http://agriprojournal.com

JOURNAL OF AGRICULTURAL PRODUCTION

ISSN: 2757-6620

https://prensip.gen.tr

RESEARCH ARTICLE

Spatiotemporal Assessment of LULC Changes Using Remote Sensing Approaches

Merve Kalaycı Kadak

Kastamonu University, Faculty of Engineering and Architecture, Department of Landscape Architecture, Kastamonu/Türkiye

ARTICLE INFO

Article History
Received: 03.09.2025
Accepted: 25.09.2025
First Published: 30.09.2025

Keywords
Dynamic World dataset
Google Earth Engine (GEE)
Land-Use/Land-Cover change
Remote sensing
Sustainable land management

ABSTRACT

The study examines changes in Land-Use/Land-Cover (LULC) in the Yenişehir district of Bursa province (Türkiye) between 2020 and 2024. Focusing specifically on the loss of agricultural land due to anthropogenic pressure, the study aims to identify changes in the LULC using remote sensing tools and techniques. In this regard, it aims to contribute to the development of sustainable land use policies. High-resolution Dynamic World dataset generated from Sentinel-2 satellite imagery was employed. The study, which was conducted by using Google Earth Engine (GEE) and ArcGIS Pro, generated annual LULC maps, inter-class transition maps that focus on agricultural land for consecutive years, and annual NDVI maps. As a result, a total of 2% decrease was detected in the crops class, accelerating particularly after 2022. NDVI values also decreased in the same areas, displaying similarity to this result. The findings are generally observed in agricultural land in peri-urban areas and are associated with both anthropogenic pressure and climate change impacts on the agricultural landscape. The study, based on data analyses, emphasizes the importance of ecology-based strategic approaches and demonstrates the need to integrate these approaches into spatial planning. Moreover, it shows the applicability of Dynamic World dataset in short-term monitoring of surface area losses in agricultural areas.

Please cite this paper as follows:

Kalaycı Kadak, M. (2025). Spatiotemporal assessment of LULC changes using remote sensing approaches. *Journal of Agricultural Production*, *6*(3), 186-196. https://doi.org/10.56430/japro.1777194

1. Introduction

Land-Use/Land-Cover (LULC) data are one of the best sources for spatial examination of processes and changes on Earth across multiple periods (Venter et al., 2022). Changes in the LULC may have many different causes. These include increased urbanization associated with population growth, climate change effects (Aklibasinda & Ozdarici Ok, 2019; Kalayci Kadak et al., 2024; Mohiuddin & Mund, 2024), changes in forest areas (Verburg et al., 2004), degradation of agricultural lands (Negese, 2021), and drought (Gul & Esen, 2024), which can occur as a result of both natural and human influences (Kalaycı Kadak, 2025). Changes in the LULC disrupt the structures of ecosystems and profoundly affect environmental sustainability (Jalayer et al., 2022; Kalayci Kadak et al., 2024; Liu et al., 2021; Muche et al., 2023). It has been observed that land has been used for inappropriate purposes (Bikis et al., 2025; Lambin et al., 2003), particularly to meet the needs of the rapidly increasing population (Kirui et al., 2013). This situation also causes changes in land cover. Although identifying these changes may not eliminate the ever-increasing pressure of humans on nature, it is known that it will help manage their impacts appropriately and thus minimize the damage as much as possible (Gabisa et al., 2025).

Correspondence
E-mail address: mkalayci@kastamonu.edu.tr

In this context, LULC change studies to be conducted, especially in regions with a dynamic socio-economic structure, are of great importance in detecting, managing and taking measures against changes in ecosystems (Alipbeki et al., 2020; Jalayer et al., 2022; Yirsaw et al., 2017).

To detect changes in the LULC, data generated at regular time intervals and with the same systematic order are required (Lv et al., 2018; Zhu & Woodcock, 2014). Remote sensing change detection is also based on comparing satellite images obtained at two different times for a given geographic location (Cheng et al., 2024). Within this context, remote sensing sources such as satellite imagery and land cover datasets can be utilized in LULC change detection studies (Cheng et al., 2024; Kalayci Kadak, 2022; Kalayci Kadak et al., 2024; Mert et al., 2024; Tewabe & Fentahun, 2020). Moreover, resources, which enable these spectral analyses, can increase the accuracy of LULC mapping studies (Azzari & Lobell, 2017; Holloway & Mengersen, 2018; Venter & Sydenham, 2021). In this regard, this study employed the Dynamic World LULC dataset. To support this data with spectral indices, NDVI maps were generated from Sentinel-2 satellite imagery.

In light of all this information, the Yenişehir district of Bursa province was selected as the study area due to its geographical location. Yenişehir harbors productive meadows that are exposed to the effects of climate change (Abbasnia & Toros, 2018; Karahasan & Pinar, 2023; Selcuk & Gulumser, 2023; Yetik & Candogan, 2024), and is under pressure from urbanization, particularly due to the development of agriculture-based industries. The study aimed to reveal annual changes in the LULC over the recent five-year period in the study area using remote sensing methods and to focus on the transition matrices of the crops class, which has the largest percentage among LULC classes. Last five years (2020-2024) were selected to observe changes in a short period in the near past. The main tools used in the study were ArcGIS Pro and Google Earth Engine (GEE), which is an accessible and scientifically sound digital laboratory with unlimited data processing capacity and cloud computing platform. The main hypothesis of this study, which employs remote sensing tools and techniques, is that the Yenişehir district has undergone changes that could be associated with the effects of climate change due to its geographical location as well as human interventions, such as urban expansion pressures and inappropriate land use decisions, particularly in the post-2020 period. The second hypothesis of the study is to investigate the possibility of using spectral analysis on the GEE platform to reveal the LULC changes with high reliability.

2. Materials and Methods

2.1. Study Area

The study was carried out in the Yenişehir district of Bursa province. Yenişehir district is located in the east of the Marmara Region, between 40°7’44.7” and 40°22’28.9” North latitudes and 29°20’23.3” and 29°49’56.9” East longitudes (Figure 1).

Figure 1. Location of the study area.

The district has an elevation of 250 meters and an area of 740 km^2 (Yenişehir Municipality, 2022). According to the Köppen climate classification, it falls within the Csa (Mediterranean climate with mild winters, very hot and dry summers) class (Boluk et al., 2023). The district is populated by 55,606 people according to 2024 data. Yenişehir, the third-largest district in the province in terms of agricultural land, had an agricultural area of approximately 328 km^2 in 2020, but this area decreased to approximately 285 km^2 in 2023 (TÜİK, 2024). Furthermore, there are 941 agricultural basins within the agricultural basin classification system implemented in Turkey since 2017. According to the latest report published by the respective ministry, Yenişehir is the district within Bursa province that receives the highest number of product support for the 2025-2027 period (Turkish Ministry of Agriculture and Forestry, 2024). Moreover, an Organized Industrial Zone was established in 2004 as part of the activities carried out in the district (YOSAB, 2022). In addition, it facilitates accessibility to the Bursa Yenişehir Airport, located within the boundaries of the study area. In this context, Yenişehir's location could attract investors who would support the development of the Organized Industrial Zone (OIZ). Examining this district, which is under the influence of climate change due to its geographical location and generally maintains its rural structure, in the context of LULC changes is of great importance for developing productive agricultural land protection strategies. Thereby, ensuring the sustainability of the district's resource assets will be possible. The district was selected as the study area because of these features.

2.2. Methodology and Data Preparation

The study was conducted in four main stages. These are: selecting the study area; formulating the hypothesis; creating the database [(determining annual LULC changes, Normalized Difference Vegetation Index (NDVI) analyses)]; and generating and interpreting maps (Figure 2), respectively.

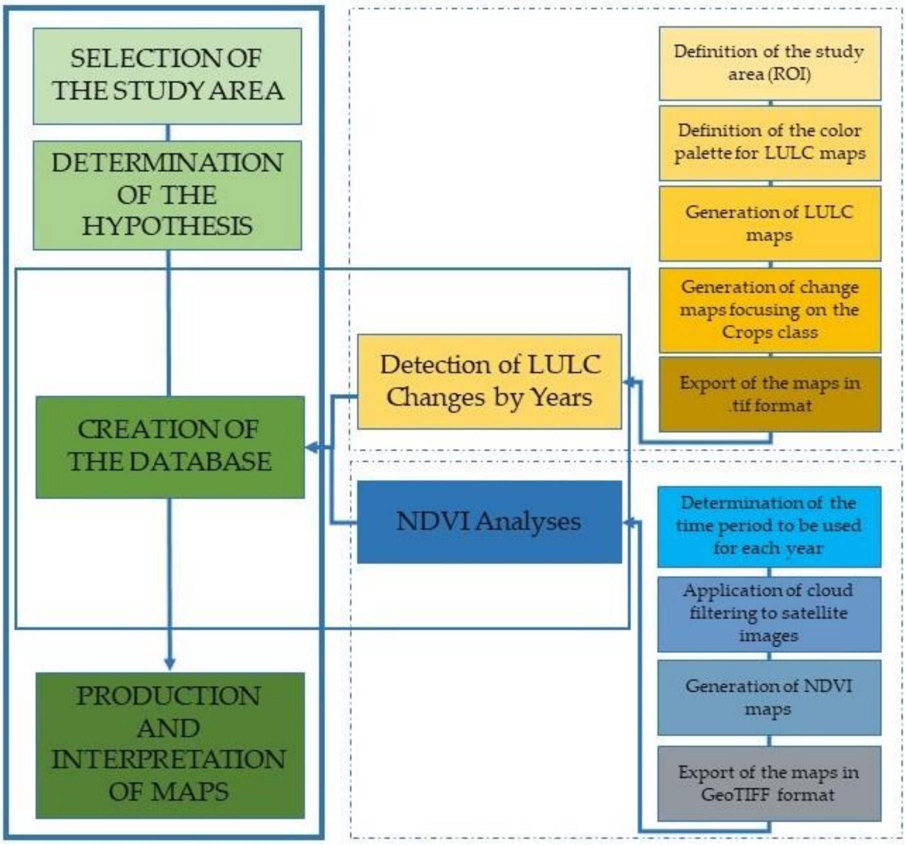

Figure 2. Flowchart of the methodology.

In the first stage, the study area was selected. While selecting, the study area was ensured to be:

- Exposed to climate change effects due to its geographical location;
- Under development, containing land uses that facilitate transportation to e.g., airports;
- Generally considered as an area where the sustainability of the rural resource values it harbors is essential.

In the second stage, the study's hypothesis was determined and the research objective was outlined. The tools, scopes, and limitations in the literature were identified, and the planned methodological stages were reviewed to avoid similar limitations within the scope of the study.

In the third stage, the database to be used throughout the study was prepared. First, the datasets to be used in the GEE platform, the first of the main tools, were determined. In this regard, it was decided to employ the Dynamic World dataset instead of the Coordination of Information on the Environment (CORINE) land cover dataset, which is frequently used in the literature (Alipbeki et al., 2020; Bikis et al., 2025; Cieślak et al., 2020; Dzieszko, 2014; Falt'an et al., 2020; Feranec et al., 2007; Myga-Piatek et al., 2021; Varga et al., 2020). The reason behind this is that the most recent data of CORINE land cover dataset, first developed in 1990 by the European Environment Agency (EEA) to monitor changes in Europe's LULC at a comparable level and updated every six years after 2000, belongs to 2018. Additionally, this dataset with a spatial resolution of 100 m, although frequently used in the literature, was deemed inappropriate for the targeted timeframe (2020-2024) and size of the area. Therefore, the Dynamic World dataset, prepared by Google and the World Resources Institute (WRI), was used in the study. This dataset is based on Sentinel-2 satellite imagery, has a spatial resolution of 10 m, is free, and is updated on a daily basis. This data, which has been recorded since 2015, includes nine different LULC classes (Table 1) (Brown et al., 2022; WRI and Google, n.d.).

The Dynamic World dataset used is generated from Sentinel-2 satellite imagery using automatic classification methods based on artificial intelligence (AI)-based deep learning procedures. No additional on-site observations or field studies were conducted within the scope of the study. The global accuracy of this dataset is reported by data producers as 70-80% (Brown et al., 2022; WRI and Google, n.d.). Based on the level of reliability at the global scale, the usability of the classification can be considered acceptable. Likewise, several research reported its accuracy above 72% (Ursu et al., 2025; Venter et al., 2022; Wang & Mountrakis, 2023). Moreover, considering that the study area focuses on the transformation of the agricultural class within the same classification system using the same dataset for each year, it is determined feasible to use it in calculating LULC change trends. Besides, to the best of my knowledge, there is no highly accurate reference dataset with this dataset's properties, such as free access, high resolution (10 m) and up-to-date features. In this context, the use of spectral indices alone was chosen for the validation of the classification system. To support the reliability of the LULC classification using spectral indices (Nasiri et al., 2022; Tesfaye et al., 2024), annual NDVI maps for the study area were prepared. NDVI takes values between -1 and 1. As it approaches 1, vegetation density increases; as it approaches 0, vegetation density decreases; and as it approaches -1, areas such as water, snow, ice, rock, bare soil, and desert are present. NDVI is a frequently used tool to distinguish between areas covered with vegetation, such as agricultural areas and forest areas, and areas devoid of vegetation, such as roads, airports and settlements (Kalayci Kadak, 2021; Kalayci Kadak et al., 2024).

The GEE model used while generating annual LULC and agriculture class change maps in dataset preparation is composed of five steps:

1. Definition of the study area (ROI): District boundaries were obtained from the Global Administrative Unit Layers (GAUL) dataset developed by the Food and Agriculture Organization of the United Nations (FAO).
2. The colors to be used in the resulting LULC maps were defined using a color palette prepared by the dataset producers (Google/WRI) for Dynamic World classes (Mashala et al., 2023).
3. Annual LULC maps were generated for 2020, 2021, 2022, 2023, and 2024. With this regard, for the ROI, the most frequently seen LULC type in each year was assigned to the map cells using the 'mode' function (Mashala et al., 2023; Pande et al., 2024). The resulting maps have a spatial resolution of 10 meters. The coordinate system is EPSG:4326.
4. Changes in the class that involve agricultural lands were particularly focused on, and annual maps were generated by pixelating agricultural land transitions (Aka et al., 2023; Pande et al., 2024). Classifications were performed on these maps. These classes are: Areas that were once agricultural land and have been converted to other LULCs; areas that were once agricultural land and have remained agricultural; and areas that are not currently agricultural land.
5. In the final step, the LULCs and transition maps were saved in .tif file format for further processing in ArcGIS Pro.

The GEE model used while generating NDVI maps in dataset preparation consisted of four steps:

1. The period to be used for the annual NDVI maps was determined as January 1st to December 31st of the respective year (the same period as the Dynamic World LULC maps).
2. Using harmonized surface reflectance data from the Sentinel-2 satellite, cloud filtering was applied to ensure cloud cover was less than 10% of the selected satellite images.
3. Satellite images were prepared in the B4 (red) and B8 (near infrared: NIR) bands at a spatial resolution of 10 m (Equation 1).

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (1)$$

4. The generated NDVI maps were cropped as per the area boundaries and exported in GeoTIFF file format for subsequent processing in ArcGIS Pro.

In the fourth stage, annual LULC data from the GEE, raster-formatted data on LULC changes, and annual NDVI data were analyzed, edited, and converted into map layouts using ArcGIS Pro 3.5.2 software. Based on the results of the study, several recommendations were developed for map interpretation and sustainability.

3. Results

In the study, changes in the LULC within the boundaries of Yenişehir district of Bursa province were analyzed annually for

2020-2024 period. The study findings were examined under three headings:

- LULC maps by year;
- Change maps focusing on agricultural land transitions in the LULC classification;
- NDVI maps by year.

3.1. LULC Maps

LULC Maps were generated from the Dynamic World dataset, which is divided into nine classes and uses imagery obtained from the Sentinel-2 satellite at 10 m spatial resolution. Five maps were generated by year for the research period, i.e., 2020-2024 (Figure 3).

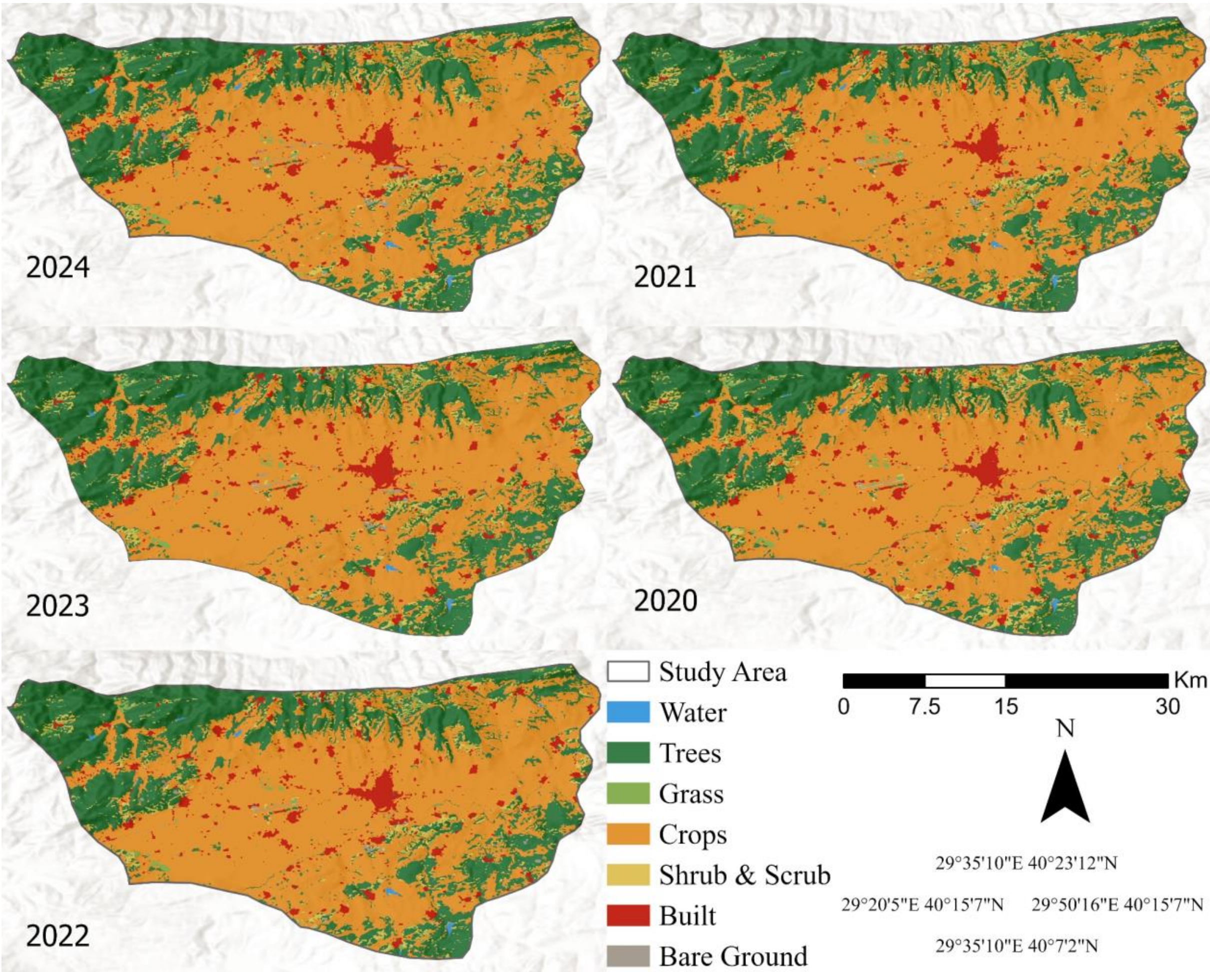

Figure 3. LULC maps.

There are no areas belonging to the flooded vegetation and snow-ice classes within the study area. The other seven different classes in the classification system are present. The crops class covers the largest area each year. On the other hand, the trees class covers the second largest area. The water class covers the smallest area. The areal percentages of the LULC classes by year are shown in Figure 4.

Although the orange color, which represents the crops class, is generally the dominant color on the maps, it can be said that the red color, which represents the built class, increased in 2020-2024 (from 4.485% to 5.265%), particularly in the north and northwest regions, indicating increased urbanization pressure. This situation reveals the impact of construction pressure on agricultural areas.

The green color representing the trees class generally remains the same in the north, but transitions to the grass or shrub-scrub class are observed in some regions. Evaluation of these classes, which typically form a transition zone near agricultural areas, with NDVI maps can reveal the actual relationship.

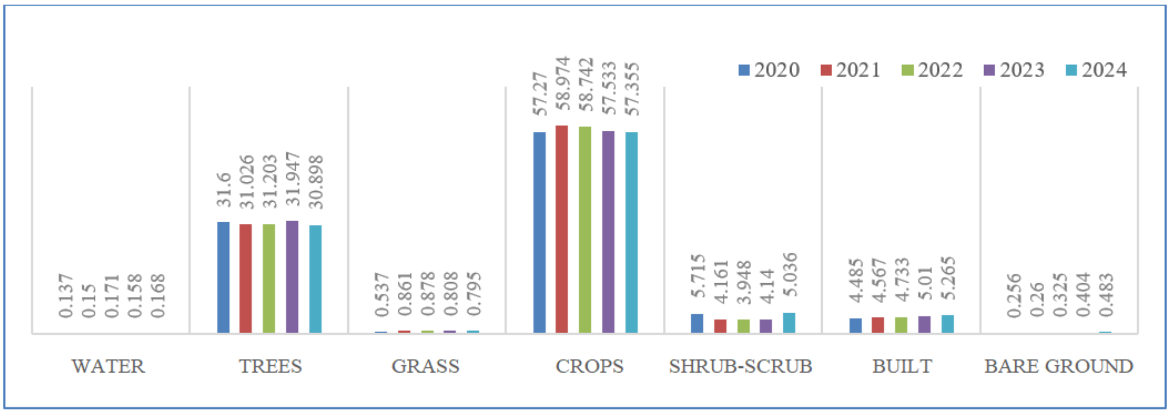

Figure 4. Area percentages of the LULC classes.

3.2. Change Maps Focusing on the Agricultural Class

The examination of the annual LULC maps produced reveals that the class with the largest surface area is agricultural land. In this context, thematic annual maps, which reveal the transition and transformation between classes, were created specifically for agricultural land (Figure 5).

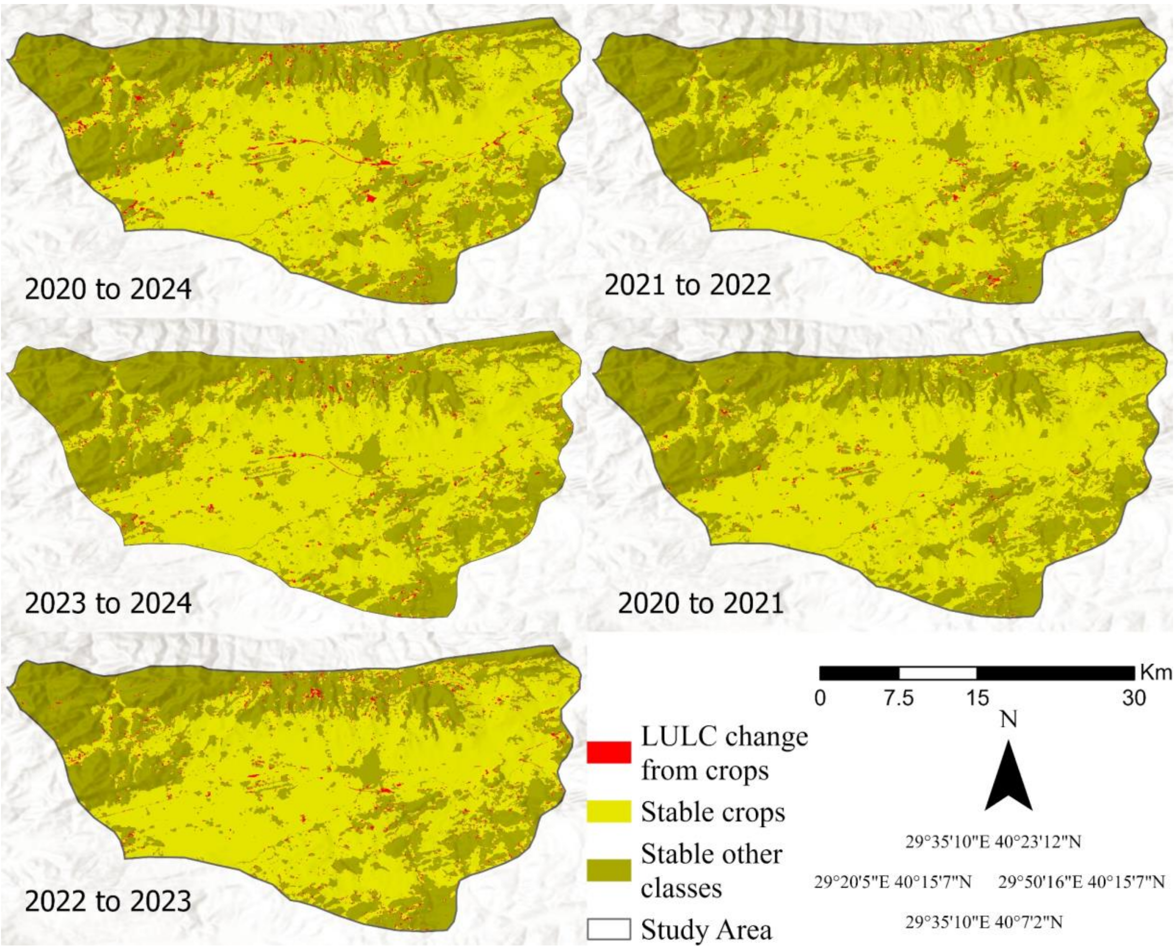

Figure 5. LULC change maps for the crops class.

In these maps, which focus on changes in crops class, the areas highlighted in red indicate areas that have transitioned from crops class to other classes. Intense changes are observed in the region's northwest, northeast, and north, particularly in the 2022-2023 and 2023-2024 periods. It can be inferred that the increasing red represents land degradation due to construction pressure.

The first map in the above figure covers the entire study period and reveals the pressure on agricultural land. The percentages of these areas, which changed between 2020 and 2024, are displayed in Figure 6.

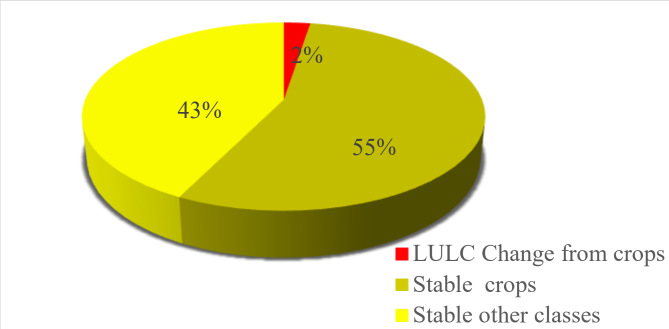

Figure 6. Change percentages of the crops class.

Furthermore, agricultural areas are the building blocks of agricultural landscape structures. Changes detected in the immediate vicinity of crop fields indicate that the agricultural landscape is changing.

3.3. NDVI Maps

NDVI maps, created for the purpose of determining vegetation density throughout the years, can also help to reliably understand and interpret changes that focus on crops class (de la Iglesia Martinez & Labib, 2023) (Figure 7).

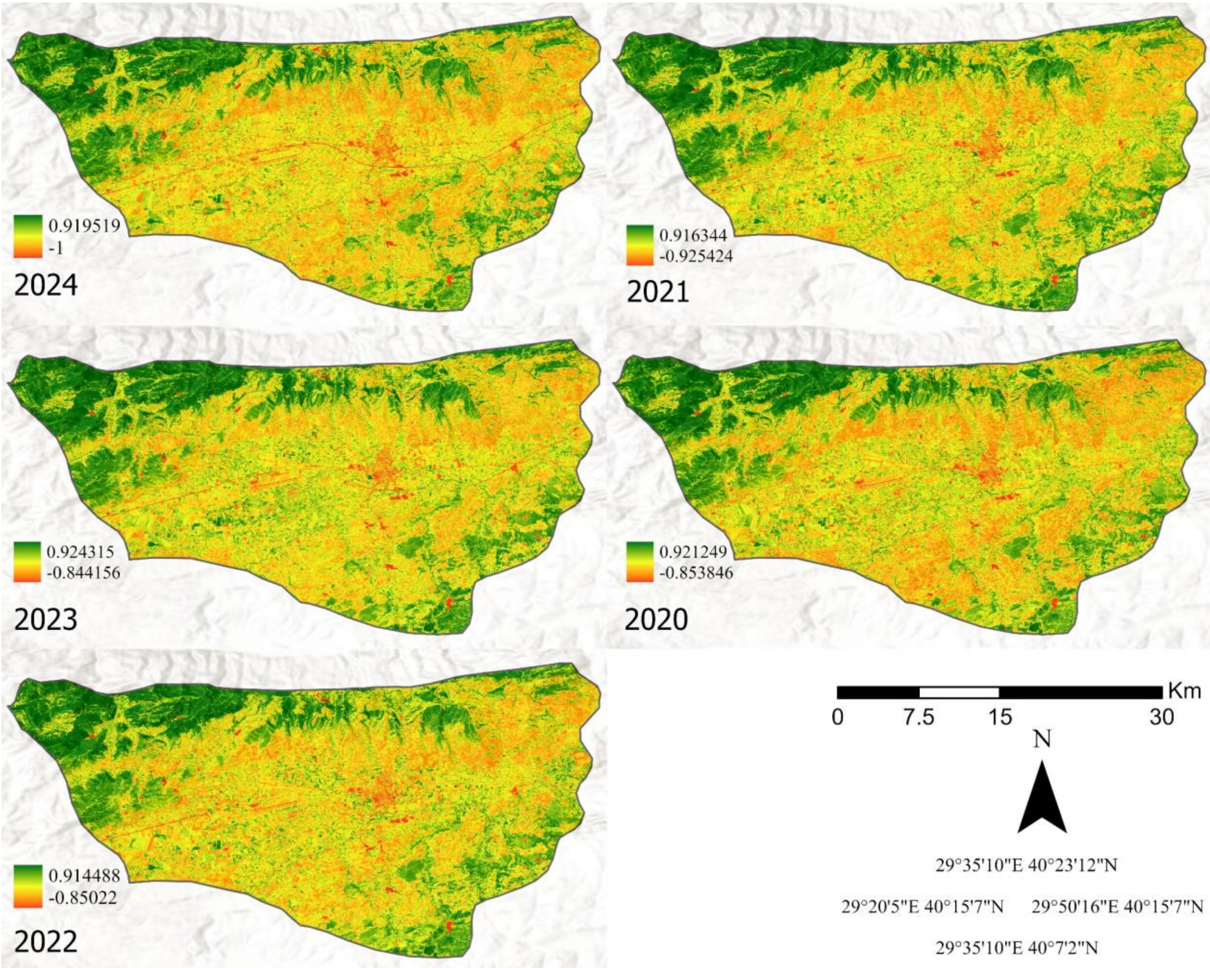

Figure 7. NDVI maps.

Thanks to the trees class, which is particularly concentrated in the northwestern regions of the area, the maps show a predominant green color every year, indicating a higher vegetation density. Moreover, the orange hues spreading across the area on the maps since 2022 show the decrease in vegetation cover and the anthropogenic pressure on the vegetation.

Maps of change areas focused on agricultural land revealed changes from 2020 to 2024, particularly in the north and northwest of the area. The changes in these areas, where construction has also accelerated, are supported by the NDVI data. The year 2022, which is halfway through the study period, represents an important point. It is observed in 2022 that cropland decreases, while built-up and shrub-scrub areas begin to increase. The increase in built-up areas, particularly near cropland, triggers adverse changes in the agricultural landscape.

These findings indicate the changes in the LULC. Ensuring the sustainability of vegetated areas, particularly crops, is crucial due to their significant ecological role. Furthermore, these changes are expected not to be solely because of anthropogenic pressures in the future. Therefore, climate change-based future status modeling, development of sectoral recommendations, and conservation interventions are required in further studies.

4. Discussion and Conclusion

In this study, LULC maps for the Yenişehir district of Bursa province for the 2020-2024 period and annual transition maps focusing on the agricultural class dominating the study area were prepared using the GEE platform with remote sensing tools and techniques (Arfa & Minaei, 2024; Ganjirad & Bagheri, 2024; Nasiri et al., 2022; Venter et al., 2022). The Dynamic World dataset was used as the classification system, and a LULC mosaic was found in the area containing seven different classes. Various academic studies have favored using this dataset because it is free, has a 10-meter resolution, and has a reliability exceeding 70% (Venter et al., 2022). Furthermore, analyses supported by NDVI maps have revealed a 2% loss in agricultural lands over a mere 5 years. As in several research emphasizing the need to use indices such as NDVI in LULC studies, NDVI values have been observed to decrease in areas of agricultural change (Ganjirad & Bagheri, 2024; Shafizadeh-Moghadam et al., 2021; Tesfaye et al., 2024). Especially after 2022, the decline in agricultural lands and the increase in shrub-scrub and built-up areas have been observed to accelerate, particularly in the north and northwest of the area. This shift could be attributed not only to urban expansion but also to administrative decisions such as increasing the industrial areas. The fact that these areas are immediate surroundings of the urban fabric, called peri-urban areas, is consistent with many studies in the literature identifying such changes (Anand et al., 2025; Mandvikar et al., 2024; Potapov et al., 2022; Taiwo et al., 2023). Peri-urban areas represent areas where the agricultural landscape pattern is very fragile. The changes in peri-urban areas mostly occurred in the north and northwest areas within the study area. Therefore, taking planned improvement steps and implementing protective measures is necessary. In this context, it is crucial to take the decline in agricultural land, which also threatens production potential, seriously as a critical threat by conducting spatial prioritization of the area. It is thought that decision-makers and policymakers should develop policies within the context of ecosystem integrity to address these transformations caused by urbanization pressures and different usage demands. In this regard, as suggested by a study conducted in Pakistan, implementing easily applicable and sustainable agricultural land planning using ecological approaches will be beneficial against the factors that pressure agricultural land (Hu et al., 2023). Although the 2% area change in the Yenişehir district, famous for its agricultural activities and fertile plains, may seem small, the severity of the situation comes to light when considering that it only occurred in a short period of just 5 years.

As a result, it is postulated that these adverse changes experienced in the short term can be mitigated by reducing anthropogenic pressures. This study contributes to the literature by demonstrating the applicability of the high-resolution Dynamic World dataset, which is free, up-to-date and accessible by every researcher, in the determination of surface area changes in agricultural areas in short periods.

Developing localized, holistic, ecology-based strategies, especially in the context of protecting agricultural areas, is of vital importance in ensuring sustainability and transferring resource values to future generations.

The fact that the study area is exposed to the effects of climate change due to its geographical location was narrated in the introduction section of this paper with current literature. In addition to the LULC changes caused by anthropogenic pressures identified in the study, this change is expected to increase due to the adverse effects of climate change. It is also known that this area will experience degradation and decline in agricultural land in the future, particularly due to the depletion of water resources (Karahasan & Pinar, 2023; Maden & Aslan, 2019; Yetik & Candogan, 2024). Considering these facts, it is thought that modeling the future situation in the study area using time series analyses would be beneficial (Kalayci Kadak, 2021; Kalayci Kadak et al., 2024).

Compliance with Ethical Standards

This study does not require ethical committee approval.

Conflict of Interest

The author declares no conflict of interest.

References

Abbasnia, M., & Toros, H. (2018). Analysis of long-term changes in extreme climatic indices: A case study of the Mediterranean climate, Marmara Region, Turkey. *Pure and Applied Geophysics*, *175*, 3861-3873. https://doi.org/10.1007/s00024-018-1888-8

Aka, K. S. R., Akpavi, S., Dibi, N. H., Kabo-Bah, A. T., Gyilbag, A., & Boamah, E. (2023). Toward understanding land use land cover changes and their effects on land surface temperature in yam production area, Côte d'Ivoire, Gontougo Region, using remote sensing and machine learning tools (Google Earth Engine). *Frontiers in Remote Sensing*, *4*, 1-22. https://doi.org/10.3389/frsen.2023.1221757

Aklibasinda, M., & Ozdarici Ok, A. (2019). Determination of the urbanization and changes in open-green spaces in Nevsehir city through remote sensing. *Environmental Monitoring and Assessment*, *191*, 756. https://doi.org/10.1007/s10661-019-7953-7

Alipbeki, O., Alipbekova, C., Sterenharz, A., Toleubekova, Z., Makenova, S., Aliyev, M., & Mineyev, N. (2020). Analysis of land-use change in shortandy district in terms of sustainable development. *Land*, *9*(5), 147. https://doi.org/10.3390/LAND9050147

Anand, S., Kumar, H., Kumar, P., & Kumar, M. (2025). Analyzing landscape changes and their relationship with land surface temperature and vegetation indices using remote sensing and AI techniques. *Geoscience Letters*, *12*, 7. https://doi.org/10.1186/s40562-024-00372-4

Arfa, A., & Minaei, M. (2024). Utilizing multitemporal indices and spectral bands of Sentinel-2 to enhance land use and land cover classification with random forest and support vector machine. *Advances in Space Research*, *74*(11), 5580-5590. https://doi.org/10.1016/j.asr.2024.08.062

Azzari, G., & Lobell, D. B. (2017). Landsat-based classification in the cloud: An opportunity for a paradigm shift in land cover monitoring. *Remote Sensing of Environment*, *202*, 64-74. https://doi.org/10.1016/j.rse.2017.05.025

Bikis, A., Engdaw, M., Pandey, D., & Pandey, B. K. (2025). The impact of urbanization on land use land cover change using geographic information system and remote sensing: A case of Mizan Aman City Southwest Ethiopia. *Scientific Reports*, *15*, 12014. https://doi.org/10.1038/s41598-025-94189-6

Boluk, E., Eskioglu, O., Çalık, Y., & Yagan, S. (2023). *Köppen iklim sınıflandırmasına göre Türkiye iklimi*. Retrieved Jul 20, 2025, from https://www.mgm.gov.tr/files/iklim/iklim_siniflandirmalari/koppen.pdf (In Turkish)

Brown, C. F., Brumby, S. P., Guzder-Williams, B., Birch, T., Hyde, S. B., Mazzariello, J., Czerwinski, W., Pasquarella, V. J., Haertel, R., Ilyushchenko, S., Schwehr, K., Weisse, M., Stolle, F., Hanson, C., Guinan, O., Moore, R., & Tait, A. M. (2022). Dynamic World, Near real-time global 10 m land use land cover mapping. *Scientific Data*, *9*, 251. https://doi.org/10.1038/s41597-022-01307-4

Cheng, G., Huang, Y., Li, X., Lyu, S., Xu, Z., Zhao, H., Zhao, Q., & Xiang, S. (2024). Change detection methods for remote sensing in the last decade: A comprehensive review. *Remote Sensing*, *16*(13), 2355. https://doi.org/10.3390/rs16132355

Cieślak, I., Biłozor, A., & Szuniewicz, K. (2020). The use of the CORINE Land Cover (CLC) database for analyzing urban sprawl. *Remote Sensing*, *12*(2), 282. https://doi.org/10.3390/rs12020282

de la Iglesia Martinez, A., & Labib, S. M. (2023). Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening. *Environmental Research*, *220*, 115155. https://doi.org/10.1016/j.envres.2022.115155

Dzieszko, P. (2014). Land-cover modelling using corine land cover data and multi-layer perceptron. *Quaestiones Geographicae*, *33*(1), 5-22. https://doi.org/10.2478/quageo-2014-0004

Falt'an, V., Petrovič, F., Ot'ahel', J., Feranec, J., Druga, M., Hruška, M., Nováček, J., Solár, V., & Mechurová, V. (2020). Comparison of CORINE land cover data with national statistics and the possibility to record this data on a local scale-case studies from Slovakia. *Remote Sensing*, *12*(15), 2484. https://doi.org/10.3390/RS12152484

Feranec, J., Hazeu, G., Christensen, S., & Jaffrain, G. (2007). Corine land cover change detection in Europe (case studies of the Netherlands and Slovakia). *Land Use Policy*, *24*(1), 234-247. https://doi.org/10.1016/j.landusepol.2006.02.002

Gabisa, M., Kabite, G., & Mammo, S. (2025). Land use and land cover change trends, drivers and its impacts on ecosystem services in burayu sub city, Ethiopia. *Frontiers in Environmental Science*, *13*, 1-17. https://doi.org/10.3389/fenvs.2025.1557000

Ganjirad, M., & Bagheri, H. (2024). Google Earth Engine-based mapping of land use and land cover for weather forecast models using Landsat 8 imagery. *Ecological Informatics*, *80*, 102498. https://doi.org/10.1016/j.ecoinf.2024.102498

Gul, E., & Esen, S. (2024). High desertification susceptibility in forest ecosystems revealed by the environmental sensitivity area index (ESAI). *Sustainability*, *16*(23), 10409. https://doi.org/10.3390/su162310409

Holloway, J., & Mengersen, K. (2018). Statistical machine learning methods and remote sensing for sustainable development goals: A review. *Remote Sensing*, *10*(9), 1365. https://doi.org/10.3390/rs10091365

Hu, Y., Raza, A., Syed, N. R., Acharki, S., Ray, R. L., Hussain, S., Dehghanisanij, H., Zubair, M., & Elbeltagi, A. (2023). Land use/land cover change detection and NDVI estimation in Pakistan's southern Punjab Province. *Sustainability*, *15*(4), 3572. https://doi.org/10.3390/su15043572

Jalayer, S., Sharifi, A., Abbasi-Moghadam, D., Tariq, A., & Qin, S. (2022). Modeling and predicting land use land cover spatiotemporal changes: A case study in Chalus Watershed, Iran. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 5496-5513. https://doi.org/10.1109/JSTARS.2022.3189528

Kalayci Kadak, M. (2021). *Bartın Çayı Havzası'nda uzaktan algılama ve coğrafi bilgi sistemleri ile iklim değişikliği senaryolarına uygun bir model önerisi* (Doctoral dissertation, Kastamonu University). (In Turkish)

Kalayci Kadak, M. (2022). Investigation of the usability of landsat satellite images in studies related to climate change effects on land use-land cover. In M. Karaboyaci & A. Demircali (Eds.), *Versatile multidisciplinary engineering research* (pp. 116-126). SRA Academic Publishing.

Kalayci Kadak, M., Ozturk, S., & Mert, A. (2024). Predicting climate-based changes of landscape structure for Turkiye via global climate change scenarios: A case study in Bartin river basin with time series analysis for 2050. *Natural Hazards*, *120*, 13289-13307. https://doi.org/10.1007/s11069-024-06706-x

Kalaycı Kadak, M. (2025). Towards a climate-resilient metropolis: A neighborhood-scale nature-based urban adaptation planning approach. *Sustainability*, *17*(16), 7356. https://doi.org/10.3390/su17167356

Karahasan, B. C., & Pinar, M. (2023). Climate change and spatial agricultural development in Turkey. *Review of Development Economics*, *27*(3), 1699-1720. https://doi.org/10.1111/rode.12986

Kirui, K. B., Kairo, J. G., Bosire, J., Viergever, K. M., Rudra, S., Huxham, M., & Briers, R. A. (2013). Mapping of mangrove forest land cover change along the Kenya coastline using Landsat imagery. *Ocean and Coastal Management*, *83*, 19-24. https://doi.org/10.1016/j.ocecoaman.2011.12.004

Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources*, *28*, 205-241. https://doi.org/10.1146/annurev.energy.28.050302.105459

Liu, B., Pan, L., Qi, Y., Guan, X., & Li, J. (2021). Land use and land cover change in the yellow river basin from 1980 to 2015 and its impact on the ecosystem services. *Land*, *10*(10), 1080. https://doi.org/10.3390/land10101080

Lv, Z., Liu, T., Zhang, P., Benediktsson, J. A., & Chen, Y. (2018). Land cover change detection based on adaptive contextual information using bi-temporal remote sensing images. *Remote Sensing*, *10*(6), 901. https://doi.org/10.3390/rs10060901

Maden, G., & Aslan, Z. (2019). Statistical analysis of vegetation index depending on precipitation. *AURUM Journal of Engineering System and Architecture*, *2*(2), 19-28.

Mandvikar, K., Kumar, N., Supe, H., Singh, D., Gupta, A., Kumar, P., Meraj, G., Khan, I. D., Kouser, A., Pandey, S. K., & Avtar, R. (2024). Evaluating heat health risk in Indian cities: Geospatial and socio-ecological analysis. *World Development Sustainability*, *5*, 100180. https://doi.org/10.1016/j.wds.2024.100180

Mashala, M. J., Dube, T., Mudereri, B. T., Ayisi, K. K., & Ramudzuli, M. R. (2023). A systematic review on advancements in remote sensing for assessing and monitoring land use and land cover changes impacts on surface water resources in semi-arid tropical environments. *Remote Sensing*, *15*(16), 3926. https://doi.org/10.3390/rs15163926

Mert, A., Tavuç, İ., Özdemir, S., & Ulusan, M. D. (2024). Future responses of the Burdur Lake to climate change and uncontrolled exploitation. *Journal of the Indian Society of Remote Sensing*, *53*, 1025-1036. https://doi.org/10.1007/s12524-024-02008-8

Mohiuddin, G., & Mund, J. P. (2024). Spatiotemporal analysis of land surface temperature in response to land use and land cover changes: A remote sensing approach. *Remote Sensing*, *16*(7), 1286. https://doi.org/10.3390/rs16071286

Muche, M., Yemata, G., Molla, E., Adnew, W., & Muasya, A. M. (2023). Land use and land cover changes and their impact on ecosystem service values in the north-eastern highlands of Ethiopia. *PLoS ONE*, *18*(9), e0289962. https://doi.org/10.1371/journal.pone.0289962

Myga-Piatek, U., Żemła-Siesicka, A., Pukowiec-Kurda, K., Sobala, M., & Nita, J. (2021). Is there urban landscape in metropolitan areas? An unobvious answer based on corine land cover analyses. *Land*, *10*(1), 51. https://doi.org/10.3390/land10010051

Nasiri, V., Deljouei, A., Moradi, F., Seyed Mohammad Moein, S., & Borz, S. A. (2022). Land use and land cover mapping using sentinel-2, landsat-8 satellite images, and Google Earth engine: A comparison of two composition methods. *Remote Sensing*, *14*(9), 1977. https://doi.org/10.3390/rs14091977

Negese, A. (2021). Impacts of land use and land cover change on soil erosion and hydrological responses in Ethiopia. *Applied and Environmental Soil Science*, *2021*(1), 6669438. https://doi.org/10.1155/2021/6669438

Pande, C. B., Srivastava, A., Moharir, K. N., Radwan, N., Mohd Sidek, L., Alshehri, F., Pal, S. C., Tolche, A. D., & Zhran, M. (2024). Characterizing land use/land cover change dynamics by an enhanced random forest machine learning model: A Google Earth Engine implementation. *Environmental Sciences Europe*, *36*, 84. https://doi.org/10.1186/s12302-024-00901-0

Potapov, P., Hansen, M. C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X. P., Baggett, A., Kommareddy, I., & Kommareddy, A. (2022). The global 2000-2020 land cover and land use change dataset derived from the landsat archive: First results. *Frontiers in Remote Sensing*, *3*, 1-22. https://doi.org/10.3389/frsen.2022.856903

Selcuk, F., & Gulumser, A. A. (2023). İklim değişikliği etkisinde Türkiye'de tarimsal ürün verimliliği: Bölgesel bir değerlendirme. *Bölgesel Kalkınma Dergisi*, *01*(04), 425-451.

https://doi.org/10.61138/bolgeselkalkinmadergisi.1347009 (In Turkish)

Shafizadeh-Moghadam, H., Khazaei, M., Alavipanah, S. K., & Weng, Q. (2021). Google Earth Engine for large-scale land use and land cover mapping: An object-based classification approach using spectral, textural and topographical factors. *GIScience & Remote Sensing*, *58*(6), 914-928. https://doi.org/10.1080/15481603.2021.1947623

Taiwo, B. E., Kafy, A. Al, Samuel, A. A., Rahaman, Z. A., Ayowole, O. E., Shahrier, M., Duti, B. M., Rahman, M. T., Peter, O. T., & Abosede, O. O. (2023). Monitoring and predicting the influences of land use/land cover change on cropland characteristics and drought severity using remote sensing techniques. *Environmental and Sustainability Indicators*, *18*, 100248. https://doi.org/10.1016/j.indic.2023.100248

Tesfaye, W., Elias, E., Warkineh, B., Tekalign, M., & Abebe, G. (2024). Modeling of land use and land cover changes using google earth engine and machine learning approach: Implications for landscape management. *Environmental Systems Research*, *13*, 31. https://doi.org/10.1186/s40068-024-00366-3

Tewabe, D., & Fentahun, T. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *Cogent Environmental Science*, *6*(1), 1778998. https://doi.org/10.1080/23311843.2020.1778998

TÜİK. (2024). *Tarım ve hayvancılık: Tarım alanı (dekar)*. https://cip.tuik.gov.tr/ (In Turkish)

Turkish Ministry of Agriculture and Forestry. (2024). *Tarım havzaları üretim ve destekleme modeli illere göre 2024 yılında desteklenecek ürünlerin listesi*. https://www.tarimorman.gov.tr/BUGEM/Belgeler/Tarım Havzaları/2024 Yılı Ürün Deseni Listesi.pdf (In Turkish)

Ursu, C. D., Benedek, J., & Temerdek-Ivan, K. (2025). Accuracy assessment of four land cover datasets at urban, rural and metropolitan area level. *Remote Sensing*, *17*(5), 756. https://doi.org/10.3390/rs17050756

Varga, O. G., Pontius, R. G., Szabó, Z., & Szabó, S. (2020). Effects of category aggregation on land change simulation based on corine land cover data. *Remote Sensing*, *12*(8), 1314. https://doi.org/10.3390/RS12081314

Venter, Z. S., & Sydenham, M. A. K. (2021). Continental-scale land cover mapping at 10 m resolution over europe (Elc10). *Remote Sensing*, *13*(12), 2301. https://doi.org/10.3390/rs13122301

Venter, Z. S., Barton, D. N., Chakraborty, T., Simensen, T., & Singh, G. (2022). Global 10 m land use land cover datasets: A comparison of dynamic world, world cover and esri land cover. *Remote Sensing*, *14*(16), 4101. https://doi.org/10.3390/rs14164101

Verburg, P. H., Overmars, K. P., & Witte, N. (2004). Accessibility and land-use patterns of the forest fringe in the northeastern part of the Philippines. *Geographical Journal*, *170*(3), 238-255. https://doi.org/10.1111/j.0016-7398.2004.00123.x

Wang, Z., & Mountrakis, G. (2023). Accuracy assessment of eleven medium resolution global and regional land cover land use products: A case study over the conterminous United States. *Remote Sensing*, *15*(12), 3186. https://doi.org/10.3390/rs15123186

WRI and Google. (n.d.). *Dynamic World V1*. Retrieved Jun 13, 2025, from https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_DYNAMICWORLD_V1

Yenişehir Municipality. (2022). *Yenişehir hakkında*. https://www.bursa-yenisehir.bel.tr/bel/yenisehir/yenisehir-hakkinda/205 (In Turkish)

Yetik, A. K., & Candogan, B. N. (2024). Climate change impacts on precipitation dynamics in the southern Marmara Region of Turkey. *Bursa Uludağ Üniversitesi Ziraat Fakültesi Dergisi*, *38*(1), 123-141. https://doi.org/10.20479/bursauludagziraat.1442146

Yirsaw, E., Wu, W., Shi, X., Temesgen, H., & Bekele, B. (2017). Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the Su-Xi-Chang region. *Sustainability*, *9*(7), 1204. https://doi.org/10.3390/su9071204

YOSAB. (2022). *Yenişehir organize sanayi bölgesi*. https://yosab.org.tr/ (In Turkish)

Zhu, Z., & Woodcock, C. E. (2014). Continuous change detection and classification of land cover using all available Landsat data. *Remote Sensing of Environment*, *144*, 152-171. https://doi.org/10.1016/j.rse.2014.01.011