- water surface, and
- shrub, grassland & sparse vegetation,

using RS and different machine learning methods over GEE. It also includes the comparison of the advantages and weaknesses of different machine learning methods in LULC map production. The GEE platform contains various classification methods provides users with fast analysis and results (Tamiminia et al., 2020). Algorithms used in this study are CART, SVM, and RF.

CART is a supervised machine learning method that generates a binary decision tree (Rokach & Maimon, 2005). A homogeneous tree structure is obtained by creating two child nodes from the parent node. The decision tree begins with a root node generated from any variable in the feature space and minimizes an impurity measure for the two sibling nodes. Then, the decision tree expands through consecutive subdivisions until it reaches a point where further subdivision does not result in a meaningful reduction in impurity (Shaharum et al. 2020). It works for both numerical and nominal values (Olfaz, Tirink, & Önder, 2019).

SVM is another supervised machine learning technique that is effective both in classification and regression. It performs the classification process by optimally separating the classes using a hyperplane (Mantero, Moser, & Serpico, 2005). Even though there are numerous ways to divide the data points, the primary goal of SVM is to locate the hyperplane with the greatest margin of separation (Shaharum et al. 2020). The LibSVM library is used in this study (Chang & Lin, 2011).

RF is an alternative supervised learning approach that generates a forest consisting of random decision trees. In order to obtain more precise and reliable predictions, RF builds numerous decision trees and ensembles them. It is applicable to both classification and regression problems (Breiman, 2001).

To evaluate the accuracy of the machine learning algorithms used in LULC map development as an image classification task, for each land use classes 300 points, thus a total of 1200 points are randomly selected from the study area. 70% of all developed samples (840 points) are used to train the algorithms, while the remaining 30% (360 points) are utilized to validate and evaluate the accuracy of the algorithms. Classification and assessment are performed in GEE, and accuracy metrics are obtained through the standard confusion matrix approach (Cohen, 1960; Parida & Mandal, 2020) based on the validation data.

Accuracy assessment is the process of checking whether pixels are assigned to the correct classes to which they belong. As a result of the classification, a pixel can be assigned to a class actually it does not belongs. This is known as classification error, and it is preferred to be small since accuracy increases as classification error decreases (Canters, 1997, Sunar, Özkan, & Osmanoğlu, 2016). In evaluating the performance of different classifiers, various accuracy assessment metrics can be derived based on the confusion matrix, producer accuracy and user accuracy metrics for class-level comparison, overall accuracy for general comparison, and kappa coefficient are widely used in LULC mapping (Lu & Weng, 2007). Overall accuracy is the ratio of the total number of correctly labeled pixels to the total number of control pixels. A success rate of 80% is considered sufficient for overall accuracy (Sunar et al., 2016). The overall accuracy is computed using Equation 1, where $P_{correct}$ is the number of pixels classified correctly by the classifier, and P_{total} is the total number of pixels (Lu & Weng, 2007; Loukika et al., 2021).

$$Overall\ Accuracy = \left(\frac{P_{correct}}{P_{total}}\right) x\ 100 \quad \textbf{(1)}$$

Kappa is used as an indicator of the overall agreement between the classifier results and ground truth. Kappa test is a statistical method that measures the reliability of agreement between two or more observers and shows whether findings are statistically better than random (Congalton & Green, 2019).

Kappa is used as an indicator of the overall agreement between the classifier results and the ground truth. It is a statistical method that measures the reliability of the agreement between two or more raters and shows whether findings are statistically better than random (Congalton & Green, 2019) (2). The value of Kappa ranges between -1 and +1. If the raters completely agree, then Kappa value is 1. Kappa is 0, if there is no agreement amongst raters beyond what would be expected by chance. It is possible for the statistic to be negative, if the evaluations of the two raters are completely opposite to each other. Kappa is calculated using Equation 2, where Po is the relative observed agreement among raters, and Pc is the probability of chance agreement (Kiliç, 2015).

$$K = (Po - Pc) / (1 - Pc) \quad \textbf{(2)}$$

3. Results

This study is examined the performance of three different machine learning algorithms on LULC classification of Muğla province using Landsat-8 and Sentinel-2 images on the GEE platform performed using the methodology outlined in the materials and methods section. Two widely utilized indices, NDWI and NDVI, which are representative of water bodies and vegetation characteristics, respectively, are utilized in the study as auxiliary classification inputs for LULC.

Figure 2 depicts the experimental results of the NDVI analysis for the province of Muğla, while Table 2 depicts the distribution of NDVI findings by study area.

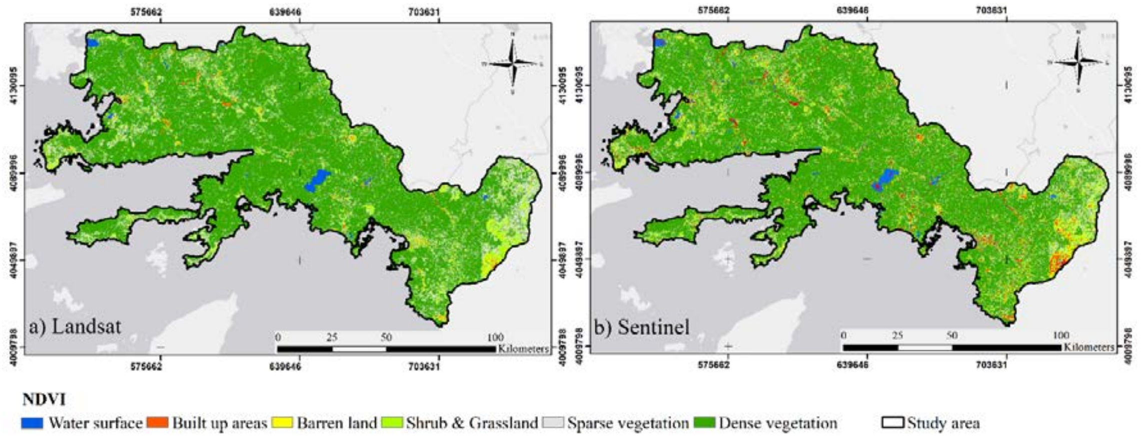

Figure 2 The results of NDVI analysis for Muğla province on (a) Landsat-8 and (b) Sentinel-2 images

As can be seen from Table 2, the results of the NDVI analysis performed with both Landsat-8 and Sentinel-2 satellite images contain similar features, and it is noteworthy that more than 70% of the study area has dense vegetation. Water surface, built-up areas, and barren land areas occupy 4% more area in total in the NDVI analysis results obtained from Sentinel-2 data.

Table 2 Distribution of NDVI results for Landsat-8 and Sentinel-2

NDVI	Landsat-8		Sentinel-2	
	Area (km^2)	Percent (%)	Area (km^2)	Percent (%)
Water surface	174	1	193	2
Built up areas	128	1	373	3
Barren land	127	1	328	2
Shrub & Grassland	881	7	1,150	9
Sparse vegetation	1,929	15	1,508	12
Dense vegetation	9,444	75	9,130	72
Total	12,682	100	12,682	100

The experimental results of the NDWI analysis for Muğla province is shown in Figure 3. Table 3, summarizes the distribution of NDWI results in the study area with Landsat-8 and Sentinel-2 satellite images. Accordingly, while 1% of the study area is covered with water surfaces, approximately 1% of it consists of shallow wetlands.

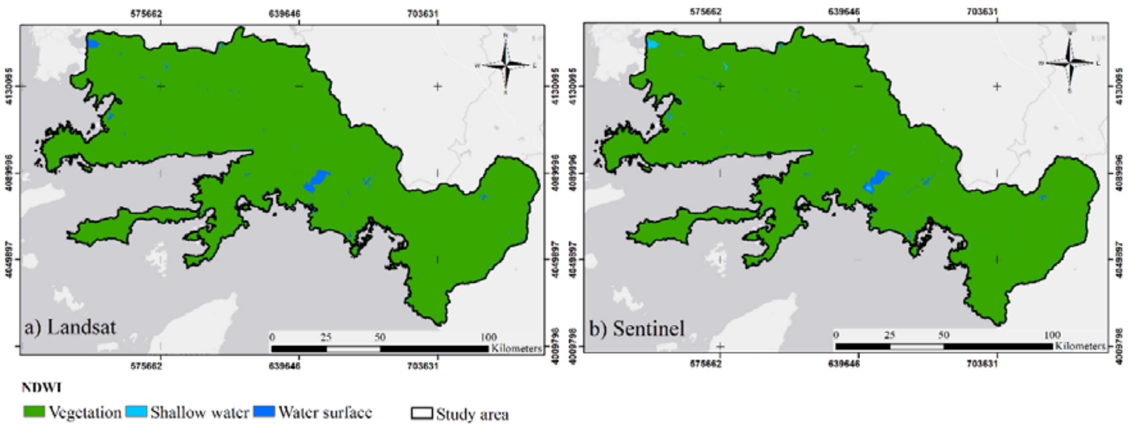

Figure 3 The results of NDWI analysis for Muğla province on (a) Landsat-8 and (b) Sentinel-2 images

Table 3 Distribution of NDWI results for Landsat-8 and Sentinel-2

NDWI	Landsat-8		Sentinel-2	
	Area (km^2)	Percent (%)	Area (km^2)	Percent (%)
Vegetation	12,493	99	12,494	98
Shallow water	28	0	82	1
Water surface	161	1	106	1
Total	12,682	100	12,682	100

In the second part, SVM, RF, and CART algorithms are utilized in the classification of four major land use classes ('built-up area & barren land', 'dense vegetation', 'water surface', and 'shrub, grassland & sparse vegetation') and the LULC maps of the Muğla province is generated.

The LULC map of Muğla province produced by the CART algorithm is given in Figure 4. According to the classification results, 17% (2,109 km^2) of the study area is classified as built-up area & barren land, 39% (4,999 km^2) as dense vegetation, 6% (801 km^2) as water surface, and 38% (4,788 km^2) as shrub, grassland & sparse vegetation class.

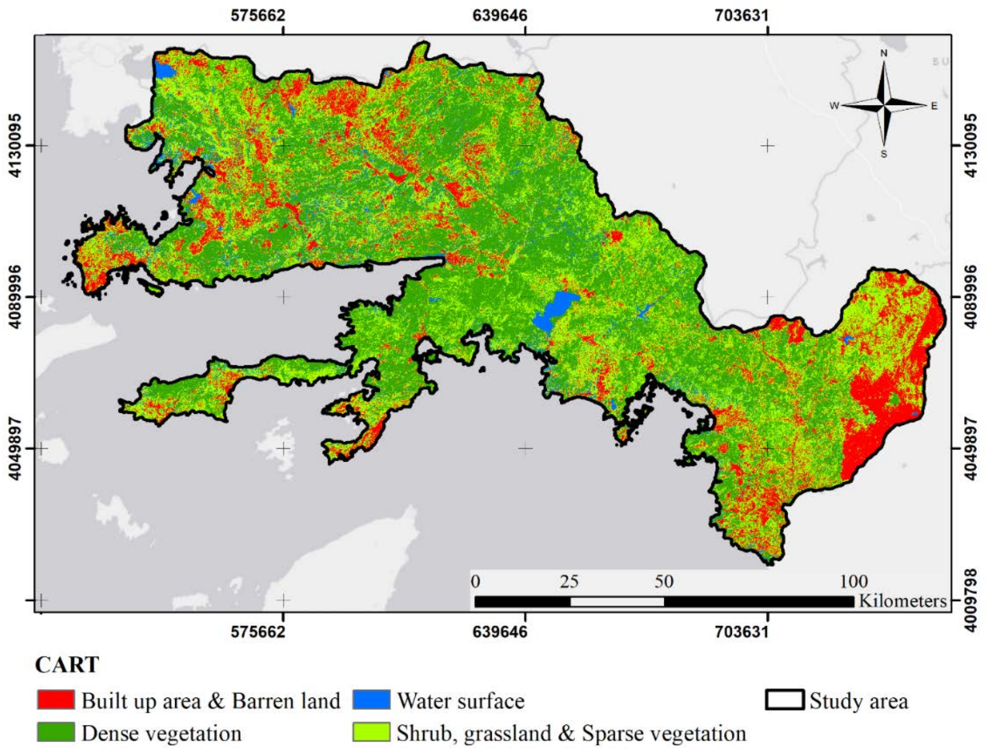

Figure 4 The LULC map of Muğla province generated using the CART algorithm in GEE

The results of the SVM algorithm in LULC map generation of Muğla province is given in Figure 5. According to the results, 9% (1,167 km^2) of the study area is classified as built-up area & barren land, 51% (6,530 km^2) as dense vegetation, 4% (446 km^2) as water surface, and 36% (4,554 km^2) is classified as shrub, grassland & sparse vegetation class.

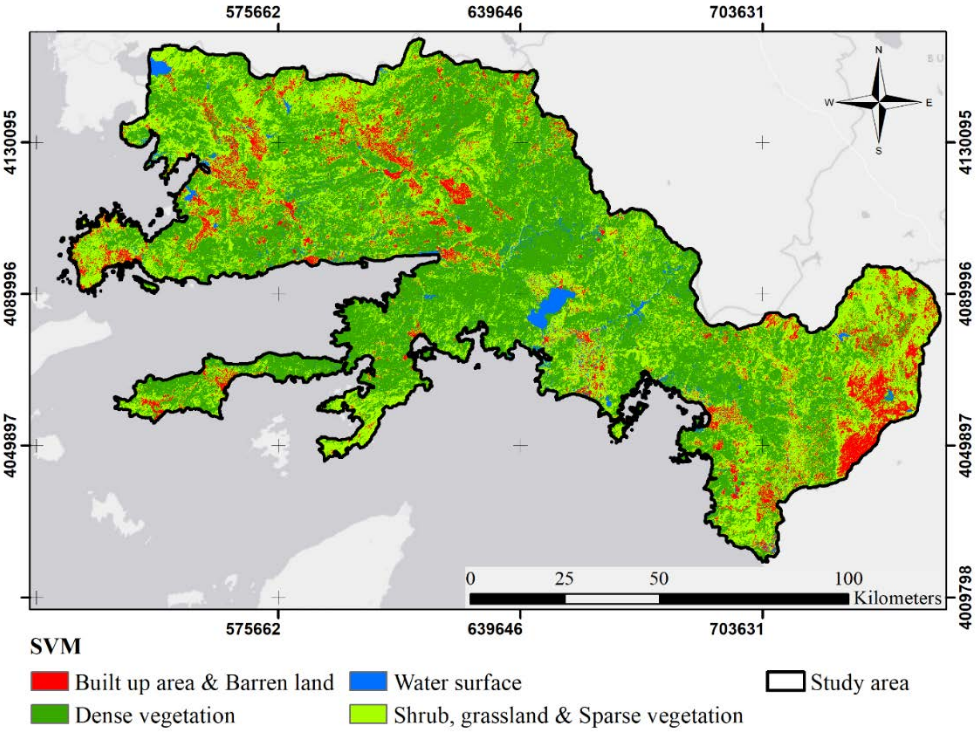

Figure 5 The LULC map of Muğla province generated using the SVM algorithm in GEE

The LULC map of Muğla province produced by the RF algorithm is given in Figure 6. Based on the results of the RF classifier, 19% (2,429 km^2) of the study region is classified as built-up area & barren land, 48% (6,135 km^2) as dense vegetation, 2% (301 km^2) as water surface and 30% (3,832 km^2) as shrub, grassland & sparse vegetation class.

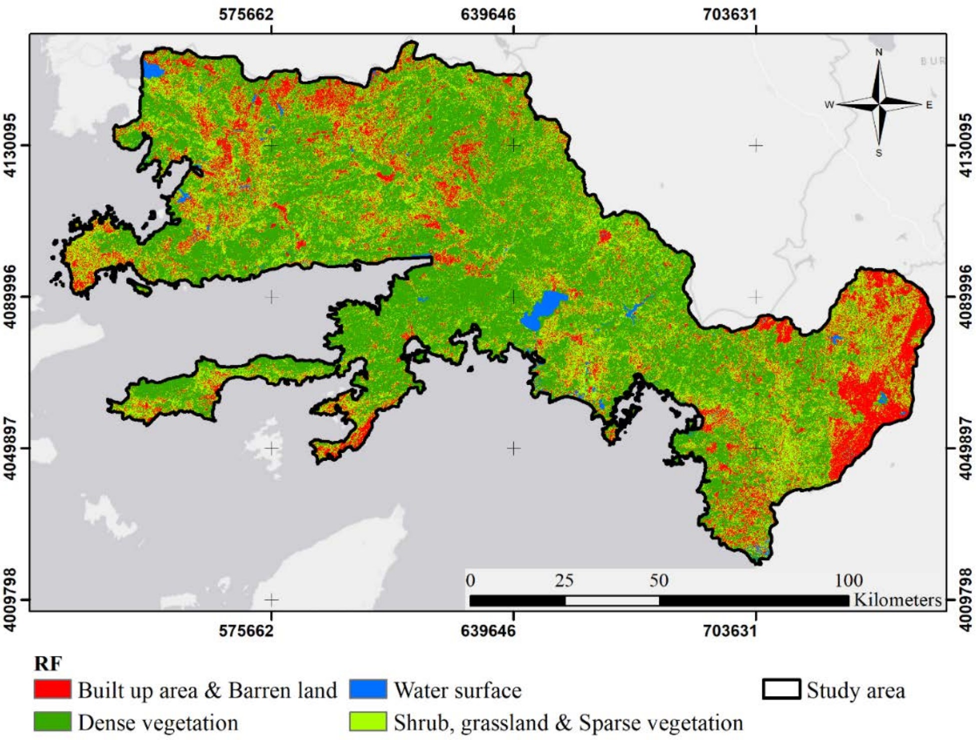

Figure 6 The LULC map of Muğla province generated using the RF algorithm in GEE

In order to evaluate the obtained results of the CART, SVM, and RF algorithms in LULC map production task, the overall accuracy, and the kappa are calculated for all classifiers. The assessment of the classifiers based on overall accuracy and Kappa are presented in Table 4.

Table 4 Overall accuracy and Kappa of the classifiers

	Overall Accuracy (%)	Kappa
CART	80	0.74
SVM	88	0.84
RF	97	0.96

Table 4 indicates that the RF algorithm is highly accurate in LULC mapping with 97% overall accuracy and 0,96 Kappa value among all three classifiers, followed by SVM with 88% overall accuracy and 0,84 Kappa value, and CART with 80% overall accuracy and 0,74 Kappa value, respectively.

4. Conclusion

High-tourism-density regions are extremely vulnerable to human activities. It is crucial to ensure sustainability by preserving the cultural aspects and ecological diversity of these areas. Muğla province is Türkiye's third-most visited city. However, especially during the summer season, forest fire danger is fairly significant. In the decade spanning the years 2012-2021, 3,312 forest fires have burned 57,242 hectares of forests (Muğla OBM, 2021). In this context, it is of the utmost importance to continuously monitor and analyze land cover by generating LULC maps in all provinces, especially high risky areas as Muğla.

Recent advancements in remote sensing and earth observation technologies, as well as the growing availability of various satellite images, have evolved remote sensing into a big data methodology requiring automated, cost-effective, and efficient approaches. GEE is a cloud-based platform that provides access to a vast collection of satellite images from across the world, as well as image processing and classification capabilities utilizing modern techniques such as machine learning and deep learning.

The aim of this study is the comparison of the performance of machine learning methods for LULC map production on the GEE platform. SVM, RF, and CART, are the three machine learning algorithms applied in the study. Landsat-8 and Sentinel-2 satellite images of Muğla province are used, as well with two supplementary indexes, in LULC classification of four land use classes - 'built-up area & barren land', 'dense vegetation', 'water surface', and 'shrub, grassland & sparse vegetation' -. Accuracy assessment is done by using the overall accuracy and Kappa value. According to the experimental results, RF showed out to be the most efficient and effective data classifier in the GEE platform with 97% overall accuracy and 0,96 Kappa value, followed by SVM, and CART, respectively.

It is commonly recognized that LULC maps can be evaluated for numerous applications such as land use planning and monitoring, as well as sustainable development assessment. This study contributes to monitoring programs of LULC changes over broad areas by applying machine learning methods. From an environmental standpoint, the results are crucial for decision-makers and authorities for understanding LULC changes and establishing relevant polices.

In future, the performance of the deep learning-based algorithms can be incorporated in the assessment. Moreover, the results can be enhanced to track more complicated earth properties, and further studies can be undertaken including hyperspectral satellite data coupled with more features like topographical data for the enhancement in LULC map production.

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Resume

MSc. Hazal Yalçın-Bayrakdar is a Ph.D. student and is working in the field of GIS and RS methodologies in machine learning algorithms. She has a master's degree in computer engineering. She also has studies on the preservation of ecological balance.

Dr. Mehtap Özenen-Kavlak is working in the field of GIS and RS methodologies in spatial decision-making processes for renewable energy resources as well as other various site selection applications. In addition, she has a bachelor's degree in business administration and examines the socio-economic and macro-economic characteristics of countries in the field of economics.

Dr. Burcu Yılmazel is an Assistant Professor at Eskişehir Technical University, Computer Engineering Department, Eskişehir, Turkey. She conducts research in the field of recommender systems, shilling attacks, and distributed data. Areas of interest include artificial intelligence, machine learning, digitalization, and sustainability.

Prof. Dr. Alper Çabuk is the vice rector of Eskişehir Technical University. He gives undergraduate and graduate courses on GIS and RS in the documentation of cultural heritage, disaster management, disaster planning, ecological planning and design processes. He also carries out academic and professional studies on these subjects and takes part in national and international projects.