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CHAPTER 3

Spatio-Temporal Monitoring of Land Use/Land Cover (LULC) Change From Clas-sified Images Supported By Artificial Intelli-gence (AI) at the Provincial Scale

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1. Introduction

Land use and land cover (LULC) change and its modeling are considered the best tools for understanding the dynamics of future urban expansion, identifying the directions of development and change in land uses, and addressing these issues (Gaur and Singh, 2023). Currently, 54.5% of the world's population lives in urban areas, and by 2050, uncontrolled population increase is expected to impact 66% of the global population. (Farhan et al., 2024). In this context, unplanned expansion, particularly in urban areas, has placed significant pressure on other land uses in order to accommodate the growing human population (Kafy et al., 2021; Li et al., 2021). This pressure alters natural ecosystem dynamics, contributes to the increase in deforestation, leads to biodiversity loss, and causes irreparable damage to ecosystem services (Puplampu and Boafo, 2021; Karakuş and Selim, 2022). Therefore, the identification of LULC change remains relevant and important today, as it enables the early identification of potential environmental issues, the implementation of necessary measures, and the development of comprehensive strategies by planners (Chughtai et al., 2021).

LULC consists of two components: land use and land cover. Land use refers to human-defined categories such as transportation infrastructure, residential infrastructure, commercial areas, and agriculture. On the other hand, land cover refers to natural features such as water bodies, forests, bare ground, and rangeland (Kumar and Agrawal, 2023). However, since these two terms have a dynamic relationship on the terrestrial surface, they influence each other and should be assessed together rather than separately (Esendağlı and Selim, 2024). Remote sensing (RS) and Geographic Information System (GIS) technologies offer significant advantages in the identification and evaluation of LULC (Abebe et al., 2022). LULC characteristics can be easily detected from aerial or satellite imagery, and changes and trends in LULC over a specific time period can be analyzed through these images (Thien et al., 2023). Remote sensing data, depending on various resolutions, provides rapid and reliable information (Ardahanlıoğlu et al., 2020). The accessibility of these images as open-source data has made them a valuable resource for LULC change studies. Therefore, the analysis of LULC change through remote sensing data and GIS technologies is a continuously developing research field globally (Sarif et al., 2022; Selim et al., 2022; Hossain et al., 2023).

The classification of satellite images is one of the key priorities in determining LULC change (Esendağlı and Selim, 2024). Geographic spatial techniques for image interpretation and classification are used for natural resource management

and planning purposes, as they can help predict future scenarios (Kumar and Agrawal, 2023; Olgun et al., 2024). Various techniques are employed in the classification of satellite images, depending on current technological developments. These techniques can be divided into three categories: unsupervised, supervised, and semi-supervised. The classifiers can further be categorized into rigid and flexible (diffuse), parametric and non-parametric, or based on pixel/subpixel and object levels (Macarringue et al., 2022). To effectively simulate LULC change, various static and dynamic models - such as logistic regression, Markov chain (Saha et al., 2022), artificial neural networks (ANN) (Souza et al., 2022), cellular automata (Halder et al., 2023), modified cellular automata–based SLEUTH (Singh et al., 2024), and artificial intelligence (Himeur et al., 2022; Alshari et al., 2023) - have been developed and integrated with GIS and remote sensing (RS) in recent years. However, the use of these methods often requires expertise. In this context, pre-classified and openly accessible images are a preferred option for making quick and efficient decisions (Gao et al., 2021; Patel et al., 2024; Yılmaz and Selim, 2024). In particular, classified images, prepared with the participation of millions of expert labelers and made available as open access, stand out as a key resource for rapidly detecting LULC change with high accuracy, thus providing valuable data for decision-makers (Prasetyadi et al., 2024). The world's most comprehensive collection of geographic data is ArcGIS Living Atlas of the World. It supports LULC research with data layers, apps, and maps (ESRI, 2025). From 2017 to 2023, the global 10m land cover was included to the time series of the LULC's annual global maps. The maps are created using 10m-resolution ESA Sentinel-2 data. To create a fair snapshot of each year, each map is a composite of LULC projections for nine classes over the course of the year. Impact Observatory created this dataset by training a deep learning model for terrain classification using billions of human-labeled pixels that were curated by the National Geographic Society. This model was used to the Sentinel-2 annual scene collections on the Planetary Computer to create the world map. The estimated average accuracy of each map is greater than 91%. These Impact Observatory-produced datasets, which Esri licensed, were obtained from Impact Observatory (Karra et al., 2021; ESRI, 2025).

The aim of this study is to monitor LULC change between 2017 and 2023 at the scale of Antalya province using classified Sentinel 2 satellite images produced with artificial intelligence support, which are available in open access, and to generate information that can support decision-makers by interpreting the results at the city level. In this context, classified satellite images provided by ESRI and

available in open access were used, the accuracy of each image was evaluated, and the produced results were assessed. The innovation of the study can be outlined as follows: 1. There is a lack of sufficient studies in the literature regarding the tracking of LULC change at the provincial scale using ArcGIS Living Atlas data, 2. The need to assess the impact of the Covid-19 pandemic, which affected the entire world in 2019, on LULC, 3. The need for up-to-date information on LULC change in Antalya, one of Turkey's most important tourism and agricultural cities, 4. The need to determine the direction and magnitude of the increase in secondary housing in Antalya due to recent earthquakes in Turkey. It is anticipated that the information produced at the end of this study will make significant contributions to decision-making processes for planners, as well as central and local authorities.

2. Study area

The study area covers the boundaries of Antalya province, one of Turkey's most important tourism and agricultural destinations, and is located at coordinates 36°53'19.20"N and 30°40'48.12"E (Fig. 1).

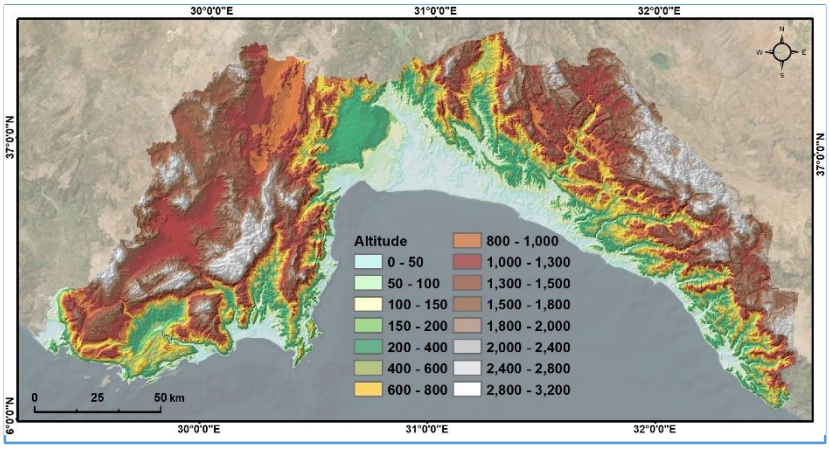


Figure 1. Study area location

The study area is 20,802 km² and is predominantly surrounded by the Taurus Mountains (Selim et al., 2023). The research area experiences warm winters and extremely hot and dry summers due to the Mediterranean climate, which is defined by the Köppen–Geiger climate classification as the Csa climatic type (Karakuş et al., 2024). The climate has mild mean annual minimum temperatures (4.8–11 °C) and maximum temperatures (17–25 °C), with 443–620 mm of precipitation, mostly in the winter. The Taurus Mountains protect the region from the northerly winds. In the South, the elevation is sea level, whereas in the North,

it is almost 3000 meters. From 0° to 60°, the slopes are steep (>18°) in high elevation and hilly areas and mild (<10°) in the southern region and valleys (Viedma et al., 2017). The plains and gently sloping regions of the South are dominated by agriculture and urban land uses, whereas the mountainous and hilly regions of the North are dominated by open and dense forests (i.e., conifer, mixed, and broadleaf forests). *Pinus brutia*, and *Pinus nigra* make up coniferous woods; broadleaf forests are rare and primarily composed of pure maquis or maquis-oak combinations, as well as oaks (*Quercus sp.*). Lastly, *Pinus brutia* and maquis typically create mixed forests (Mutlu et al., 2017; Selim et al., 2018). Antalya province, consisting of 19 districts (Akseki, Aksu, Alanya, Demre, Döşemealtı, Elmalı, Finike, Gazipaşa, Gündoğmuş, İbradı, Kaş, Kemer, Kepez, Konyaaltı, Korkuteli, Kumluca, Manavgat, Muratpaşa, Serik) and 913 neighborhoods, has a total population of 2,696,249 as of 2023. It is known that the majority of this population resides in urban settlements close to the sea (TUIK, 2024; Eyileten and Selim, 2023).

3. Data sets

In this study, a 10-meter annual map of Earth's land surface from 2017-2023 was used. These maps are published in open access by Esri in collaboration with Impact Observatory and Microsoft. Artificial Intelligence (AI) land classification models have been used in these maps. The maps were created by applying these models to the whole Sentinel-2 scene collection for every year, which consists of more than 2,000,000 Earth observations from six spectral bands. Six bands of Sentinel-2 L2A surface reflectance data—visible blue, green, red, near infrared, and two shortwave infrared bands—are used by the underlying deep learning model. The model is run on several imaging dates throughout the year to produce the final map, and the results are combined to produce a final representative map for each year. The output provides a 9-class map of the surface, including vegetation types, bare land, rangeland, water, crops and built areas (ESRI, 2025).

4. Methods

The methodology of the study consists of the key stages of obtaining satellite data, defining classes, conducting accuracy analysis, and comparing and evaluating the LULC classified images for different years (2017-2021-2023). Satellite data for the relevant years were downloaded free of charge from the website https://livingatlas.arcgis.com/landcoverexplorer. Subsequently, subset operations were applied based on the boundaries of Antalya province. In the

satellite images, LULC classes were defined (Table 1), and thematic maps were created.

Table 1. Defined LULC classes (Karra et al., 2021)

No	Class Name	Description
1	Water	Water areas such as ponds, lakes, oceans, flooded salt plains.
2	Trees	Any significant clustering of tall (~15 feet or higher) dense vegetation, typically with a closed or dense canopy
4	Flooded vegetation	Heavily irrigated and inundated lands.
5	Crops	Human planted cereals, grasses, and crops not at tree height.
7	Built Area	Human made structures; examples: houses, dense villages / towns / cities, paved roads, asphalt.
8	Bare ground	Areas of rock or soil with very sparse to no vegetation, examples: exposed rock or soil, desert and sand dunes, dry salt flats/pans, dried lake beds, mines.
9	Snow/Ice	Large homogenous areas of permanent snow or ice.
10	Clouds	No land cover information due to persistent cloud cover.
11	Rangeland	Open areas covered in homogenous grasses with little to no taller vegetation

Accuracy assessment was conducted separately for the LULC maps of the three different years. For this, 500 random points were assigned to each map, and the class corresponding to each point was compared with the actual land cover, and percentage accuracy was calculated. The segmentation and classification tool in ArcGIS spatial analysis was used for this process.

Finally, area data for each class in the classified satellite images of the three different years were generated, and the increases and decreases in the areas covered were visualized through graphs. The results were interpreted based on the 2019-Covid pandemic and potential earthquake agendas.

5. Results

Accuracy assessments for the maps produced with artificial intelligence support for the years 2017, 2021, and 2023, and revised according to the boundaries of Antalya province, are provided in Table 2.

Table 2. Accuracy rate of classified satellite images

Years	True value	False value	Accuracy rate
2017	462	38	92.4
2021	452	48	90.4
2023	459	41	91.8

In these maps, expert labelers used a convolutional neural network (CNN) with a UNet architecture containing nine class outputs to classify each individual image, and it is reported that the generated maps achieved at least 91% accuracy (Karra et al., 2021). In the accuracy assessment created using 500 randomly distributed sample points within the study area, the result was also an average of 91%. The accuracy assessment in the study revealed that the rangeland class and the crops class were mixed in some areas. Additionally, it was observed that fragmented settlements, especially in rural areas, caused changes in the build area class values. The Water class was easily distinguishable from other classes with very high accuracy, although there was some mixing with flooded vegetation in rivers, streams, and lakes. In areas where agricultural production takes place under greenhouses (glass and plastic), the crops class was partially mixed with the rangeland class, causing changes in the spatial extents. However, when evaluated at the provincial scale, it can be said that the AI-supported LULC classification produced high accuracy.

The maps produced by Impact Observatory's deep learning AI land classification model, trained using billions of human-labeled image pixels from the National Geographic Society, show LULC classes for Antalya province for the years 2017, 2021 and 2023 (Fig. 2,3,4).

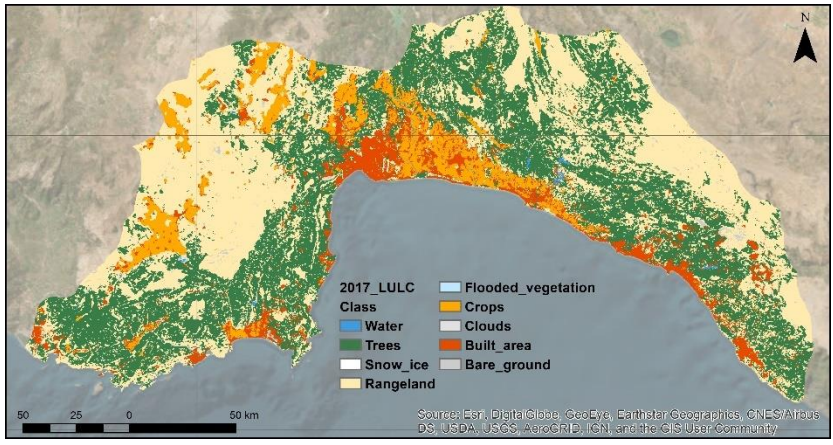


Figure 2. LULC map of Antalya province in 2017

In 2017, within the boundaries of Antalya province, nine classes were defined in the AI-supported classified images. The snow-ice class, clouds class, and flooded vegetation class were filtered and excluded from the assessment, as they had values below 1%. The area data for other LULC classes were determined as follows: built area 156,189.76 ha, crops 166,086.38 ha, trees 787,925.42 ha, bare ground 19,156.68 ha, rangeland 908,383.18 ha, and water class 7,159.97 ha. The total land asset of the province was determined to be 2,044,901.39 ha.

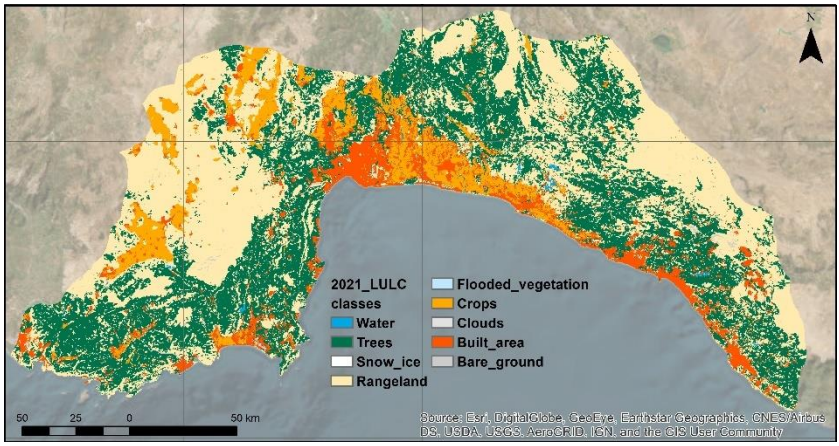


Figure 3. LULC map of Antalya province in 2021

In the 2021 LULC classes, the classes with the highest share were rangeland with 906,870.00 ha and trees with 762,622.40 ha. These were followed by built area with 184,957.47 ha, crops with 171,885.35 ha, bare ground with 11,240.38 ha, and water with 7,335.89 ha.

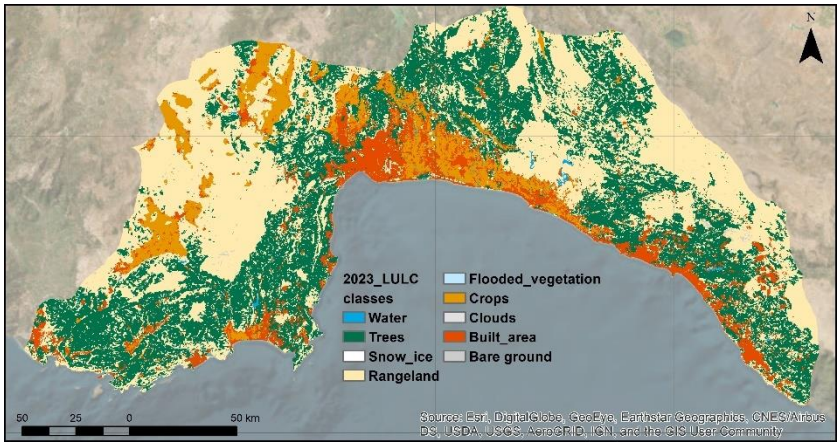


Figure 4. LULC map of Antalya province in 2023

In the 2023 LULC classes, the following areas were recorded: 916,247.98 ha for rangeland, 745,366.21 ha for trees, 199,789.55 ha for built area, 166,240.77 ha for crops, 9,407.64 ha for bare ground, and 7,849.34 ha for water.

The changes in LULC classes over the years for the classified images of the three different years, in terms of both hectares and percentages, are provided in Table 3.

Table 3. Percentage and ha rates of LULC classes by year

Class / years	**2017**	**%**	**2021**	**%**	**2023**	**%**
Built area	156,189.76	7.64	184,947.47	9.04	199,789.55	9.77
Crops	166,086.38	8.12	171,885.35	8.41	166,240.77	8.13
Trees	787,925.42	38.53	762,622.4	37.29	745,366.21	36.45
Bare ground	19,156.68	0.94	11,240.38	0.55	9,407.64	0.46
Rangeland	908,383.18	44.42	906,870.00	44.35	916,247.98	44.81
Water	7,159.97	0.35	7,335.89	0.36	7,849.34	0.38
Total ha / %	2,044,901.39	100%	2,044,901.49	100%	2,044,901.49	100%

According to Table 3, over the 6-year period, the built area class has shown a significant increase, while the trees class has decreased by a similar proportion. It can be said that the increase in the built area class has exerted pressure on the trees and bare ground classes, leading to a reduction in the bare ground class. Compared to 2017, the built area class has increased by approximately 40,000 ha in 2023. This increase is mostly concentrated in the eastern-western and northern inner parts of the city center. Due to the steep mountainous terrain in the western part of the city, urban sprawl has primarily expanded toward the east and north. Although the crops class showed an increase from 2017 to 2021, it has decreased back to approximately its previous level in 2023. A consistent decrease has been observed in the trees class, with an estimated reduction of approximately 40,000 ha. The bare ground class, which includes bare rock or soil ground with very sparse or no vegetation throughout the year; large sandy areas with little or no vegetation, and vacant lands, has decreased by approximately 10,000 ha over the 6-year period. No significant change was detected in the rangeland class, which includes open areas covered with homogeneous grasses with little or no tall vegetation; pastures with no obvious human settlement; small plant clumps with exposed soil or rock; and clearings covered with shrubs. No significant changes were observed in the water class over the years.

6. Discussion and Conclusion

In this study, which involves the evaluation of AI-supported classified satellite images within the boundaries of Antalya province, provided by Esri in collaboration with Impact Observatory and Microsoft using the UNet architecture with a CNN model, the changes in LULC from 2017 to 2023 were identified. According to the accuracy assessment applied to the classified images, the achieved accuracy of approximately 91% aligns with the accuracy specified by the producer (at least 91%) (Karra et al., 2021). The literature indicates that high accuracy is required for the interpretation of results in image classification processes to ensure the results are logical and realistic (Chughtai et al., 2021; Mehmood et al., 2022; Dou et al., 2024), and it is clear that the results obtained from this study were produced with high accuracy. Increasing the accuracy rate in classified maps will allow for more accurate interpretation of the results (Maxwell et al., 2021; Tripathi, 2021). However, increasing the number of sample points requires significant time and effort. In this context, the lack of studies aimed at determining the optimal sample size for specific areas stands out (Selim et al., 2023). The main limitation of the study is the time and effort loss involved in comparing a large number of sample points for each year's satellite images with real land data to achieve high accuracy in the classified images.

The determination of LULC changes in Antalya province for the years 2017, 2021, and 2023 has been influenced by the effects of the Covid-19 pandemic, which affected the entire world in 2019, as well as the 2023 Kahramanmaraş earthquake and the pre-earthquake concerns. During the pandemic, people were confined to apartments for months, and after the pandemic, they started to prefer houses with gardens or villas based on their economic situation (Çukurlu et al., 2024). This led to the expansion of settlements towards rural areas and, in this study, resulted in a significant increase in the built area class. However, this increase in the built area class has naturally led to a decrease in the trees and bare ground classes. The Crops class experienced a periodical increase between 2017 and 2021; however, it saw a significant decrease between 2021 and 2023 (Fig. 5).

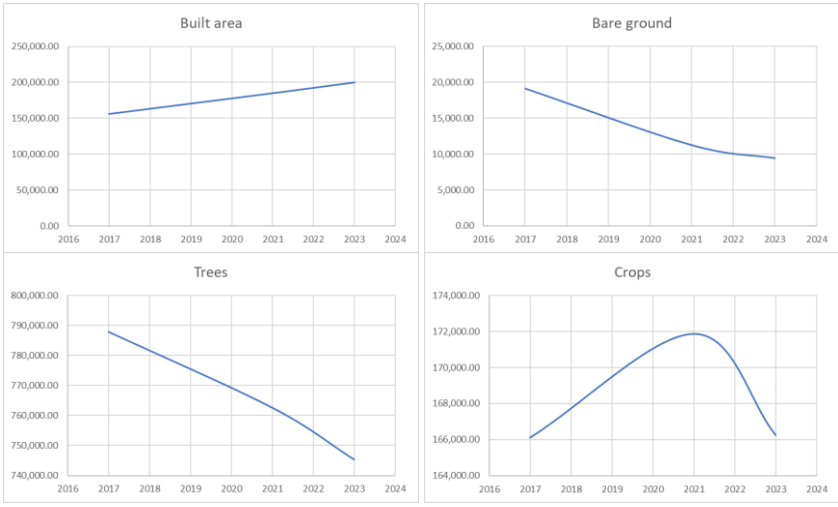


Figure 5. Change trends for some LULC classes

Similarly, Turkey's largest earthquake and earthquake concerns can be considered as factors contributing to the rise of secondary housing and urban sprawl. On February 6, 2023, at 4:17 AM, an M7.8 earthquake occurred close to the boundary between the provinces of Kahramanmaraş and Gaziantep. Nine hours later, and 95 kilometers northeast, an M7.5 earthquake occurred. Approximately 60,000 people were killed and millions more were homeless as a result of the terrible effects of the earthquake sequence that struck a large area of southern Turkey and northern Syria (EERI, 2025). The pre-earthquake news regarding seismic concerns and the occurrence of this earthquake have had a significant impact on the increase in secondary housing (Murakami et al., 2017; Silva and Poul, 2021; Huang et al., 2022; Wang and Ng, 2023). In this context, for the population of Antalya province, which is near the East Anatolian Fault, the need for more reliable and individual housing has become a prominent issue, particularly after the major earthquake and the pandemic. This has led to a rapid increase in the production and spread of one- or two-story houses. According to the results obtained, this increase is approximately 2.5%. Considering the direction and magnitude of this increase, as can be understood from the produced maps, reductions in the trees and bare ground classes have occurred, urban sprawl has exerted pressure on these classes, and this has led to changes in LULC.

In conclusion, the LULC maps, which are freely provided by ESRI and generated with artificial intelligence support, can be easily used for determining LULC change due to their accessibility, cost-effectiveness, and high accuracy. The use of these maps in determining LULC change can provide a valuable data

source and serve as a guide for central and local governments, as well as non-governmental organizations. Furthermore, in this study conducted specifically for Antalya province, the relationship between LULC change and pandemic and earthquake agendas was discussed without considering other factors (population growth, climate change, social and cultural influences etc.), and it was found that there was a significant increase in the built area class in the short term. This study provides a scientific basis for evaluating AI-supported classified images at the provincial scale, determining LULC change, and potentially guiding planners and stakeholders in the process.

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