

ASSESSING AGRICULTURAL LAND CONVERSION TO URBAN DEVELOPMENT USING HIGH-RESOLUTION SATELLITE AND DRONE IMAGES

Arzu Erener^{1*}, Cenan Baş¹, Murat Selim Çepni¹, Gülcan Sarp²

¹Department of Geomatics Engineering, Faculty of Engineering, Kocaeli University, Umuttepe Campus, 41001 İzmit, Kocaeli, Türkiye

²Department of Geography, Faculty of Humanities and Social Sciences, Suleyman Demirel University, 32260 Isparta, Türkiye

*Corresponding author: arzu.erener@kocaeli.edu.tr

Received: October 31st 2025 / Accepted: June 5th 2026 / Published: October 1st 2026

<https://doi.org/10.24057/2071-9388-2026-4348>

ABSTRACT. The protection of agricultural lands is crucial for maintaining food security and environmental sustainability, especially in regions undergoing rapid urbanization. This study examines temporal land use changes in the Tahtalı Neighborhood of Derince District, Kocaeli Province, between 2014 and 2024. Three zones along the lakeshore, identified as highly attractive for human activity, were selected as study plots. High-resolution satellite images, orthophotos, and drone data were processed using the MeanShift segmentation method and classified with the Support Vector Machine algorithm to differentiate built-up areas from agricultural lands. Training samples were prepared based on spectral, textural, shape, and contextual features to ensure high classification accuracy. The classification performance was evaluated using confusion matrices, yielding overall accuracies ranging from 0.90 to 0.97 and Kappa coefficients between 0.72 and 0.93 across the study zones and years. The results indicate a substantial decline in agricultural lands due to urban expansion, temporary structures, and stone wall constructions, reflecting the increasing pressure of urbanization on rural landscapes. The integration of high-resolution drone data with machine learning classification effectively captured both fine-scale and broader land use patterns, offering a robust framework for monitoring spatial and temporal land use dynamics. These findings support informed land management decisions and emphasize the importance of sustainable land use policies in rapidly developing peri-urban regions.

KEYWORDS: Agricultural land; urban expansion; high-resolution satellite images; UAV imagery; land use change; SVM classification

CITATION: Erener A., Baş C., Çepni M. S., Sarp G. (2026). Assessing Agricultural Land Conversion to Urban Development Using High-Resolution Satellite and Drone Images. *Geography, Environment, Sustainability*, 3 (19), 218-228

<https://doi.org/10.24057/2071-9388-2026-4348>

ACKNOWLEDGMENTS: This study is partially derived from the master's thesis entitled "Spatiotemporal Analysis of Agricultural Land Use Changes Through Information Technologies: A Case Study of Tahtalı in Derince District", completed at the Graduate School of Natural and Applied Sciences, Kocaeli University. The authors would like to thank the Department of Geomatics Engineering, Kocaeli University, for their support during the research process. Additionally, the authors used ChatGPT for language editing, workflow organization, and text refinement. The authors take full responsibility for the accuracy and originality of the final manuscript.

Conflict of interests: The authors reported no potential conflict of interests.

INTRODUCTION

The increase in natural disasters driven by climate change, wars occurring in various parts of the world around Türkiye, and the rising frequency of pandemics have all underscored the critical importance of food supply and security. Despite the growing need to protect agricultural lands and develop productivity-enhancing agricultural policies, these lands are being unconsciously destroyed. To ensure the protection of agricultural areas, it is vital to promote sustainable agricultural practices, monitor land use changes, and preserve natural resources. Monitoring land use enables the more efficient and sustainable management of natural resources and facilitates the early detection of changes in agricultural production areas. This,

in turn, helps prevent potential environmental threats and planning errors, especially in critical domains such as agriculture, forestry, and water resources. monitoringnges in areas of agricultural production and identifying threats that may arise after planning requires regular monitoring of land use over time. Polat and Yalçın (2020) noted that for many years, ground survey methods were used to examine land use/land cover information and its changes. However, these methods are costly, time-consuming, and of limited reliability. With the advancement of technology, the processing of high-resolution satellite imagery using Remote Sensing (RS) and Geographic Information System (GIS) software has led to the development of practical, reliable, economical, consistent, and more detailed mapping techniques (Congalton et al., 2014; Şimşek,

2017). Remote sensing technologies, GIS, and other digital monitoring tools facilitate the observation of agricultural lands, support decision-making processes, and enhance the effective implementation of agricultural policies.

Spatial change analysis using GIS is a method employed to examine changes in geographic data over time. This type of analysis helps to understand how the features in a specific geographic area change over time and to identify the causes behind these changes. Numerous studies at both national and international levels have addressed agricultural lands and spatial change analysis (Serra et al., 2008; Gargiulo et al., 2012; Foley et al., 2005; Sarp & Erener, 2012; Erener, 2013; Chou et al., 2015; Kerr et al., 2017; ; Prabhakar, 2021; Tariq et al., 2021; Muhammad et al., 2022; Viana, 2022; Díez-Echavarría et al., 2025; Ituen et al., 2025; Purnamasari et al., 2025; Ngo et al., 2026).

The integration of unmanned aerial vehicles (UAVs) into remote sensing processes is becoming increasingly common due to technological advancements and their numerous advantages. These technologies are frequently used to observe land use changes, and many scientific studies have investigated agricultural land transformations and their impacts (Chen et al., 2019; Lambin et al., 2001; Zang et al., 2024).

The area surrounding the Tahtalı pond in the Tahtalı Neighborhood of Derince District, Kocaeli Province, has experienced significant land use changes due to rapidly increasing construction activities. In recent years, newly constructed buildings have led to the reduction of agricultural land and the degradation of natural areas. This poses a serious threat to both environmental sustainability and the continuity of agricultural production in the region.

Despite these ongoing transformations, threats to food security and the implications of land use change in the area have not been sufficiently investigated. In particular, the spatial and temporal dynamics of structural transformation in agricultural lands are of great importance for the development of land management policies. Furthermore, the full extent to which land use changes in the region poses a threat to food security, the natural landscape, and environmental stability remains unclear. In this context, it is essential to accurately analyze land use changes in the Tahtalı Neighborhood. Utilizing techniques such as satellite imagery and GIS to reveal the spatial and temporal dimensions of these changes will contribute both to understanding the current situation and to developing forward-looking strategies for planning and agricultural policies.

STUDY AREA

Kocaeli is located in the northwestern part of Türkiye, within the Marmara Region (Figure 1a). Owing to its geographical position, it occupies a highly strategic location. Kocaeli is situated to the east of Istanbul and to the west of Sakarya. Its strategic location provides significant advantages in terms of transportation as well as commercial and economic activities. This position has played a crucial role in the region's industrialization, the development of trade, and the enhancement of its tourism potential. Kocaeli is one of Türkiye's major industrial hubs, hosting key sectors such as automotive, chemical, metal, and food industries, as well as logistics and warehousing. Kocaeli Province comprises a total of 12 districts (Figure 1b). These districts form a geographical

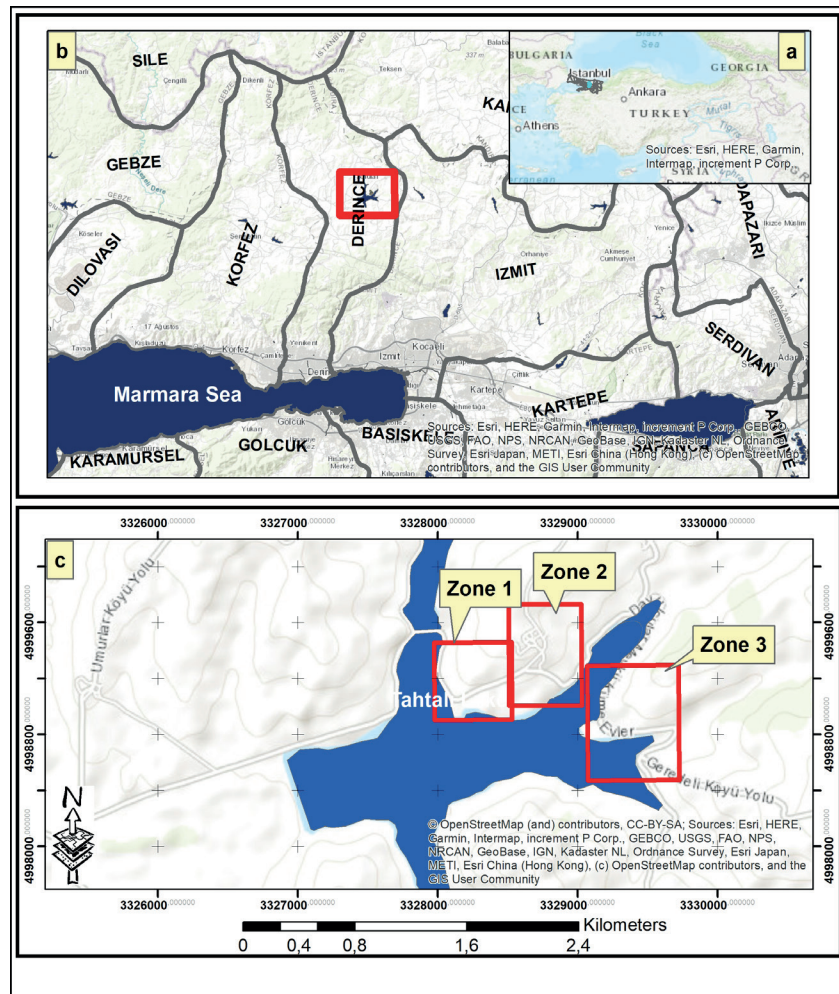


Fig. 1. a. Location of the study area within Türkiye, b. Location of the study area within Kocaeli Province, c. Tahtalı Lake and the designated study zones (Zone 1, Zone 2, Zone 3)



Fig. 2. Example image of Zone 3 showing areas with disrupted agricultural integrity

unity with diverse characteristics, each addressing different needs of the province. Derince, one of the oldest districts of Kocaeli, is an important trade center with its port. Derince District consists of 10 urban neighborhoods and 7 rural neighborhoods. Within the boundaries of Tahtalı Neighborhood in Derince District, the areas surrounding the pond that have undergone the most significant changes over the past decade were selected as the research area. These areas also serve as representative examples of transformations in other agricultural lands. To reflect the aim of the study, three zones (Figure 1c, Zones 1, 2, and 3) were selected where human-induced structures have markedly increased and where the plan notes allow for different land-use observations, such as agricultural and residential areas. The stone walls and similar structures constructed in the third pilot area are shown in Figure 2. These structures demonstrate the disruption of agricultural integrity and indicate a deviation from the intended land-use plan in the area.

An examination of agricultural activities shows that a total of 35,869 decares of land are under agricultural use, with Tahtalı ranking first with 8,844 decares. Tahtalı Neighborhood is designated as “rural residential areas” within the 1:25,000-scale Master Development Plan approved by the Kocaeli Metropolitan Municipality Council on 14 November 2007 (Decision No. 754). The aim of this plan is to ensure that land use, settlement, and construction comply with planning, health, and environmental standards; to reduce disaster risks; and to protect, preserve, and enhance natural, historical, cultural, and ecological systems. According to the plan, rural residential areas refer to settlement zones outside urban residential areas that were classified as villages or village neighborhoods prior to legal restructuring, with defined settlement boundaries and rural characteristics.

DATA AND METHODOLOGY

Data

The data used in this study were obtained from the Kocaeli Metropolitan Municipality and the Derince Municipality. High-resolution satellite imagery and orthophoto data were used to analyze temporal land-use changes. The WorldView-2 images acquired in 2014 provides insight into the historical state of the study area. WorldView-3 imagery from 2017 and orthophoto imagery from 2022 illustrate the spatial evolution of land-use patterns over time. In addition, drone

data obtained in 2024 provide observations of the most recent conditions of the area. All datasets used in the study have sub-meter spatial resolution. To capture current land conditions, drone surveys were conducted using a DJI Mavic 3 RTK UAV. Autonomous flight plans were executed, and the collected images were processed in DJI Terra software to generate point clouds and produce the 2024 orthophoto map. The characteristics of the datasets used in the study, including acquisition methods and spatial resolution, are summarized in Table 1.

METHODOLOGY

Three zones located along the lakeshore, identified as highly attractive for human activity and exhibiting rapid land-use change, were selected as plot study areas. Temporal variations in land-cover changes were analyzed using the Support Vector Machine (SVM) algorithm in conjunction with image segmentation techniques. In this study, SVM was selected as the classification method due to its strong performance in high-resolution remote sensing applications and its robustness when working with limited and heterogeneous training datasets. Image segmentation, extensively used for classifying satellite imagery and orthophoto maps, enhances interpretation by dividing images into meaningful objects (homogeneous regions) rather than individual pixels. This approach integrates spectral, shape, texture, and contextual features, thereby improving classification accuracy, reducing data volume, and shortening processing time. The resulting segments closely resemble real-world objects, facilitating visual interpretation. The methodological workflow is presented in Figure 3. To capture current land conditions, drone surveys were conducted using a DJI Mavic 3 UAV with RTK. Autonomous flight plans were executed, and the collected images were processed in DJI Terra software to generate point clouds and produce the 2024 orthophoto map. Historical land-use data were derived from high-resolution WorldView-2 imagery (2014), WorldView-3 imagery (2017), and orthophoto maps (2022). All datasets were processed using the MeanShift segmentation method to generate homogeneous regions prior to classification. Following segmentation, SVM classification was applied to distinguish anthropogenic structures and agricultural land classes. Classification accuracy was evaluated using a confusion matrix, which compares model predictions with reference data to assess performance.

Table 1. Data sources used in this study

Material Used	Data Inventory	Year of Data Acquisition	Resolution	Source
Satellite Imagery	WorldView-2	2014	0.5 m	Kocaeli Metropolitan Municipality
Satellite Imagery	WorldView-3	2017	0.3 m	Kocaeli Metropolitan Municipality
Digital Orthophoto Imagery	BRM Aero Bristell TDO aircraft & Phase One iXm-RS 150F Digital Camera	2022	0.2 m	Kocaeli Metropolitan Municipality
Photogrammetric Imagery	DJI MAVIC 3 RTK UAV	2024	0.02 m	Derince Municipality
Master Development Plan	1:25,000 Scale	2007	-	Kocaeli Metropolitan Municipality
Address Map	1:1,000 Scale	2024	-	Kocaeli Metropolitan Municipality
Cadastral Map	1:1,000 Scale	2018	-	Derince Municipality

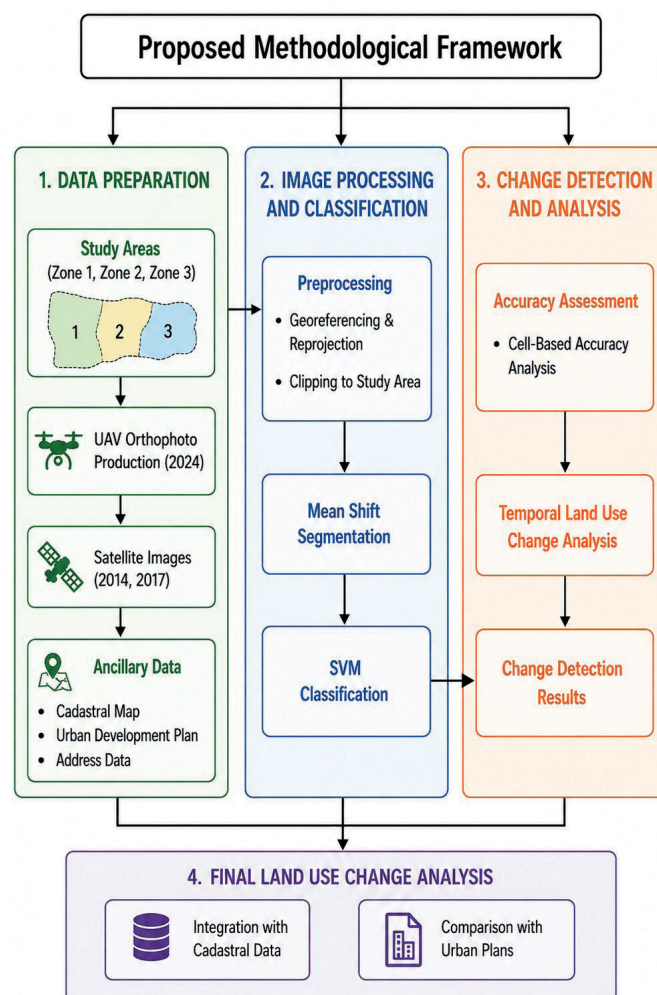


Fig. 3. Workflow of the study

Preprocessing

Prior to temporal and spatial change detection and image processing analyses, conducting preliminary image pre-processing is of critical importance. Therefore, in this study, data acquired in different years using various technologies underwent pre-processing steps such as atmospheric correction, reflectance normalization, and geometric correction. Atmospheric correction is performed to eliminate or reduce the effects of the atmosphere on remote sensing data,

thereby enabling more accurate extraction of surface features. The images were examined and found to be largely free from cloud cover and haze effects. To ensure uniform distribution of brightness levels within the images, histogram equalization was applied, enhancing low-contrast areas for better clarity. Moreover, for change detection analyses, all datasets were projected into a common datum and coordinate system. Accordingly, all data used in this study were reprojected into the WGS-84 WGS 84 / UTM Zone 35N coordinate system (EPSG:32635) to ensure spatial consistency across all data

sources. Due to the very high spatial resolution of the datasets, analyzing the entire study area requires computers with high RAM and processing capabilities. Additionally, opening and processing the entire dataset is time-consuming. Therefore, to enable more detailed and faster analyses, three focus areas were selected based on zones exhibiting notable changes. Following preliminary analyses, masking was performed on images from four different years for three zones where land-use changes were observed within the study area. The masking of the designated study areas on satellite and orthophoto maps from different years was carried out separately for each of the four zones and time intervals using clip operations on raster files. At this stage, data management functions within GIS were employed. Raster data clipping for the three zones across the four time periods resulted in the datasets presented in Figure 4.

Image Segmentation

Image segmentation is the process of dividing an image into smaller and more meaningful regions and is widely used in remote sensing data analysis. In this study, segmentation was applied to the images obtained for the three study zones (Figure 5), covering the years 2014, 2017, 2022, and 2024, in order to generate homogeneous regions prior to classification. The Mean Shift algorithm was preferred due to its ability to produce object-based segments that better represent real-world features compared to pixel-based approaches. This improves classification performance by reducing spectral noise and incorporating spatial context, which is particularly important for high-resolution datasets. The Mean Shift algorithm is a density-based clustering method that shifts data points toward regions of higher density. In the context of image segmentation, it groups pixels into clusters with similar

characteristics (Cheng, 1995; Comaniciu & Meer, 2002). For each pixel, the mean shift vector is calculated using Equation (1):

$$m(x) = \frac{\sum_{i=1}^N K(x_i - x) \times x_i}{\sum_{i=1}^N K(x_i - x)} \quad (1)$$

where x_i represents neighboring pixels, $K(x_i - x)$ is the kernel function, and x is the updated pixel position. Compared to directly using original pixel-based imagery in SVM classification, segmentation enables more consistent and meaningful feature representation by grouping similar pixels into homogeneous objects. The segmentation process was performed using ArcMap based software, and parameter values were determined experimentally. Spectral and spatial detail values were tested within a range of 1 to 20, and optimal results were obtained using values of 15, 5, and 15, respectively. Minimum segment sizes of 10, 15, and 30 were evaluated, and a value of 20 was selected for the final analysis. The algorithm iteratively updates pixel positions until convergence is achieved, after which pixels are assigned to segments corresponding to density centers. This process allows the identification of homogeneous regions within the image. Resulting segmentation maps for the three study areas over four different years are presented in Figure 5. Segmentation was used as a preprocessing step to generate homogeneous image objects, improving the consistency of input data for subsequent SVM classification.

Classification Using Support Vector Machines (SVM)

In this study, SVM was selected as the classification method due to its strong performance in high-resolution remote sensing applications and its robustness when

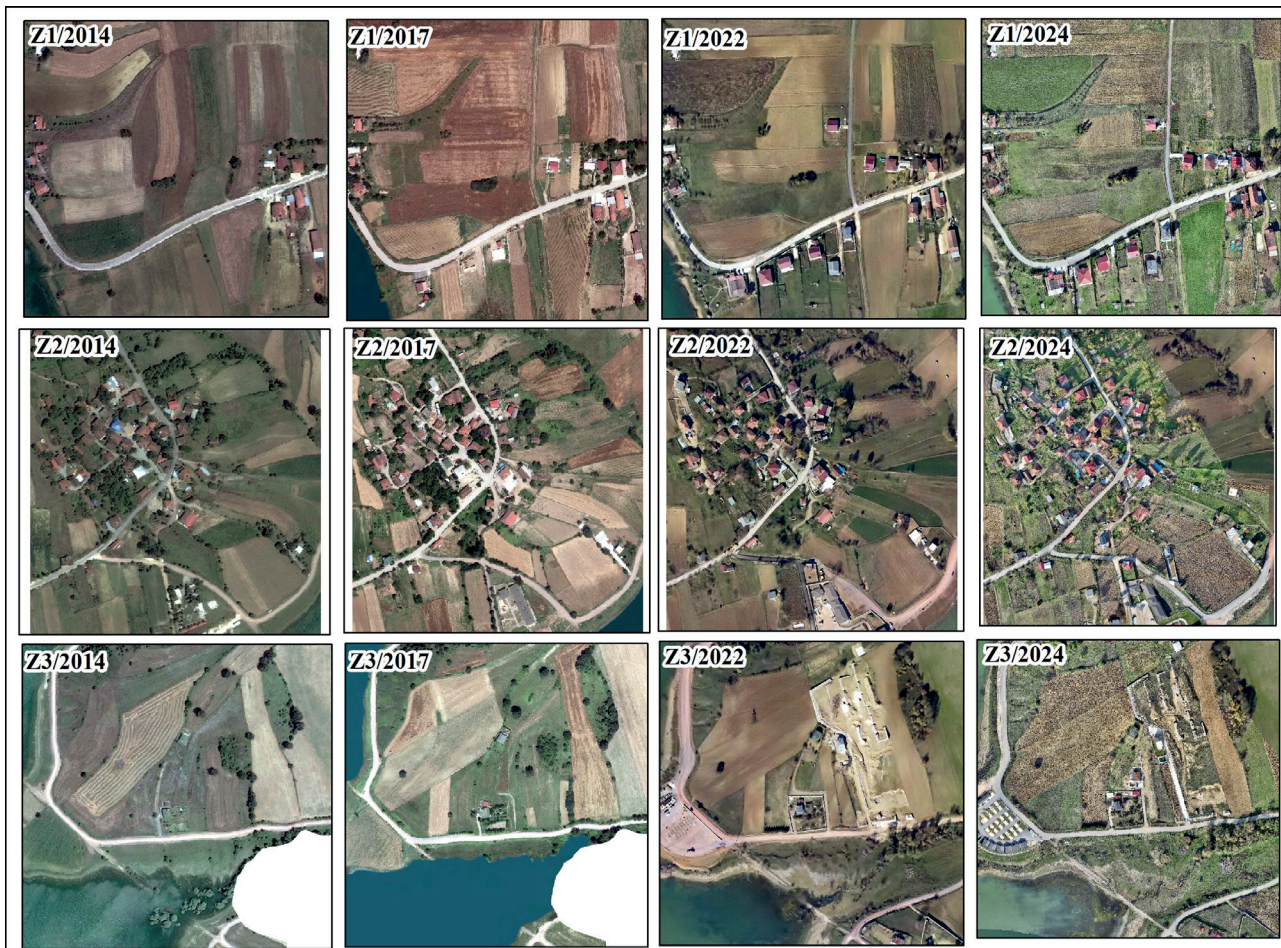


Fig. 4. Preanalysed and Masked Images of the Study Areas for Different Years (Z represents zone number)

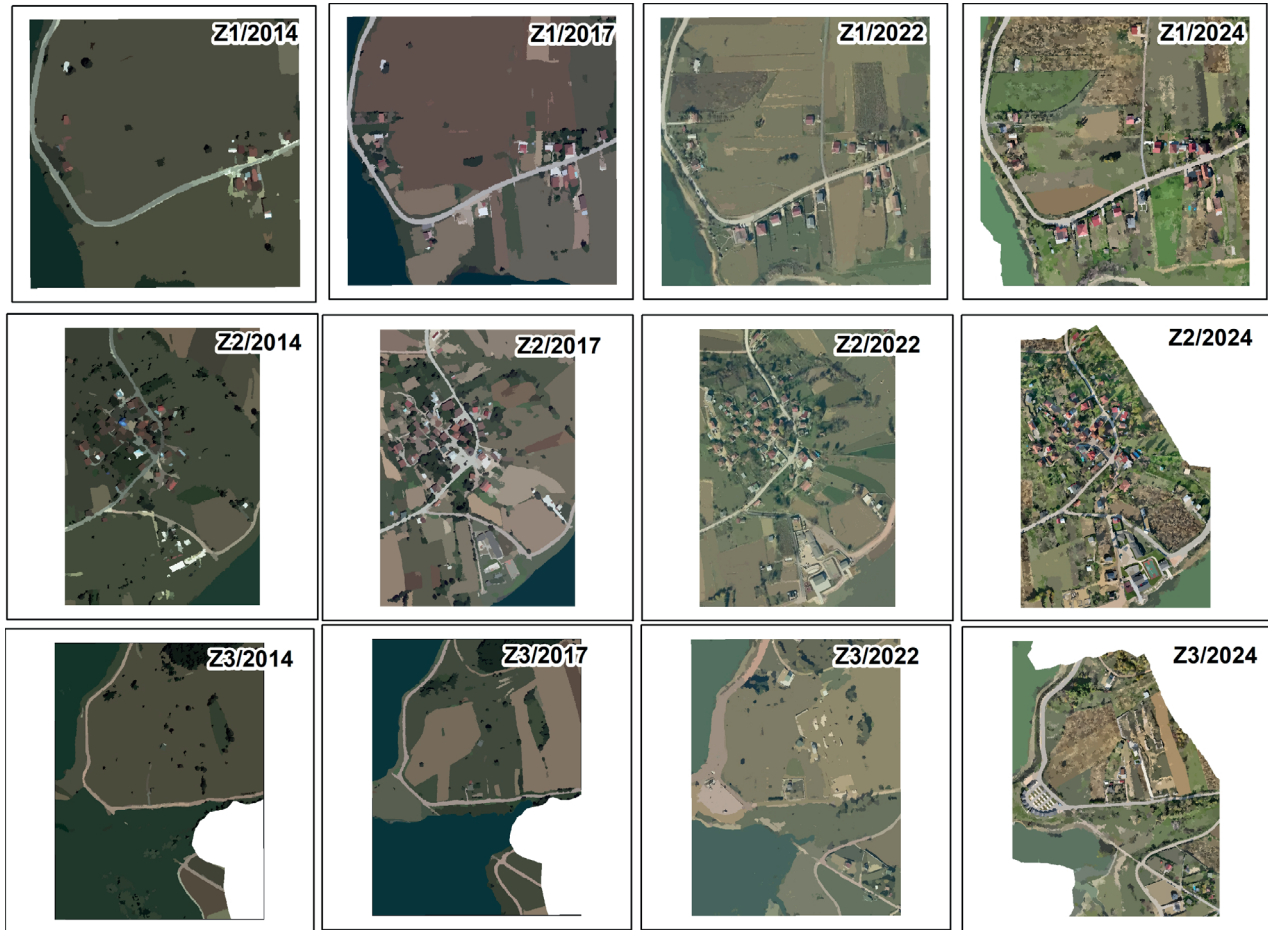


Fig. 5. Segmentation-Based Classification Results in Test Zones

working with limited and heterogeneous training datasets. Since the primary aim of the study is to analyze spatiotemporal land-use changes rather than to compare classification algorithms, a single, well-established classifier was preferred to ensure methodological consistency across different datasets and time periods. SVM is a supervised learning algorithm that aims to separate classes by determining an optimal decision boundary. In its basic form, the decision boundary is defined as: Equation (2):

$$w^T x + b = 0 \quad (2)$$

where w is the weight vector, x is the input feature vector, and b is the bias term.

Training samples were generated from segmented image objects using features such as color, texture, shape, and spatial characteristics. In this study, land use was classified into two categories: Disturbed Areas (DA), representing human-altered features such as buildings, roads, and stone walls, and Natural Areas (NA), representing relatively undisturbed regions. The classification was implemented using the same software environment as the segmentation process and the RBF kernel was applied to handle nonlinear patterns and improve classification performance.

Results and Discussion

This section presents the results of the segmentation-based classification and analyzes the spatiotemporal land-use changes observed across the three study areas. The findings are evaluated based on classification outputs derived from multi-temporal and multi-source datasets, including satellite imagery and UAV-derived orthophotos. Particular emphasis is placed on identifying patterns of urban expansion and changes in agricultural land use, as

well as assessing the reliability of the classification results through accuracy evaluation.

Classification Results

The classification results provide a comprehensive overview of land-use changes across different time periods and study zones. Figure 6 illustrates the spatial distribution of classified land-use categories for the years 2014, 2017, 2022, and 2024.

The results reveal significant temporal variations across the study zones. In Zones 1 and 2, rapid urban expansion is evident, particularly along transportation corridors where new structures have progressively increased over time. In contrast, Zone 3 exhibits limited building development; however, noticeable changes are observed in human-induced features such as stone walls, access roads, and small structures, which contribute to the gradual alteration of agricultural land integrity. These findings highlight the effectiveness of segmentation-based SVM classification in identifying land-use changes across multi-temporal and multi-source datasets. The classification outputs are influenced by segmentation parameters, training data quality, and spatial resolution differences between datasets.

Accuracy Assessment of Classified Images for Validation of Segmentation-Based Classification

After the classification process, it is essential to evaluate accuracy metrics to measure the performance of the model. First, the classified data were overlaid on the original images for visual evaluation. Second, cell-based ground truth data were collected, and an error matrix was generated to calculate the overall accuracy and Kappa

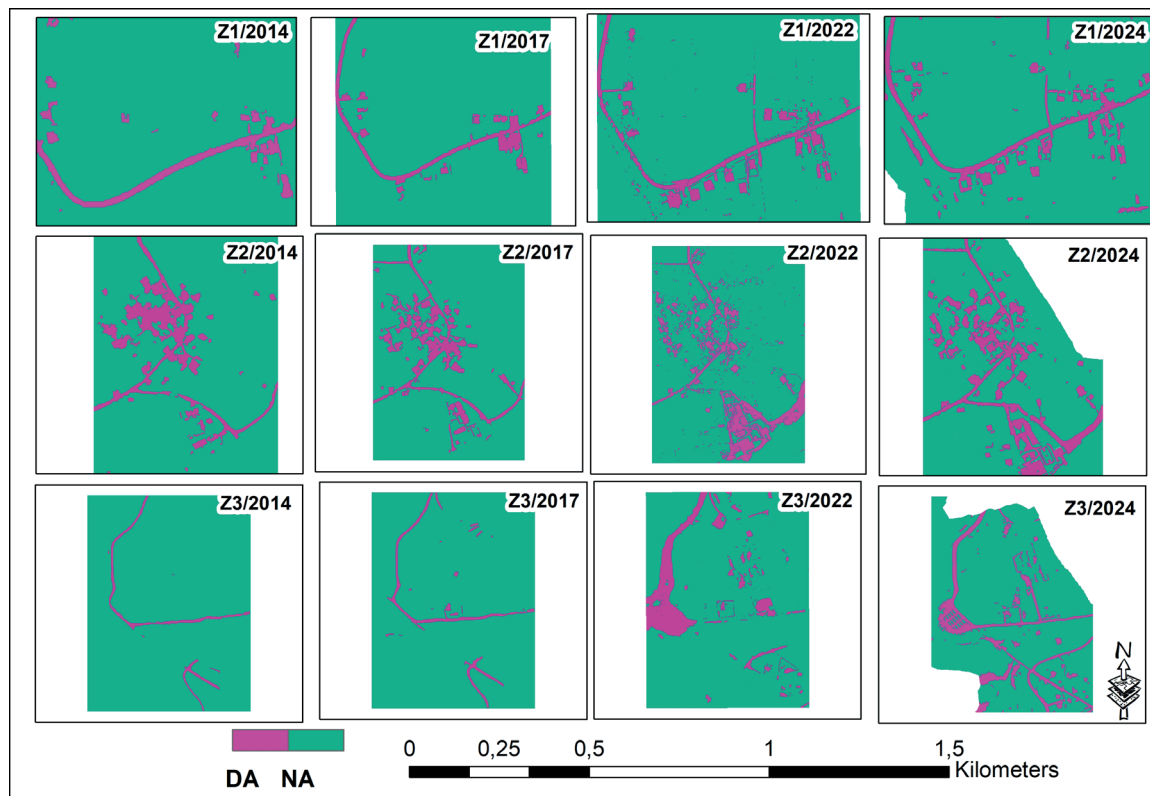


Fig. 6. Classified Segment Maps Showing Four-Year Changes in Three Study Zones. Land use classification results showing DA (Disturbed Areas) and NA (Natural Areas)

statistics for the human-made and other area categories. When performing temporal overlay analysis for Zone 1, it was observed that buildings in the area were largely detected in 2014, although a large building located in the southeast was not captured (Figure 7). By 2017, new constructions appeared along a road curve, and the previously undetected building was clearly identified. In 2022 and 2024, the number of buildings along the roadside further increased and was successfully detected through classification. However, in 2024, the very high-resolution UAV imagery, combined with segmentation parameter choices, likely caused soil cover in agricultural areas to appear as different colors, which led to some of these areas being incorrectly classified as buildings.

The second study area was selected as a rural settlement, historically classified as a village, and exhibits relatively higher building density (Figure 8). Consequently, the area has a structurally more complex configuration, which affects the classification assessment. Comparing the classified structures with the raster imagery in Figure 8, it was observed that the classification rate for buildings in 2014 was high. When examining object-level details of buildings and associated structures, particularly in the 2024 dataset, some elements such as canopies and outbuildings were only partially classified, resulting in less complete building representation compared to other years. Factors such as varying satellite image resolutions, weather conditions at the time of acquisition, and segmentation parameter choices likely influenced the classification quality.

The area evaluated as Zone 3 is characterized by low building density (Figure 9). In this region, structures generally consist of elements such as stone walls and swimming pools, which fall under the “other built” category and may impact agricultural land use. In 2014, agricultural use predominated, and object-based classification included road features in addition to minimal built structures. By 2017, two buildings and road objects were present, while in 2022, an increase in stone wall structures was observed.

The 2024 classification mapped roads, small tree clusters, and non-built areas as classified objects. During the zonal evaluation, the focus was on buildings and disturbances to agricultural integrity. Comparing vector-based maps derived from the segmentation data revealed a relatively high error rate in 2024. This was primarily due to roads and structures being interpreted as single objects and other features such as shrubs, mounds, and areas with significant elevation differences being misclassified as buildings, contributing to increased classification errors.

To construct the error matrix, ground truth data were first collected from satellite imagery for human-made and other classes across three study areas and four years. The ground truth points ranged from 100 to 200 per dataset, and each point's class was determined based on the corresponding year's satellite imagery and entered into the database. Subsequently, these sample points were overlaid on the classification results, allowing the underlying classified information to be recorded in the database. This process created a dataset containing both the ground truth and predicted values for each sample point. The accuracy of classification is highly dependent on the location of the sample points. Therefore, points were carefully selected to ensure a sufficient number and to best represent their respective classes. Figure 10 visually illustrates the effects of sample point locations on classification outcomes. The left-hand images in the figure show the satellite imagery of the selected structures, while the corresponding images on the right display the classification results for the same areas. In Figure 10a, a sample point placed on the roof of a building classified as a human-made object was correctly assigned to the “human-made structure” category. However, in Figure 10b, shadows or trees partially covering the roof negatively affected classification accuracy, causing misclassification, particularly for points placed on unclassified or partially classified portions of the building. Similarly, Figure 10c shows a sample point on a partially collapsed roof being assigned to a different land cover

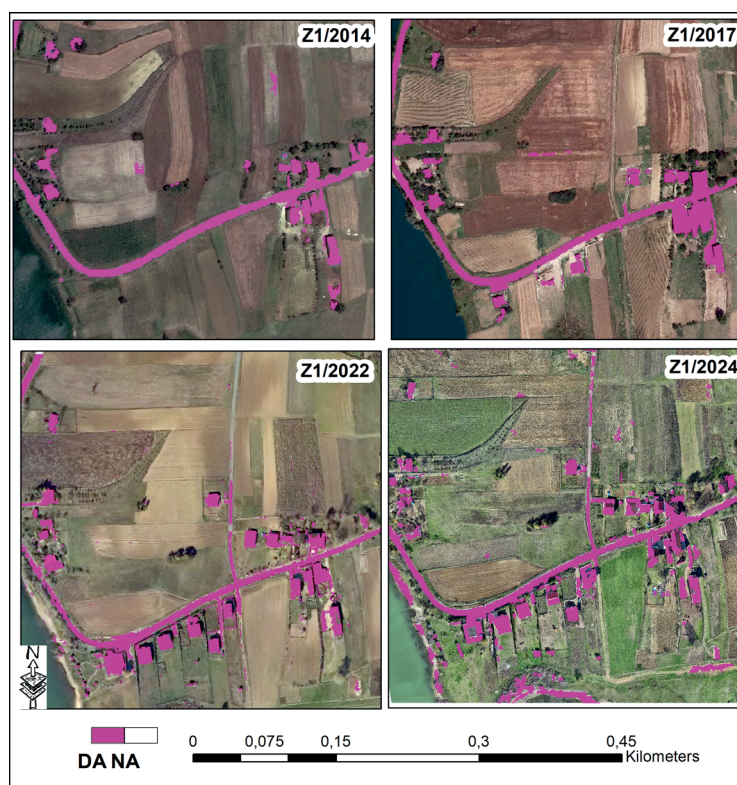


Fig. 7. Overlay of Classified Maps and Satellite Imagery for Different Years in Zone 1 (Z1). Land use classification results showing DA (Disturbed Areas) pink label color and NA (Natural Areas) transparent label color

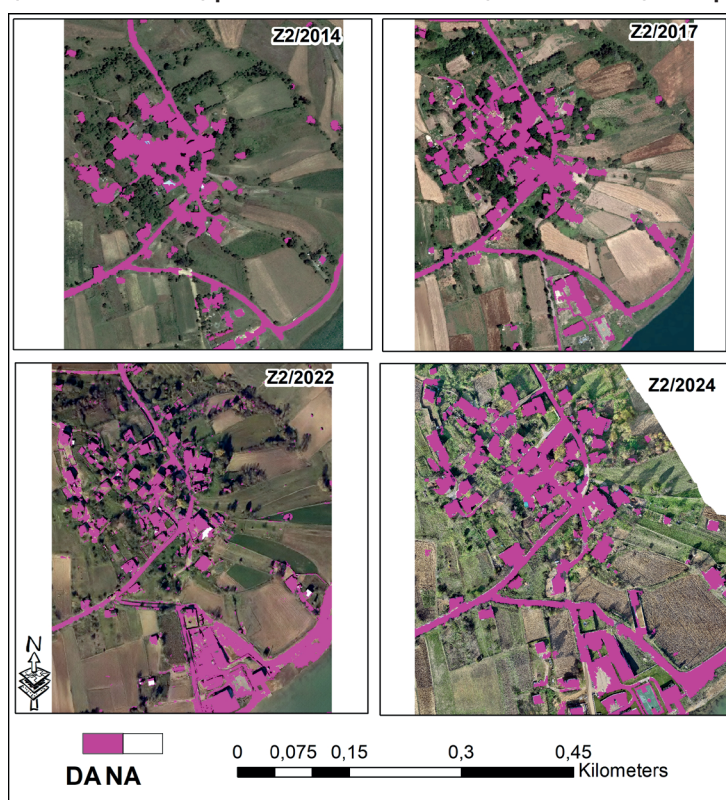


Fig. 8. Overlay of Classified Maps and Satellite Imagery for Different Years in Zone 2 (Z2). Land use classification results showing DA (Disturbed Areas) pink label color and NA (Natural Areas) transparent label color

class, illustrating that physically damaged structures can contribute to classification errors. These examples highlight the importance of considering the physical condition of structures, natural obstructions, and shadowing effects when selecting sample points for accuracy assessment. Careful selection ensures that the ground truth data accurately reflect the intended classes and improves the reliability of error matrix evaluations.

An error matrix was used for the accuracy assessment. This two-dimensional table is a fundamental tool for evaluating the performance of classification models, comparing ground truth values with the values predicted by the model (Table 2). It is typically constructed based on the number of observations for each class, providing a clear representation of classification accuracy and misclassification patterns.



Fig. 9. Overlay of Classified Maps and Satellite Imagery for Different Years in Zone 3. Land use classification results showing DA (Disturbed Areas) pink label color and NA (Natural Areas) transparent label color

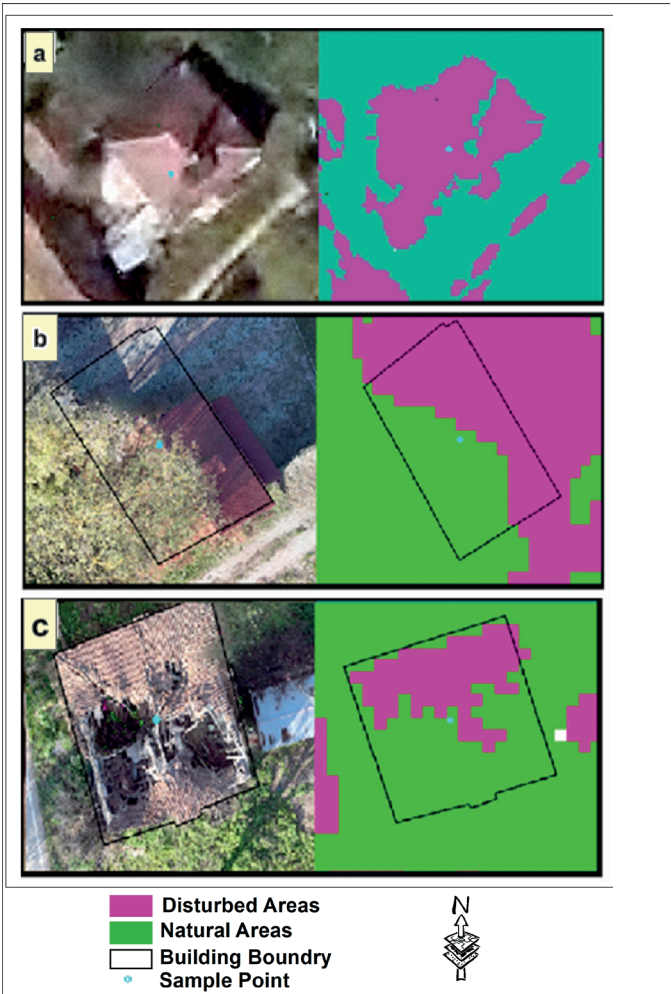


Fig. 10. Examples of Sample Point Location Effects: (a) Point located on a roof, (b) Misclassification caused by a tree on a roof, (c) Impact of a collapsed roof on classification results

Table 2. Basic Structure of an Accuracy Matrix for Binary Classification

	Predicted: Positive	Predicted: Negative
Actual: Positive	True Positive (TP)	False Negative (FN)
Actual: Negative	False Positive (FP)	True Negative (TN)

Overall Accuracy (OA) is the proportion of correct predictions made by the model relative to the total number of predictions (3).

$$\text{Overall Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

This metric indicates the proportion of predictions that the model classified correctly. However, in datasets with class imbalance, overall accuracy can be misleading. The Kappa coefficient measures the model's accuracy relative to the likelihood of random agreement and is particularly useful in multi-class classification (4).

$$K = \frac{P_o - P_e}{1 - P_e} \quad (4)$$

P_o : overall accuracy

P_e : Expected Accuracy

Table 3 presents the statistical data on the accuracy of the classification results. The primary objective is to evaluate the accuracy of the human-made class based on the sample points. For three different study areas, OA and Kappa coefficients were calculated, providing detailed insight into the effectiveness of the classification method. Overall accuracy ranged from 90% to 97%, indicating high classification performance, as accuracy above 85% is generally considered satisfactory in literature. Kappa values ranged between 0.78 and 0.89, demonstrating a generally high and reliable classification outcome across all years.

The relatively lower Kappa values observed in the second study area may be attributed to increased structural complexity and potential data-related factors such as image quality or illumination differences. In contrast, the first and third study areas, characterized by lower building density, exhibit higher classification performance. Additionally, the high spatial resolution of the UAV-derived orthophoto from 2024 contributed to improved classification accuracy. Overall, these results confirm the robustness of the SVM classifier in effectively distinguishing land-use classes over time, despite variations in data sources and temporal differences.

RESULTS AND DISCUSSION

In this study, spatio-temporal land use changes were analyzed within four different plot areas located around the Tahtalı Pond, situated in the Tahtalı neighborhood of Derince district, Kocaeli province, using satellite and aerial

imagery from the years 2014, 2017, 2022, and 2024. In this context, a comprehensive comparison was conducted by utilizing medium-resolution satellite images from 2014 and 2017, an orthophoto map from 2022, and high-resolution orthophoto data produced by an UAV in 2024. The images were classified using the Mean Shift Segmentation method, and the obtained classification results were validated through the error matrix approach. The findings revealed a significant change in agricultural lands in the region over the last decade. Between 2014 and 2024, a portion of agricultural lands was converted into urban areas, while some areas became idle or shifted toward alternative uses. Another striking factor in the region's land use changes is the agricultural land consolidation project, which started in 2014 and was completed in 2018. During this process, physical interventions such as parcel reorganization, construction of agricultural roads, and reshaping parcels into more regular forms were carried out. Although these efforts aimed to enhance agricultural productivity, the improvement of infrastructure and increased accessibility of land also triggered growing rural settlement pressures. Consequently, a rapid acceleration in construction activities was observed in the post-consolidation period, especially after 2018. Losses in agricultural lands detected in the 2022 and 2024 datasets coincide with this construction phase, indicating that the post-consolidation period represents a critical threshold for land use transitions. The study conducted across various zones indicated that over time, construction activities within agricultural lands have disrupted the integrity of the terrain, with a notable increase in such activities observed especially during the last two years. Additionally, the Tahtalı neighborhood, located within the Derince district of Kocaeli, has experienced increased demand for rural areas in recent years due to its proximity to the Istanbul Metropolitan Area, particularly during and after the COVID-19 pandemic. This growing demand directly influenced land use dynamics in the region. In the post-pandemic period, rural settlement trends and rising construction pressures on agricultural lands, commonly observed around Istanbul, have also been evident in Tahtalı. The land use data indicates that these pressures have intensified over time and that unplanned development poses a significant threat to agricultural lands. When evaluated in the context of broader trends in Türkiye, these findings are consistent with national patterns indicating increasing conversion of agricultural lands into urban and semi-urban uses, particularly in regions experiencing rapid population growth and industrialization. However,

Table 3. Accuracy Statistics of Confusion Matrices for Different Years

		2014	2017	2022	2024
Zone 1	Overall Accuracy	0.97	0.96	0.92	0.90
	Kappa	0.93	0.92	0.80	0.73
Zone 2	Overall Accuracy	0.90	0.91	0.89	0.92
	Kappa	0.72	0.78	0.71	0.82
Zone 3	Overall Accuracy	0.93	0.92	0.95	0.93
	Kappa	0.82	0.78	0.89	0.82

the study area appears to exhibit relatively higher rates of agricultural land conversion compared to general national trends. This can be attributed to its proximity to major industrial zones and the Istanbul Metropolitan Area, which intensifies development pressure and accelerates land-use transformation processes.

The different datasets used in this study, including satellite images, orthophoto maps, and UAV-produced orthophotos, provided varying levels of detail and accuracy for land use change analysis. While the satellite images from 2014 and 2017 were suitable for comparing large-scale temporal patterns, the 2022 orthophoto map, despite offering higher resolution, highlighted the importance of image quality, atmospheric conditions, and classification precision at the time of data acquisition. In contrast, the UAV orthophoto from 2024, with its high spatial resolution, enabled the accurate detection of small-scale changes, new constructions, and detailed land use transitions. This study emphasizes the importance of UAV technology for analyzing small-scale changes, offering both cost-effectiveness and planning efficiency. The study also revealed that many of the structures built on agricultural lands within the study area have been transformed into

residential properties such as weekend houses, hobby gardens, or rural retreats, with many of them not being used for agricultural production. This situation has led to two major issues affecting agricultural integrity:

First, residential constructions within agricultural lands fragment production areas, obstruct the movement of agricultural machinery, and interfere with irrigation infrastructure, thereby disrupting land continuity. Second, such developments undermine the systems that support sustainable production within agricultural areas, including collective irrigation, marketing chains, and production planning. This fragmentation ultimately threatens overall production efficiency and competitiveness. Moreover, these patterns of construction pose long-term risks to food security.

Overall, this study provides valuable insights into monitoring temporal changes for the protection of agricultural lands. By integrating multiple methodologies, the study demonstrates the potential of combining remote sensing techniques, GIS applications, cadastral data, and master zoning plans to achieve faster comparisons, improved efficiency, and more informed decision-making for future land use planning. ■

REFERENCES

- Chen, N., Liu, W., Bai, R., & Chen, A. (2019). Application of computational intelligence technologies in emergency management: a literature review. *Artificial Intelligence Review*, 52(3), 2131-2168.
- Cheng, Y., (1995). Mean shift, mode seeking, and clustering, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(8), 790-799.
- Chou, J., Dong, W., Wang, S., & Fu, Y. (2015). Quantitative analysis of agricultural land use change in China. *Physics and Chemistry of the Earth, Parts A/B/C*, 87, 3-9.
- Comaniciu, D., & Meer, P. (2002). Mean shift: A robust approach toward feature space analysis, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(5), 603-619.
- Congalton, R., Gu, J., Yadav, K., Thenkabail, P., & Ozdogan, M. (2014). Global land cover mapping: A review and uncertainty analysis. *Remote Sensing*, 6(12), 12070-12093.
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273-297.
- Diez-Echavarría, L., Villegas-Palaciob, C., & Arango-Aramburo, S. (2025). Scaling the Landscape: Revealing Land Use and Cover Change Patterns in the Colombian Andes. *GEOGRAPHY, ENVIRONMENT, SUSTAINABILITY*, 18(2), 48-62.
- Erener, A. (2013). Classification method, spectral diversity, band combination and accuracy assessment evaluation for urban feature detection. *International Journal of Applied Earth Observation and Geoinformation*, 21, 397-408. <https://doi.org/10.1016/j.jag.2011.12.008>
- Foley, J. A., et al. (2005). Global consequences of land use. *Science*, 309(5734), 570-574.
- Gargiulo, V., Sateriano, A., Di Bartolomei, R., & Salvati, L. (2012). Urban sprawl and the environment. *Geography, Environment, Sustainability*, 5(4), 46-62.
- Iuen, U., Elijah, U. D., Jimmy, U. J., Udofia, U., Antai, B. E., Inwang, S., ... & Unyime, J. (2025). Spatial-temporal dynamics of urban expansion and land cover transformation in Uyo Capital City, Akwa Ibom State, Nigeria. *Canadian Social Science*, 21(4), 42-52.
- Kerr, J., et al. (2017). Agricultural land use change in response to urban expansion: A case study in China. *Land Use Policy*, 66, 314-322.
- Lambin, E. F., et al. (2001). The causes of land-use and land-cover change: Moving beyond the myths. *Global Environmental Change*, 13(4), 435-444.
- Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. (2022). Spatiotemporal change analysis and prediction of future land use and land cover changes using QGIS MOLUSCE plugin and remote sensing big data: A case study of Linyi, China. *Land*, 11(3), 419.
- Ngo, D. T., Ba, D. D., & Nguyen, H. H. V. (2026). Analysis of forest vegetation changes in Vietnam's Central Highlands and southeast regions using remote sensing and machine learning. *Geography, Environment, Sustainability*, 19(2), 67-83.
- Polat, P., & Yalçın, F. (2020). Erzincan ili arazi kullanıymıny (2000-2018 yılları arası) CORINE sistemi ile deđerlendirilmesi. *Dođu Cođrafya Dergisi*, 25(44), 125-150.
- Prabhakar, S. V. R. K. (2021). A succinct review and analysis of drivers and impacts of agricultural land transformations in Asia. *Land Use Policy*, 102, 105238.
- Purnamasari, R. A., Setiawan, M., & Wardah, W. (2025). Land degradation detection in urban areas using spatial modelling and semiautomatic classification of satellite imagery data. *Tropical Aquatic and Soil Pollution*, 5(2), 110-124.
- Sarp, G., & Erener, A. (2012). The effects of sample size selection on classification accuracy. In *Lecture Notes in Information Technology*, 30, 374-379. 2012 International Conference on Earth Science and Remote Sensing (ESRS 2012), Hong Kong.
- Serra, P., Pons, X., & Saurí, D. (2008). Land-cover and land-use change in a Mediterranean landscape: A spatial analysis of driving forces integrating biophysical and human factors. *Applied Geography*, 28(3), 189-209.
- Pimpek, H. (2017). CORINE 4. Seviye arazi örtüsü/kullanım sınıflarının belirlenmesi ve yüzey akıyp risk haritasının oluşturulması (Bartın Çay Havzası Örneđi) [Master's thesis, Bartın University]. Bartın University Repository.
- Tariq, A., Shu, H., Siddiqui, S., Imran, M., & Farhan, M. (2021). Monitoring land use and land cover changes using geospatial techniques, a case study of Fateh Jang, Attock, Pakistan. *Geography, Environment, Sustainability*, 14(1), 41-52.

Viana, C. M. (2022). Spatial analysis, geospatial data and land-change models for modelling agricultural land changes. In *Mapping and Forecasting Land Use: The Present and Future of Planning* (pp. 95 -113).

Zang, Y., Hu, S., & Liu, Y. (2024). Rural transformation and its links to farmland use transition: Theoretical insights and empirical evidence from Jiangsu, China. *Habitat International*, 149, 103094.