

FORECASTING URBANIZATION DYNAMICS ON İSTANBUL'S EUROPEAN SIDE USING DEEP LEARNING AND EXTRAPOLATION TECHNIQUES

GİZEM DİNÇ

Süleyman Demirel University, Faculty of Architecture, Department of Landscape Architecture, Isparta, Turkey

ORCID: 0000-0003-2406-604X

**Corresponding author email: gizemdinc@sdu.edu.tr*

Received: 21st October 2025, **Accepted:** 23rd May 2026

ABSTRACT

Rapid urbanization in metropolitan regions poses significant environmental, social, and infrastructural challenges, necessitating advanced analytical approaches to monitor and predict urban growth. This study investigates the spatio-temporal dynamics of urbanization on the European side of Istanbul from 2013 to 2024 using Landsat 8 imagery and a deep learning (DL)-based Land Cover Classification model integrated within ArcGIS Pro. The U-Net-based pre-trained model generated 15-class Land Use/Land Cover (LULC) maps, which were validated against the Urban Atlas dataset, resulting in high classification accuracies for forest and water classes (PA: 0.84–0.94; UA: 0.87–0.87) and an overall binary urban/non-urban accuracy of 87 %, confirming the robustness of the employed DL approach. Spatio-temporal analyses of LULC data were conducted using both Ordinary Least Squares (OLS) and nonlinear regression functions to examine urban growth trends and project future development for 2025, 2026, and 2027. The results indicate a strong linear increase in urbanized areas across most districts, with total developed area on the European side projected to reach approximately 807 km² by 2027, representing a nearly 50% increase compared to 2013. These findings highlight the significant pressure of urban expansion on natural and agricultural lands and emphasize the need for informed planning strategies. By integrating remote sensing, deep learning, and predictive modeling, this study provides actionable insights for sustainable urban development, offering a replicable framework for monitoring rapid urbanization and supporting policy decisions to mitigate environmental and socio-spatial impacts in rapidly growing metropolitan regions.

Keywords: Urbanization, Spatio-temporal analysis, Land use/land cover (LULC), Deep learning, Landsat 8, Remote sensing, Istanbul

INTRODUCTION

The concept of urbanization refers to the spatial and demographic process of population concentration in urban areas, while its analysis has increasingly incorporated technology-driven and data-intensive approaches. With rapid urban development, multiple environmental challenges such as ecosystem degradation, biodiversity loss, urban heat island

phenomenon, ecosystem disruption, and congestion have emerged (Hao *et al.*, 2018; Jorge *et al.*, 2018; Yao *et al.*, 2021). Particularly in cities that do not develop resiliently against climate change, effects like flooding, earthquakes, and droughts result in both human and economic impacts. The process of urbanization exerts significant pressure on air quality, with the rapid expansion of newly industrialized countries resulting in larger ecological footprints and elevated PM2.5 emissions (Cristaldi *et al.*, 2022; Yan *et al.*, 2022; Akiner & Ghasri, 2025). As a result, sustainable urban development has emerged as an increasing global priority and is a key component of the United Nations' 2030 Agenda for Sustainable Development Goals (Sun *et al.*, 2020). Accordingly, cities must implement effective urban planning to mitigate climate change impacts (Clarke *et al.*, 2019). Urban climate interventions include mitigation measures aimed at reducing greenhouse gas emissions and adaptation measures designed to enhance the capacity to cope with changing climate conditions (Gargiulo & Zucaro, 2023). Mitigation targets the reduction of current and potential emissions, while adaptation aims to strengthen social and ecological resilience against secondary climate-related hazards. The importance of addressing mitigation and adaptation simultaneously, supported by decision-making systems, is emphasized in IPCC reports (Klein *et al.*, 2007; Jones *et al.*, 2007; Peker & Ataöv, 2024).

In this context, researchers and urban planners are utilizing contemporary technological and methodological approaches to promote more sustainable urban growth. Recent advancements in remote sensing and deep learning allow researchers to observe LULC changes and generate spatial representations of urban areas. In addition, future urban development trajectories can be assessed using statistical or extrapolation-based forecasting methods. Such predictions are essential for guiding policy and decision-making, mitigating outcomes, and securing livelihoods. Various studies have presented numerous models that predict medium-term physical changes based on past trends (Soltani & Karimzadeh, 2013; Arsanjani *et al.*, 2018; Dinç & Gül, 2021). These models are crucial for understanding the global impacts of human activities. A fundamental step in producing reliable predictions is effectively identifying historical data and the current situation, as well as incorporating key spatial and environmental factors such as topography, road networks, and other accessibility-related variables that influence urban growth dynamics. In studies addressing LULC change, the analytical framework primarily focuses on two core objectives: (i) determining the accuracy of change classification results and (ii) quantitatively estimating the extent of areas undergoing change (Olofsson *et al.*, 2014).

Recently, machine learning systems and remote sensing have become a major part of land surveys. These systems have replaced traditional methods by enabling accurate analysis in LULC classification and maximizing the use of big data (Helber *et al.*, 2018). In traditional machine learning systems, feature extraction is performed separately from the classifier, and it requires careful engineering and domain expertise to design meaningful features that facilitate the discrimination of different LULC classes. In contrast, deep learning models have the ability to automatically learn hierarchical feature representations from raw input data, reducing the need for manual feature engineering (LeCun *et al.*, 2015).

Recent advancements in *deep learning* (DL) have significantly improved classification tasks, including land use/land cover (LULC) mapping, by leveraging multi-layer neural networks that iteratively refine predictions through forward and backpropagation (Boonpook *et al.*, 2023; Deng & Yu, 2014). Pre-trained models available in platforms such as the ArcGIS Living Atlas provide an efficient solution, enabling the generation of 30 m resolution LULC maps from high-resolution imagery without extensive computational resources or AI expertise. While these models offer significant advantages in terms of accessibility and

efficiency, their performance may still be influenced by certain methodological constraints. In particular, they may exhibit reduced transferability across different geographic regions, challenges in adapting to varying feature domains, and decreased generalization performance when applied to areas that differ significantly from the datasets on which they were originally trained. For instance, the Land Cover Classification (Landsat 8) model, trained using the 2016 NLCD, supports applications in long-term environmental monitoring, resource management, and climate change studies.

Despite these technological opportunities and facilitators, the inability to adequately examine the environmental and social impacts of urbanization before implementing planning applications remains a significant shortcoming in Turkey. The decline in agricultural and livestock activities in Turkey has led to a growing concentration of the population in cities that offer employment opportunities, resulting in a rapid urbanization trajectory (Dinç & Gül, 2021). In particular, coastal cities in Turkey experience significant challenges associated with uncontrolled urbanization and improper planning, especially in relation to flood risk (Ercanli & Savaşır, 2022). Moreover, the discharge of large volumes of urban waste into marine environments has made marine mucilage a persistent environmental issue that requires continuous attention (Yılmaz & Saler, 2023). In Istanbul, with a population of 15.655 million, continuous investments are made to resolve traffic and congestion, sometimes at the expense of natural areas and important historical values that need to be preserved (Kızıldaş & Kültür, 2023). In Turkey, there is a need for a breakthrough to take measures against these problems, ensure controlled urbanization, and create resilient cities. As a first step for this breakthrough, increasing LULC change observations and conducting more academic studies on satellite imagery and artificial intelligence in this field can contribute to developments. This can help develop policies aimed at improving rapid and accurate decision-making mechanisms in planning processes.

Natural and cultural values in Istanbul are under pressure in the face of rapid urbanization unless significant planning decisions are made. Planning decisions that control rapid changes and produce solutions to potential problems are needed. Monitoring urban sprawl provides important insights for creating a resilient city against other problems brought about by rapid urbanization, such as flooding, earthquakes, drought, urban heat island effect, and traffic issues. In addition, another limiting factor in effectively addressing these challenges is the lack of adequate regulations or the insufficient enforcement of existing regulations. Proactive planning decisions based on information derived from LULC changes are essential for fostering sustainable and resilient cities capable of addressing these challenges.

The main objectives of this study are (i) to map land use and land cover (LULC) changes on the European side of Istanbul using a pre-trained deep learning model integrated into ArcGIS Pro, (ii) to quantify spatio-temporal urban expansion patterns between 2013 and 2024 using both linear and nonlinear regression approaches, (iii) to project future urban growth scenarios for 2025–2027 through extrapolation-based modeling, and (iv) to evaluate the reliability of the deep learning outputs through validation against the Urban Atlas dataset provided by the Copernicus Land Monitoring Service.

In this study, the urbanization of Istanbul's European Side was monitored using the Land Cover Classification (Landsat 8) deep learning model and extrapolation method, which is integrated into ESRI's ArcGIS Pro software. To conduct these operations, Landsat 8 satellite images of Istanbul's European Side spanning from 2013 to 2024 were acquired from the U.S.

This study holds significant importance in understanding urbanization processes, urban growth, and their impact on environmental changes in the European side of Istanbul. Unlike previous research that predominantly relies on traditional statistical or GIS-based approaches, this study adopts a deep learning-based framework that enables the precise

quantitative identification of urban development patterns over a period exceeding a decade. To ensure the reliability of the proposed deep learning-based classification framework, the model outputs were validated using an independent reference dataset, demonstrating a high level of agreement between predicted and observed land use/land cover classes. In this context, the innovative aspect of the study lies in integrating advanced remote sensing, deep learning, and predictive modeling to inform sustainable urban planning. This approach offers actionable insights for policymakers to manage rapid urban expansion while considering environmental and socio-spatial impacts.

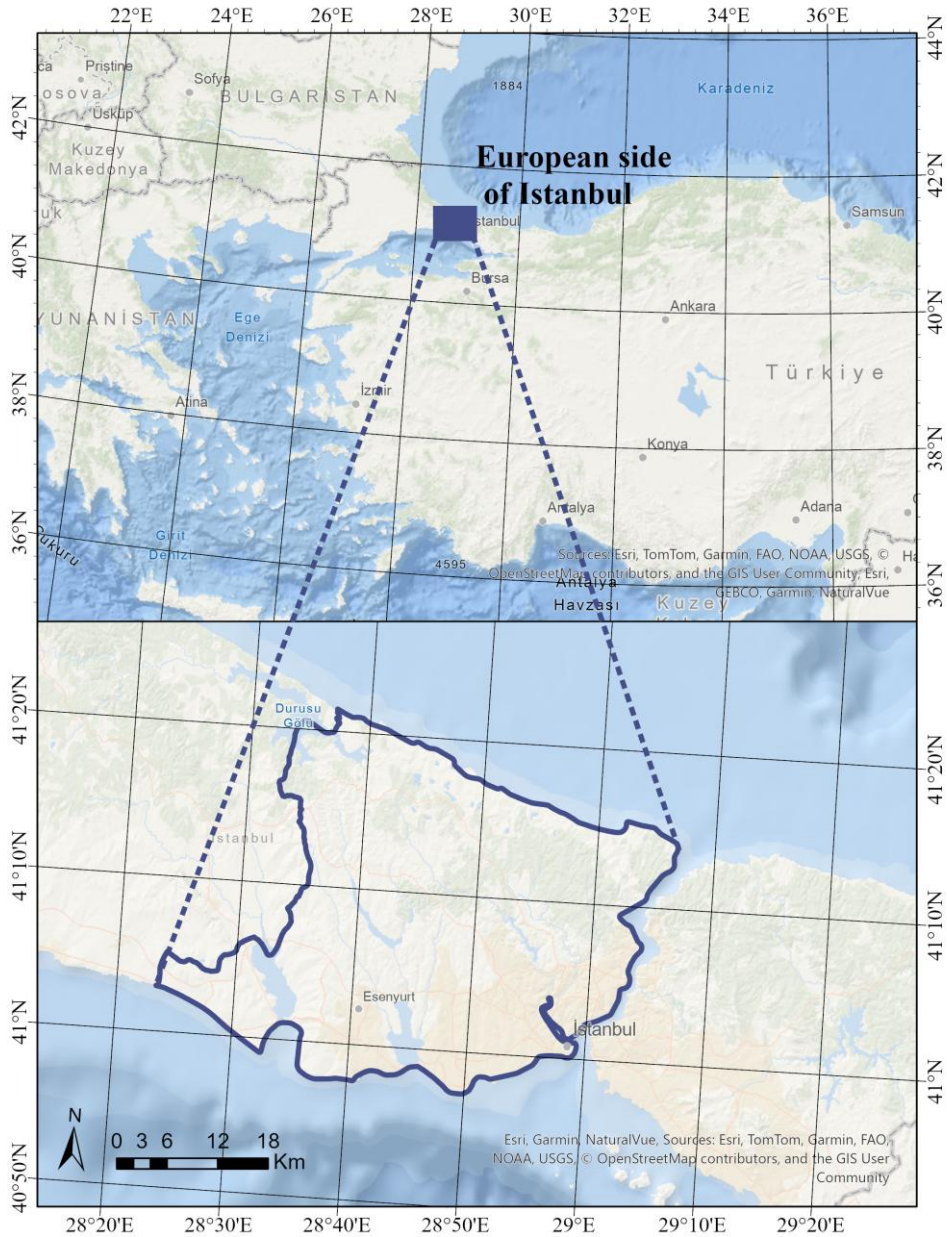
METHODOLOGY

In this study, Land Use and Land Cover (LULC) information was derived from high-resolution satellite imagery using a deep learning (DL) model to investigate the spatio-temporal dynamics of urban expansion on the European side of Istanbul. The extracted data were analyzed using both Ordinary Least Squares (OLS) and nonlinear regression methods to quantify historical urban growth patterns and to project urbanization probabilities for the years 2025, 2026, and 2027. Resulting outputs were validated during the model validation stage by using the Urban Atlas dataset provided by the Copernicus Land Monitoring Service as reference (ground truth). The methodology is organized into four main stages: (i) data acquisition and preprocessing, (ii) deep learning classification, (iii) analysis of urbanization, and (iv) model validation, which are subsequently described in detail in the following sections.

Study area

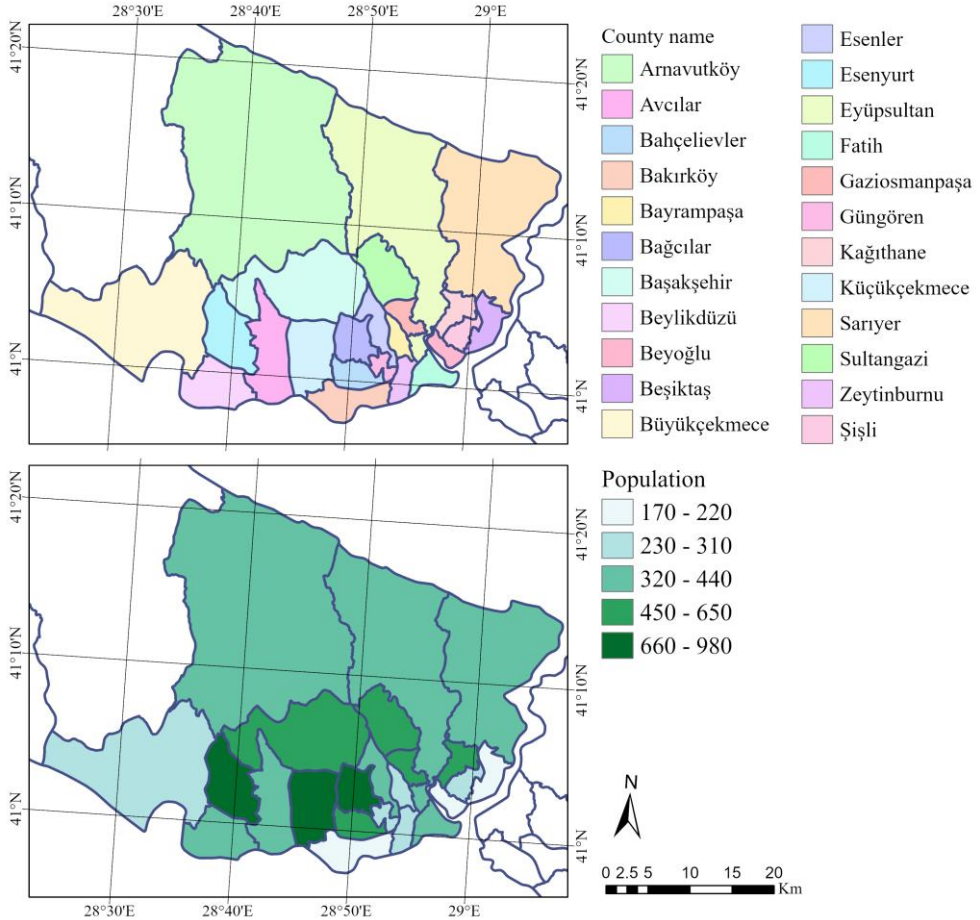
Istanbul, situated in the northwest of Turkey, serves as a vital link between the continents of Asia and Europe. Spanning between 27° 54' - 29° 55' E longitude and 41° 38' - 40° 48' N latitude, it covers a total area of 5,461 km², encompassing both its province and 39 districts. Bordered by Kocaeli province to the east, Tekirdag province to the west, the Black Sea to the north, and the Marmara Sea to the south, Istanbul's geographic diversity is striking. The altitude ranges from sea level to its highest peak, Aydos Hill, standing at 537 meters. Forests cover a significant portion, constituting 43.9 % of the province, according to Turkey's Forest Assets report in 2015 (Turkey's Forest Assets, 2015). The region is characterized by Mediterranean-type shrublands and temperate forest ecosystems, with the Belgrad Forest, located approximately 20 km north of the city, representing one of its most notable wooded areas. With an average annual precipitation of 662.5 mm and a mean temperature of 15.3 °C, the city experiences moderate weather throughout the year (TSMS, 2023).

In this study, the spatio-temporal dynamics of urbanization were analyzed across the districts forming the main urban core and rapidly expanding metropolitan areas of the European side of Istanbul, including Arnavutköy, Avcılar, Bağcılar, Bahçelievler, Bakırköy, Başakşehir, Bayrampaşa, Beşiktaş, Beylikdüzü, Beyoğlu, Büyükçekmece, Esenler, Esenyurt, Eyüpsultan, Fatih, Gaziosmanpaşa, Güngören, Kağıthane, Küçükçekmece, Sarıyer, Şişli, Sultangazi, and Zeytinburnu (Fig. 1).

Fig. 1: European side of İstanbul - Study Area (Generated by the author).

The population of these 23 districts, where 10 % of Turkey's population resides, was determined to be 8 million people in the year 2023 (TSI, 2023). According to the 2023 census, the three most populous districts on İstanbul's European Side are Esenyurt, Bağcılar, and Küçükçekmece. Among the least populous districts on İstanbul's European Side are Şişli, Beyoğlu, and Bakırköy (Fig. 2).

Fig. 2: Population distribution of the European side of İstanbul (Generated by the author).



Istanbul has expanded to a larger area in the last sixty years than ever before. The most important reason for this expansion is the rapid population growth after World War II and the structural changes the country has undergone in parallel. During this period, the transition from a state-controlled economy to a liberal economy in Türkiye created opportunities for foreign capital (Hayır Kanat, 2017). During this process, İstanbul emerged as a global city and regional center in finance, logistics, tourism, and culture at the intersection of Europe, Asia, and the Middle East (Derudder, 2012; Scott, 2001, 2011; Gündoğan, 2021). Over time, some functions such as trade, education, and finance located in the center shifted to surrounding settlements, initiating a post-suburbanization urbanization process in İstanbul. Recently, urban sprawl in the region has continued with mega projects and increasing housing stock. These developments include major infrastructure investments such as bridges connecting the European and Asian sides of İstanbul, airport projects claimed to be among the largest in the world, large-scale mass housing and luxury residential developments, as well as extensive transportation projects (Çalışkan & Kubat, 2021).

Data acquisition and preprocessing

To perform LULC classification using a deep learning model, Landsat 8 Operational Land Imager (OLI) satellite images with a spatial resolution of 30 m, covering Istanbul for the years 2013–2024, were obtained from the U.S. Geological Survey (USGS) Earth Explorer platform. For each year, cloud-free scenes were selected based on visual inspection and metadata information to minimize cloud-related effects on classification results. The imagery was utilized in a standardized form compatible with the pre-trained deep learning model implemented in ArcGIS Pro, ensuring consistency across the temporal dataset.

Additional atmospheric correction and QA-band-based cloud/shadow masking were not applied, as cloud-free scene selection at the acquisition stage was considered sufficient to minimize atmospheric and cloud contamination, and the deep learning model used in ArcGIS Pro was trained to operate on standardized Landsat reflectance inputs without requiring further scene-specific radiometric normalization. Moreover, Landsat Collection 2 Level-2 Surface Reflectance products were used, which already include atmospheric correction performed by the USGS processing chain, eliminating the need for additional atmospheric correction at the user level.

For model validation, pan-European LULC maps from Urban Atlas, with a spatial resolution of 10 m, were used, while the deep learning–derived LULC maps, generated from Landsat 8 imagery at a spatial resolution of 30 m, were produced using a pre-trained deep learning model implemented in ArcGIS Pro. To enable pixel-based comparison, both datasets were harmonized through reprojection, resampling, clipping, and spatial alignment. Nearest-neighbor resampling was applied to preserve categorical class values, and the DL raster was aligned to the Urban Atlas grid to ensure identical spatial resolution, extent, and raster dimensions. NoData and background pixels were excluded from the analysis to prevent bias in the accuracy assessment.

Deep learning classification

Deep learning is a subset of machine learning that enables computational models to automatically learn hierarchical representations from data through layered neural network architectures (LeCun *et al.*, 2015). “Deep learning (DL) techniques are considered highly promising for classification tasks (Boonpook *et al.*, 2023; Kussul *et al.*, 2017). These methods are based on multi-layer representation learning, in which artificial neural networks model complex input–output relationships by processing information through successive, interconnected layers parameterized by weights and biases. The performance of these networks is primarily driven by the backpropagation algorithm, which computes prediction errors and systematically updates the network parameters by propagating the error signal backward through the layers. In conjunction with forward propagation, this iterative optimization process enables the network to progressively minimize the loss function and improve predictive accuracy over successive training epochs (IBM, 2024). Consequently, with sufficient training data, artificial neural networks can learn highly complex nonlinear functions (Deng & Yu, 2014).

In the context of LULC mapping, the main challenge is the limited availability of labeled training data. To address this issue, the ArcGIS Living Atlas of the World provides access to pre-trained deep learning models, enabling the generation of LULC maps from high-resolution imagery without requiring extensive computational resources or specialized AI expertise. These models are developed using large datasets and are designed to extract meaningful information efficiently (ESRI, 2024; Fickas *et al.*, 2024). Therefore, they offer a practical and faster alternative to traditional methods that depend on complex manual feature engineering and extensive training data. The Land Cover Classification (Landsat 8) model,

applied to Landsat 8 images, was trained using the 2016 National Land Cover Database (NLCD) and associated scenes. It serves as a valuable resource for obtaining 30-meter resolution LULC maps and can support long-term analysis and resource management. However, since the NLCD is specifically developed for the United States, its transferability to other geographical regions may be limited due to differences in spectral characteristics, landscape composition, and spatial patterns of land cover types (e.g., urban forms such as suburban structures varying between countries), which may introduce classification uncertainties when applied outside its original training domain.

In this study, the acquired satellite images were classified using a Landsat 8-based Land Cover Classification deep learning model integrated into ArcGIS Pro. The selected model is based on the U-net architecture, implemented via the ArcGIS API for Python, which is widely used in image segmentation tasks due to its capability of capturing both global context and fine details (Ronneberger *et al.*, 2015). This model structure was preferred because it has been proven effective in land cover mapping tasks in various studies (e.g., Ulmas & Liiv, 2020; Solórzano *et al.*, 2021). The resulting LULC maps include 15 categories, such as open water, perennial snow/ice, developed open space, barren land, evergreen forest, and cultivated crops. Subsequently, the area of each LULC class for each year was calculated using ArcGIS Pro software from the LULC maps obtained for the specified dates.

Analysis of urbanization

To quantify and analyze urbanization dynamics over time, a post-classification analysis framework was adopted based on the temporal LULC datasets generated through the deep learning classification process. This approach enables a consistent comparison of urban land cover changes across different years by extracting and aggregating urban-related classes from classified outputs. The derived spatial information was subsequently used to compute temporal trends in urban expansion and to support statistical modeling of urban growth patterns. To monitor urbanization, the LULC classes representing urban development areas, namely Developed, High Intensity, Developed, Low Intensity, Developed, Medium Intensity, and Developed, Open Space, were extracted from the LULC classification. The area of urban settlements was calculated in ArcGIS Pro based on the spatial geometry of the classified LULC polygons (attribute-based area calculation). These spatio-temporal calculations were transferred to the Excel interface. These data were analyzed using Least Squares Regression Function and Nonlinear Regression Functions.

Least Squares Regression is a statistical method used to determine the equation of the best-fit line for a set of observed data. This is achieved by calculating the least-squares regression line, which minimizes the sum of the squared differences between the observed and predicted values. The equation of the least-squares regression line can be expressed as:

$$y = n + mx \quad (1)$$

here y is the dependent variable, x is the independent variable, n is the y –intercept, and m is the slope of the line. The slope m indicates the average change in the dependent variable for a one-unit change in the independent variable. This equation represents the slope-intercept form of a linear equation. The slope (m) and intercept (n) can be calculated using the following formulas:

$$m = \frac{N \sum(xy) - \sum x \sum y}{N \sum(x^2) - (\sum x)^2} \quad (2)$$

$$n = \frac{\Sigma y - m \Sigma x}{N} \quad (3)$$

where N is the number of observations, and Σ denotes summation. The correlation coefficient (R or r) measures the proportion of variance in y explained by the regression on x , providing an indication of how well the independent variable accounts for the variation in the dependent variable. The correlation coefficient ranges between -1 and 1 and is calculated as:

$$r = \frac{1}{N-1} \sum \left(\frac{x_i - \bar{x}}{s_x} \right) \left(\frac{y_i - \bar{y}}{s_y} \right) \quad (4)$$

where s_x and s_y are the standard deviations of x and y , respectively, and $\bar{x}$ and $\bar{y}$ are their means.

In this study, nonlinear regression analysis was performed using polynomial regression models (second- and third-order), fitted to capture non-linear temporal trends in LULC change. Nonlinear regression is a type of regression analysis where data is fitted to a model and represented as a mathematical function. While simple linear regression connects two variables (x and y) with a straight line ($y = n + mx$), nonlinear regression captures a non-linear relationship between the two variables. In this model, the sum of squares measures how much the observed values of y deviate from the predicted values based on the non-linear function. Nonlinear regression models can utilize various functions, such as logarithmic, trigonometric, exponential, power, Lorenz curves, Gaussian, and other fitting techniques, depending on the nature of the data. Regression analysis allows for tracking generally discernible linear and nonlinear trends in urban growth patterns over time. This makes regression a suitable method for forecasting future urbanization scenarios. While Ordinary Least Squares (OLS) Regression is used to capture linear trends, Nonlinear Regression provides insights into more complex growth dynamics. This dual approach enhances the robustness of the findings and is supported by similar applications in urbanization studies (Talib *et al.*, 2022; An *et al.*, 2025). These methods better capture complex growth dynamics and prevent unrealistic predictions, such as negative or extreme values. Among the tested functions, those exhibiting stronger correlation coefficients and higher r^2 values were selected as the basis for predictions. Thus, the limitations of linear regression were effectively addressed.

In the functions created using the data from this study, time (or year) was considered the independent variable (x -axis), and LULC change observations were considered the dependent variable (y -axis). The linear and polynomial functions and correlation coefficients between the independent and dependent variables for the LULC of the European side of Istanbul were calculated according to the mathematical formulas specified in formulas 1, 2, 3, and 4. This approach was used to analyze the temporal trends of urban growth over time.

In this study, functions with correlation coefficients of $r \geq 0.6$ were interpreted as representing strong linear relationships, whereas lower coefficients were considered indicative of weak or random associations. While very low (<0.1) and very high (>0.9) correlation coefficients are generally interpreted as negligible and strong relationships, respectively, the interpretation of intermediate values is less consistent and depends on context and applied criteria (Schober *et al.*, 2018).

The correlation coefficient (r) was used to characterize the direction and strength of the linear relationship between time and LULC class areas, while the coefficient of

determination (r^2) was employed to evaluate model explanatory power and goodness-of-fit. Both r and r^2 values were also presented in the corresponding regression graphs for linear and nonlinear (polynomial) models across all districts.

In addition, potential urbanization trends for the years 2025, 2026, and 2027 were estimated using linear regression models based on the temporal relationship between year and urban development area on the European side of Istanbul.

Model validation

The deep learning (DL)-based land use and land cover (LULC) classification was validated in ArcGIS Pro using Python, with the Urban Atlas dataset serving as reference, obtained from the Copernicus Land Monitoring Service. For the European side of Istanbul, Urban Atlas originally provides 25 LULC classes. These were reclassified to match the 15 LULC classes of the DL output, and both datasets were further aggregated into 12 common classes based on class compatibility (see Table 1).

A confusion matrix was constructed to evaluate the agreement between the DL-based classification and the reference data. Overall accuracy (OA), producer's accuracy (PA), and user's accuracy (UA) were calculated using standard definitions, as expressed by the following equations:

$$OA = \frac{\sum_{i=1}^n x_{ii}}{N} \quad (5)$$

$$PA_i = \frac{x_{ii}}{\sum_{j=1}^n x_{ij}} \quad (6)$$

$$UA_i = \frac{x_{ii}}{\sum_{j=1}^n x_{ji}} \quad (7)$$

where x_{ij} represents the number of pixels classified as class i in the reference and class j in the DL-derived map, n is the number of classes ($n=12$), and N is the total number of evaluated pixels. Overall accuracy (OA) represents the proportion of correctly classified pixels among all evaluated pixels and provides a general measure of classification performance. Producer's accuracy (PA) indicates how well the model correctly identifies pixels of a given reference class and is associated with omission error, whereas user's accuracy (UA) reflects the reliability of the predicted class labels and is associated with commission error. This approach follows recent recommendations in accuracy assessment literature, which emphasize the use of error-based measures derived from the confusion matrix framework (Pontius & Millones, 2011).

The pixel-based validation of the 12-class classification resulted in an overall accuracy of 62.6 %. Class-specific accuracy metrics are presented in Table 1.

Table 1: Class-specific accuracy metrics (PA and UA).

class no	Urban atlas –based classes	DL / raster-based classes	PA	UA
1	water	open water	0.9408	0.8659
2	discontinuous very low density urban fabric / discontinuous low density urban fabric/ green urban	developed, open space	0.1786	0.1364
3	discontinuous medium density urban fabric / isolated structures	developed, low intensity	0.3671	0.0769
4	discontinuous dense urban fabric / other roads and associated land / railways and associated land	developed, medium intensity	0.3959	0.3151
5	industrial, commercial, public, military and private units / continuous urban fabric / fast transit roads and associated land	developed, high intensity	0.2972	0.5376
6	land without current use / mineral extraction and dump sites / construction sites / open spaces with little or no vegetation	barren land	0.3961	0.7290
7	forests	deciduous forest / evergreen forest / mixed forest	0.8407	0.8667
8	herbaceous vegetation associations	shrub/scrub / herbaceous	0.2710	0.2186
9	pastures	hay / pasture	0.2161	0.4639
10	arable land (annual crops) / permanent crops	cultivated crops	0.4615	0.3637
11	wetlands	woody wetlands / emergent herbaceous wetlands	0.3506	0.0531
12	<null>	<null>	0.9974	0.9986

The highest accuracy was obtained for Water (Class 1), with PA and UA values of 0.94 and 0.87 %, respectively, while Forests (Class 7) also showed high classification performance with a PA of 0.84 and a UA of 0.87. In contrast, urban-related classes (Classes 2–5) and heterogeneous vegetation classes (Classes 8–10) exhibited relatively low accuracy values. The lowest UA values were observed for Developed, Low Intensity (Class 3) and Wetlands (Class 11), indicating a high proportion of commission errors in these classes. These inaccuracies are mainly attributed to inconsistencies between Urban Atlas and DL class definitions, differences in spatial resolution between the datasets, mixed-pixel effects, and spectral similarity among urban land-cover types.

To further evaluate the performance of the DL model in detecting urban areas, both datasets were reduced to a binary classification scheme. Discontinuous and continuous urban

fabric classes in the Urban Atlas dataset (Classes 2–5) were merged into a single urban class, while all remaining classes were grouped as non-urban. The binary maps were generated through conditional reclassification and compared on a pixel-by-pixel basis within a common grid and spatial extent. A 2×2 confusion matrix was constructed, and accuracy metrics were recalculated (equation 5, 6, 7).

Overall, while the 12-class validation results demonstrate moderate agreement and notable class confusion, the binary urban and non-urban assessment confirms that the DL model reliably captures the general spatial distribution of urban areas. This suggests that the model is more robust for generalized urban extent mapping than for detailed urban density classification.

RESULTS

This study utilized satellite imagery and AI-based analytical models to analyze temporal changes in urban development areas on the European side of Istanbul and to quantify urban growth dynamics (Fig. 3). Future urban development for 2025, 2026, and 2027 was estimated by applying regression-based extrapolation to historical urban area time series, producing annual projections of total urban extent as a continuation of observed temporal trends. Subsequently, spatio-temporal changes in district-level urban areas were analyzed based on observed data.

In some districts on the European side, development areas changed linearly or polynomially, while in other districts, a random distribution was observed. In the district-wise analysis, high correlation coefficients for linear and polynomial relationships between independent (time or year) and dependent (LULC change) variables were observed in Arnavutköy, Başakşehir, Beyoğlu, Esenyurt, Eyüpsultan, Gaziosmanpaşa, Kağıthane, Küçükçekmece, Sarıyer, and Sultangazi (Fig. 4). The values of $r=0.93$ and $r=0.92$ in Arnavutköy and Başakşehir, respectively, are strong indicators that linear growth will continue systematically. In all districts, except Esenyurt, where a linear or polynomial relationship was observed between 2013-2024, an expansion of urbanized areas was observed.

Fig. 3: LULC of the European side of İstanbul classified using deep learning (Generated by the author).

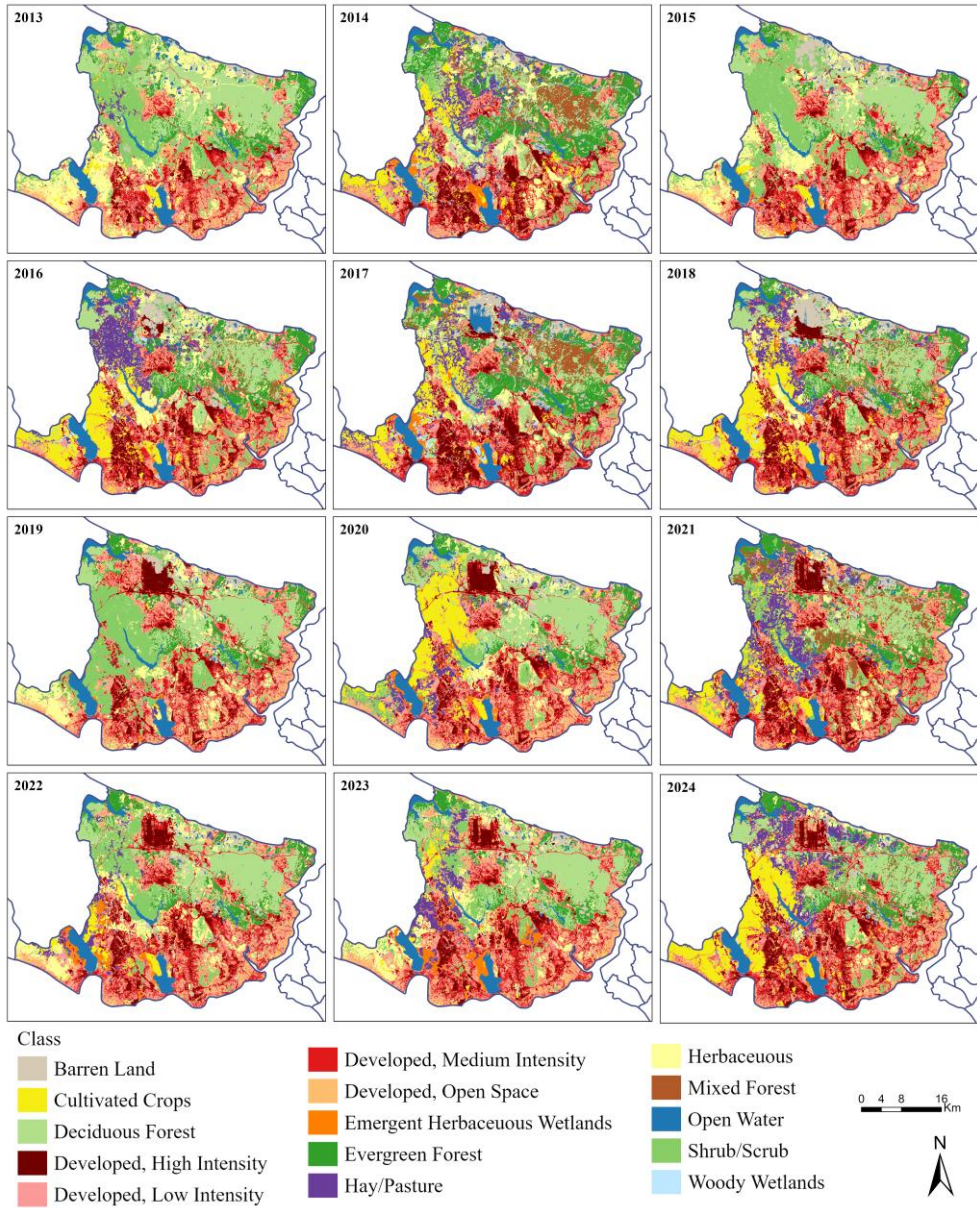
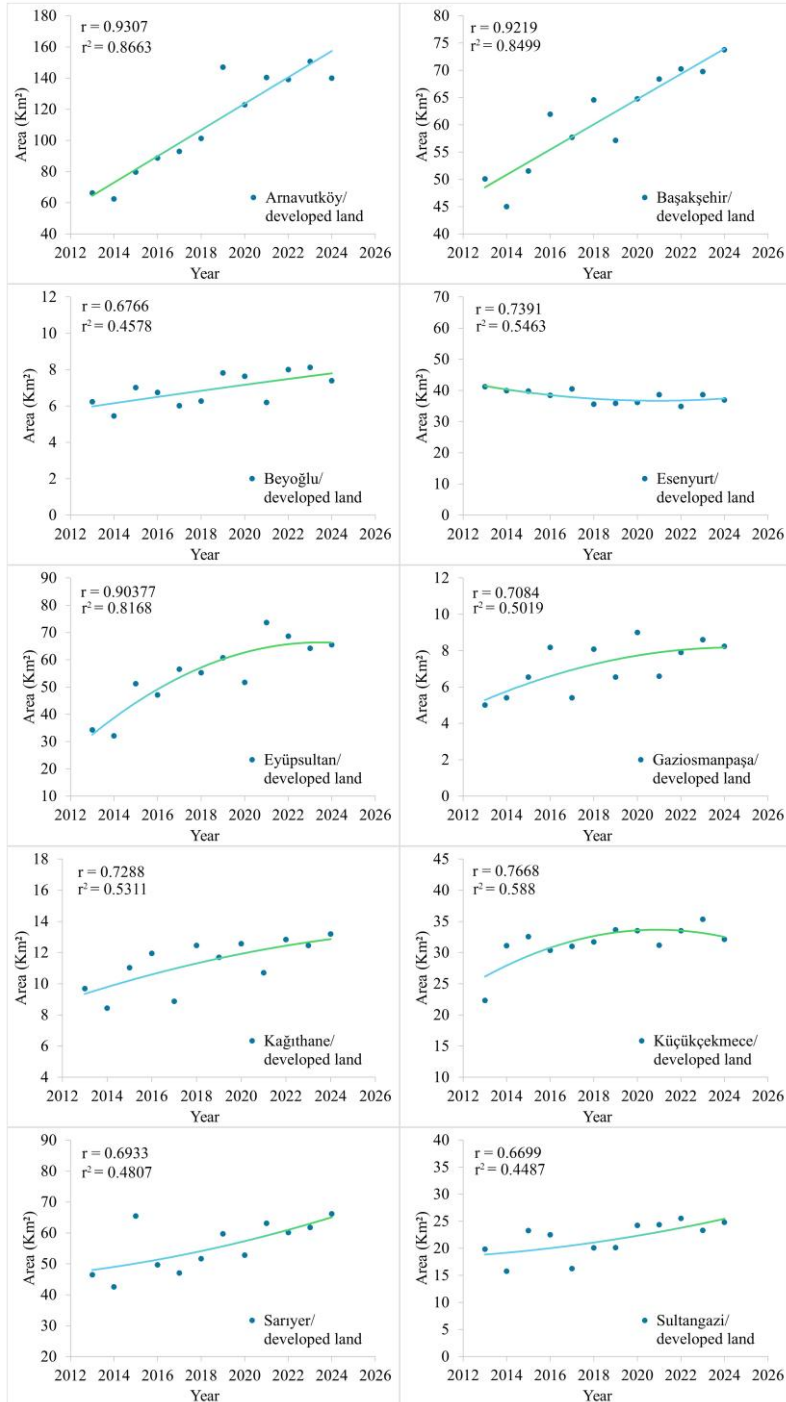
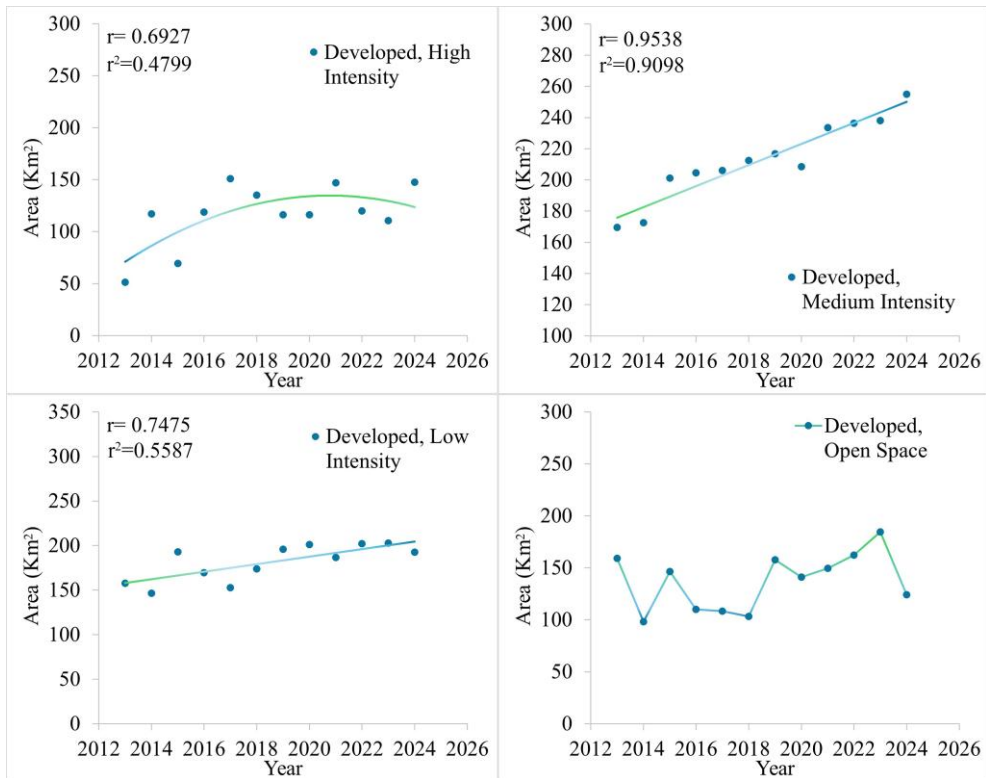


Fig. 4: Districts on the European side of İstanbul where linear and polynomial urbanization processes are observed (Generated by the author).



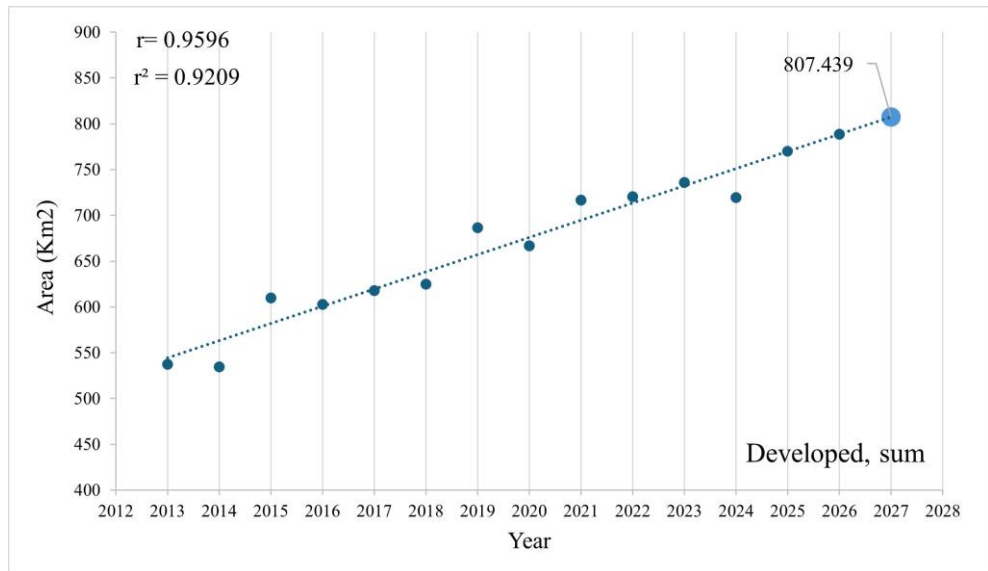
In the analysis based on the Developed, High Intensity-Developed, Low Intensity-Developed, Medium Intensity, and Developed, Open Space classes to monitor the urban development across the European side, linear and polynomial (or non-linear) relationships with high correlation coefficients were observed in the Developed, High Intensity-Developed, Low Intensity-Developed, and Medium Intensity classes. However, a random distribution was observed in the Developed Open Space class (Fig. 5).

Fig. 5: Development classes on the European side of Istanbul where linear and nonlinear changes are observed (Generated by the author).



The developed area on the European side of Istanbul exhibited a linear increase between 2013 and 2024. The correlation coefficient of spatio-temporal data for developed areas ($r = 0.96$) indicates a strong linear relationship, supporting the reliability of future projections. Based on the extrapolation model, the total developed area on Istanbul's European Side is estimated to reach approximately 770 km² in 2025, 788.7 km² in 2026, and 807.4 km² by 2027. This projection represents an increase of nearly 50% compared to the 538 km² of developed land recorded in 2013, highlighting the rapid and continuous urban expansion in the region over a 14-year period (Fig. 6).

Fig. 6: Temporal change in total developed area and projected urbanization by 2027 on the European Side of Istanbul (Generated by the author).



As part of the classification validation, a binary urban–non-urban assessment was conducted to further evaluate the performance of the DL-based model in detecting urban areas. The results of this assessment are presented below. The binary classification results indicate that 485,904 pixels were correctly classified as urban, 104,556 urban pixels were misclassified as non-urban, 212,074 non-urban pixels were misclassified as urban, and 1,647,738 pixels were correctly classified as non-urban. The overall accuracy of the binary classification was 0.8708, indicating that approximately 87 % of pixels were correctly identified as urban or non-urban. For the urban class, the producer’s accuracy was 0.8229, while the user’s accuracy was 0.6962, reflecting the presence of commission errors in urban predictions. These errors are primarily associated with spectral mixing, mixed-pixel effects, and the coarser spatial resolution of Landsat imagery.

DISCUSSION

In this study, a pre-trained deep learning model was employed to ensure consistent and reproducible extraction of urban land cover over a long-term period. In addition, linear (Ordinary Least Squares) and nonlinear regression analyses were applied to quantitatively characterize historical urban growth patterns and to estimate future urbanization potential.

Model performance was evaluated through pixel-based validation using the Urban Atlas dataset as reference data. Although moderate overall accuracy was obtained for the multi-class comparison (OA = 62.6 %), lower accuracies were primarily observed for urban density classes. These uncertainties are mainly attributable to differences in class definitions, spatial resolution mismatches between datasets, and mixed-pixel effects. In contrast, a simplified binary (urban versus non-urban) validation yielded substantially higher accuracy values (OA = 87 %), indicating that the proposed approach reliably captures the overall

spatial distribution and temporal dynamics of urban areas despite limitations at finer classification levels.

In this context, the findings further suggest that the accuracy of LULC models depends not only on the classification algorithm itself but also on the sampling design and validation strategy, highlighting the need for additional area-specific validation studies to robustly assess model performance across different urban environments (Tyukavina *et al.*, 2025). The use of a pre-trained deep learning model without any fine-tuning introduces an important methodological limitation. While such models provide significant advantages in terms of computational efficiency, ease of transfer to new study areas, and rapid implementation, they are inherently influenced by the characteristics of the datasets used during their original training. In this study, the model was trained using Landsat 8 imagery and the U.S.-based NLCD dataset, which may result in a bias toward urban forms, spectral reflectance properties, and landscape patterns characteristic of U.S. cities. Consequently, this may reduce model performance when applied to regions with different urban morphologies, building densities, and construction materials, such as Türkiye. In particular, the relatively lower accuracy values observed in medium- and low-intensity urban classes in this study further support the presence of a domain shift issue. Future research could improve model performance by fine-tuning the model using region-specific Landsat-based labeled datasets and by recalibrating the model with training samples representing local urban structures. Such approaches would enhance the model's sensitivity to local urban patterns and improve both classification accuracy and generalizability.

In this study, the Copernicus Urban Atlas dataset was used exclusively as an independent reference for the validation of the deep learning (U-Net-based) LULC classification results. It is important to note that Urban Atlas provides high-quality spatial information for European cities; however, it is not available at a global scale and does not offer consistent annual temporal coverage. Therefore, it was not used for urban growth estimation but solely for accuracy assessment purposes. The proposed deep learning framework, in contrast, enables the generation of temporally consistent and transferable LULC maps from multi-temporal satellite imagery, allowing for continuous monitoring of urban expansion beyond the spatial and temporal limitations of existing reference datasets. While potential uncertainties in the reference data may influence validation outcomes, such effects were minimized by complementary accuracy assessments, including both multi-class and binary urban–non-urban evaluations, which demonstrated strong model performance in capturing general urban extent patterns.

Understanding the patterns and associated factors of urbanization is crucial for evaluating the sustainability and resilience of rapidly growing metropolitan areas. Istanbul, as Turkey's largest city and a major economic hub, has experienced significant urban expansion over the past decades, particularly on its European side. The spatial and temporal dynamics of this growth are widely discussed in the literature as being influenced by multiple factors, including demographic pressures, policy interventions, economic incentives, and environmental constraints. Within this context, examining urban growth patterns enables the assessment of the pace, extent, and implications of urban sprawl in terms of environmental, social, and infrastructural change.

The study's findings indicate that urbanization on Istanbul's European side has consistently increased almost every year since 2013. This pattern is quantitatively supported by a strong linear relationship between time and total developed area ($r = 0.96$), indicating a persistent and systematic expansion of urban land throughout the study period. The observed increase is consistent with the sustained residential construction boom observed since the early 2000s, suggesting a strong association between residential development

dynamics and urban expansion patterns (Can, 2022). Therefore, agricultural lands and natural areas in major cities have been rapidly converted into built-up areas, and inadequate urban planning practices have amplified the impacts of natural disasters. Such continuous growth highlights the need to examine both the driving factors and the environmental and infrastructural implications of urban development in this region. One of the primary spatial manifestations of the neoliberal urban restructuring operations in İstanbul since the early 2000s is the construction of residential projects, with the highest concentration of residences noted in Şişli and Beşiktaş on the European side (Bal, 2015). Meanwhile, historic centers like Fatih and Beyoğlu have become urban development areas where urban renewal and tourism-related uses have become prevalent (Hayır Kanat, 2017).

Since the 1950s, İstanbul's urban area has rapidly expanded towards rural areas due to increasing demographic expansion. This transformation has not only altered the spatial structure of the city but also reshaped settlement representation and demographic dynamics, as highlighted by Tekeli (2015). Additionally, researchers have noted that with Law No. 6360, rural forms were lost (Mutlu, 2013; Şahin, 2015; Doğan & Gökburun, 2019). According to the law, the legal personality of villages within İstanbul province boundaries was abolished, and they were included as neighborhoods within the districts of their affiliated municipalities (Regulation No. 6360). During this expansion process, gaps between some rural settlements and the city gradually filled, transforming the villages into neighborhoods of the city. For example, Kağıthane, a district with a population of 445,672, was a small village with a population of 1,431 under the administration of Beyoğlu district in 1950. Due to increasing population, Şişli, located within Beyoğlu boundaries, gained district status. Kağıthane, located within Şişli's borders, became a village with a population of 22,818 in 1960. Over the next decade, the population of Kağıthane Village grew 16-fold (Şahin, 2015). Recently, the number of refugees in Turkey has emerged as a significant factor contributing to demographic pressure in İstanbul. According to data published by the Directorate of Migration Management (2023), a total of 1,182,157 foreign nationals reside in İstanbul under various legal statuses. This population includes 670,988 individuals holding residence permits, 531,381 Syrian nationals under temporary protection, and 3,784 individuals registered as refugees or conditional refugees. Most of these refugees reside on the European side. Furthermore, 314,588 individuals migrated to Türkiye from abroad in 2024, and an examination of the spatial distribution of international migration reveals that İstanbul received the highest share of migrants, accounting for 32.8 % of the total inflow (TSI, 2025). This population increase coincides with the spatial expansion of urban residential areas toward forests and watersheds, indicating a potential linkage between demographic pressure and land cover change. However, it should be noted that urban expansion processes may also be influenced by additional factors such as real estate speculation, land market dynamics, and planning decisions, beyond demographic pressure alone. The urban residential areas of İstanbul are expanding even further due to increasing demand (Doğan & Gökburun, 2019).

Due to the 3 km engineered landfill extension along the shoreline of the Marmara Sea on the European side, the natural coastline has completely disappeared (Döker, 2012; Kurt *et al.*, 2010). Green (2008) states that until the late 1990s, most of the houses in İstanbul did not even meet the minimum standards of earthquake regulations. Another infrastructure element in İstanbul that is highly vulnerable is the transportation system. İstanbul's status as an important logistics center, rapid population growth, and urban sprawl increases the city's dependence on the transportation system. Additionally, the road-dominated transportation system causes congestion and high carbon emissions (Kaya, 2018). These environmental and infrastructural pressures are closely associated with uncontrolled urban expansion on the

European side of Istanbul. Therefore, monitoring the spatial and temporal dynamics of urban growth is essential for identifying areas exposed to future environmental risks and infrastructure stress. In this context, the present study contributes by extracting urban development classes from LULC data and analyzing their temporal growth patterns through linear and nonlinear regression models. The prediction of future urbanization trends for 2025–2027 provides a scientific basis for evaluating how ongoing urban expansion may further increase vulnerability in coastal, transportation, and densely built-up areas, thereby supporting sustainable and risk-sensitive urban planning strategies.

Other studies using remote sensing technologies draw attention to urbanization in Istanbul in a similar way to the findings of this study. These studies show that in the last few decades, there has been significant settlement pressure on sensitive ecosystems such as river corridors, water basins, forests, and agricultural areas in Istanbul (Kucukmehmetoglu & Geymen, 2009; Toros *et al.*, 2017; Canberk *et al.*, 2015; Kaya, 2018; Doğan & Gökburun, 2019). The spatial patterns revealed by the regression analyses in this study align with these findings, particularly in districts exhibiting high growth rates ($r > 0.90$), which are located near ecologically sensitive zones. The observed patterns of urban expansion are commonly associated in the literature with non-resilient and unsustainable planning approaches in rapidly growing metropolitan regions.

The approximately 50% increase in urbanized areas observed during the 2013–2027 period in this study provides a quantitative framework for interpreting the environmental, economic, and social impacts of urban sprawl discussed in the literature. Although the present study does not directly quantify these impacts, the findings are consistent with trends reported in previous studies. Ecological effects are particularly prominent, including the loss of agricultural and food production areas, increased energy demand, higher transportation needs, air pollution, and a reduction in ecosystem resilience (Öncel & Levend, 2023). In Europe, approximately 1,117.9 km² of natural and semi-natural areas were converted to urban development area between 2000 and 2006 (Hennig *et al.*, 2015). In Turkey, research in this area remains insufficient. Therefore, urban sprawl exerts considerable pressure on the ecosystems surrounding urban areas, and their degradation is regarded as a critical environmental issue in many countries (Oueslati *et al.*, 2015).

To address these challenges, LULC maps play a crucial role in urban planning, resource management, change detection, agriculture, and other areas that require detailed information about the land surface. LULC classification is intricate and challenging to achieve using conventional methods.

Deep learning models, however, excel at capturing complex semantic information and can deliver more accurate and efficient results. In particular, the U-Net architecture provides a significant advantage in remote sensing-based urban analysis because it simultaneously captures both spectral and spatial patterns within imagery. While traditional machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM) primarily rely on spectral information derived from pixel values, U-Net additionally learns spatial context, neighborhood relationships, textures, object boundaries, and hierarchical features through its encoder–decoder structure and convolutional operations (Ronneberger *et al.*, 2015). This capability is especially important in heterogeneous urban environments such as Istanbul, where urban structures, transportation networks, vegetation, water surfaces, and built-up areas exhibit highly complex spatial configurations. In the model validation phase of this study, high classification accuracies obtained for forest and water classes indicate the robustness of the employed deep learning approach. These results are in line with previous findings, such as those reported by Ulmas & Liiv (2020) and Solórzano *et al.* (2021), who demonstrated strong performance of U-Net–based models for water, wetlands,

and forest classes using Sentinel-2 imagery. Therefore, the present study suggests that U-Net architectures can achieve comparable classification accuracy when applied to Landsat 8 data.

The skip connections within the U-Net architecture also help preserve fine-scale spatial details and improve segmentation accuracy by combining low-level and high-level feature representations. Therefore, U-Net can more effectively distinguish complex urban land-use and land-cover classes compared to conventional machine learning approaches. The integration of remote sensing technologies and deep learning models in İstanbul thus represents a critical tool for understanding and managing the challenges associated with rapid and uncontrolled urban growth. These technologies enable the detection of urban sprawl, forest loss, changes in water resources, and other environmental transformations with higher spatial sensitivity and classification accuracy. Consequently, urban planners and policymakers can make more informed decisions to support sustainable, resilient, and risk-sensitive urban development in İstanbul.

As a result, the management of İstanbul's urban sprawl and its environmental impacts can be significantly improved through the effective use of modern remote sensing technologies and deep learning models. The integration of these technologies will play an important role in efforts to protect İstanbul's natural resources and sensitive ecosystems. Furthermore, it will help adopt more sustainable and resilient approaches in future urban development and planning processes. In addition to technological monitoring and prediction capabilities, achieving sustainable and resilient urban development also requires effective urban policies, strong legal frameworks, strict enforcement of construction regulations, and environmentally sensitive planning strategies. Particularly in rapidly urbanizing megacities such as İstanbul, the integration of scientific analyses with policy-making and regulatory mechanisms is essential to reduce environmental risks, prevent uncontrolled urban sprawl, improve disaster resilience, and ensure long-term urban sustainability.

By situating these results within the broader literature, it becomes evident that sustained residential construction, migration, and demographic growth have consistently driven urban sprawl in İstanbul, reflecting patterns observed in other rapidly urbanizing cities (Bal, 2015; Doğan & Gökburun, 2019; Can, 2022).

CONCLUSION

Conducting field-based research across large-scale landscapes requires extensive spatio-temporal analysis and is often constrained by practical limitations. Remote sensing coupled with deep learning models offers a viable alternative by enabling rapid and accurate land cover mapping while reducing dependence on expert knowledge.

Moreover, the results indicate that urbanization in İstanbul exhibits a linear growth trend, underscoring the necessity of advanced spatio-temporal analysis and deep learning approaches to comprehensively understand urbanization dynamics in rapidly expanding metropolitan regions. Such methods offer valuable insights into the environmental and socio-spatial consequences of unregulated urban expansion, including the conversion of natural and agricultural lands and the intensification of pressure on infrastructure systems.

Metropolitan cities like İstanbul are attractive centers due to their natural and cultural structures, leading to high population growth and migration. Another source of this migration is the job opportunities offered by the city, making urban sprawl inevitable. In Turkey, there has been no approach developed to prevent this migration and rapid urbanization. On the contrary, political decisions have reduced agricultural activities and increased migration to the city. Therefore, it is of great importance to protect historical, natural, and agricultural

areas in cities from the pressures of dense urban fabric such as transportation systems, infrastructure systems, and industrial areas, and to create resilient cities against other risks. For this purpose, integrating developments like remote sensing and artificial intelligence into the planning system to carefully monitor the urbanization process, identify problems, and generate solutions accordingly forms the basis of sustainable planning.

In practice, quantitatively predicting the developed areas of Istanbul allows for proactive measures to mitigate significant changes or prevent the degradation of natural and semi-natural environments. From the results obtained, it would be possible to redirect erroneous planning decisions towards a healthier direction for urban sprawl in the future.

The study also emphasizes the importance of proactive urban planning interventions. Integrating remote sensing and AI-based predictive models can enable policymakers to anticipate urban growth trends, design resilient infrastructure, and protect sensitive ecosystems.

Future research should explore multi-dimensional models that combine environmental, socio-economic, and policy variables to improve urban planning decisions. Additionally, assessing the effectiveness of interventions such as green space preservation, land-use regulation, and sustainable infrastructure development could provide actionable strategies to mitigate the negative impacts of urban sprawl.

In conclusion, this study contributes to the understanding of urbanization processes in Istanbul and demonstrates the value of evidence-based approaches for promoting sustainable and resilient metropolitan development.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

REFERENCES

- Akiner, M.E., & Ghasri, M. (2025). Integrating remote sensing and machine learning to analyze urban growth and its environmental effects: A 30-year assessment in Başakşehir, Turkey. *Pure and Applied Geophysics*, 1–25. <https://doi.org/10.1007/s00024-025-03727-w>.
- An, R., Hu, X., & Sun, S. (2025). The nonlinear relationship between urbanization and ecological environment in China under the PSR (Pressure–State–Response) model: Inflection point identification and policy pathways. *Sustainability*, 17(10), 4450. <https://doi.org/10.3390/su17104450>.
- Arsanjani, J.J., Fibæk, C.S., & Vaz, E. (2018). Development of a cellular automata model using open source technologies for monitoring urbanisation in the global south: The case of Maputo, Mozambique. *Habitat International*, 71, 38–48. <https://doi.org/10.1016/j.habitatint.2017.11.003>.
- Bal, E. (2015). Residences as a spatial manifestation of neoliberal urbanization: The case of Istanbul. *Dokuz Eylül University Faculty of Engineering Journal of Science and Engineering*, 17(51), 176–190.
- Boonpook, W., Tan, Y., Nardkulpap, A., Torsri, K., Torteeka, P., Kamsing, P., & Jainaen, M. (2023). Deep learning semantic segmentation for land use and land cover types using Landsat 8 imagery. *ISPRS International Journal of Geo-Information*, 12(1), 14. <https://doi.org/10.3390/ijgi12010014>.

- Çalışkan, E.K., & Kubat, A.S. (2021). Policies and facts for mega-urbanization: Middle and outer fringe belt developments of Istanbul. In *ISUF 2020 Virtual Conference Proceedings* (Vol. 1).
- Can, A. (2022). Housing and urbanization policies of Istanbul, Turkey from central to the local. *Urban Research & Practice*, 15(3), 454–463. <https://doi.org/10.1080/17535069.2022.2085376>.
- Canıberk, M., Maraş, E.E., & Durğut, T. (2015). Examination of the relationship between urban forest and agricultural areas with historical orthophotos. *Harita Dergisi (Journal of Maps)*, 153, 9–17.
- Clarke, M., Davidson, M., Egerer, M., Anderson, E., & Fouch, N. (2019). The underutilized role of community gardens in improving cities' adaptation to climate change: A review. *People, Place and Policy Online*, 12(3), 241–251. <https://doi.org/10.3351/ppp.2019.3396732665>.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Cristaldi, A., Fiore, M., Conti, G.O., Pulvirenti, E., Favara, C., Grasso, A., et al. (2022). Possible association between PM2.5 and neurodegenerative diseases: A systematic review. *Environmental Research*, 208, 112581. <https://doi.org/10.1016/j.envres.2021.112581>.
- Deng, L., & Yu, D. (2014). Deep learning: Methods and applications. *Foundations and Trends® in Signal Processing*, 7(3–4), 197–387. <https://doi.org/10.1561/20000000039>
- Derudder, B. (2012). *International handbook of globalization and world cities*. Edward Elgar Publishing.
- Dinç, G., & Gül, A. (2021). Estimation of the future land cover using CORINE Land Cover data. *TeMA – Journal of Land Use, Mobility and Environment*, 14(2), 177–188. <https://doi.org/10.6093/1970-9870/7671>.
- Directorate of Migration Management, Istanbul Provincial Directorate. (2023, June 18). *Press release on foreigners residing in Istanbul*. <https://istanbul.goc.gov.tr/istanbul-ilinde-bulunan-yabancilar-hakkinda-basin-aciklamasi-18062023>.
- Doğan, Ö.S., & Gökburun, İ. (2019). Settlements which evolved into neighborhoods from villages. *Coğrafya Dergisi*, (39), 73–87. <https://doi.org/10.26650/JGEOG2019-0020>
- Döker, M.F. (2012). Determination of temporal changes along the Marmara Sea coastline in Istanbul Province. *International Journal of Human Sciences*, 9(2), 1350–1370. <https://j-humansciences.com/index.php/IJHS/article/view/2437>.
- Ercanlı, Ç., & Savaşır, G. (2022). Assessing adaptation strategies against flood risk in urban coastal areas through Izmir Karşıyaka coastline case. *Megaron*, 17(2). <https://doi.org/10.14744/MEGARON.2022.46666>.
- ESRI. (2024). *Deep learning in ArcGIS Pro*. <https://pro.arcgis.com/en/pro-app/latest/help/analysis/deep-learning/deep-learning-in-arcgis-pro.htm>.
- Fickas, K., Viswambharan, V., & Tuteja, P. (2024, May 14). Unlocking landscapes: Land cover mapping using pretrained deep learning models. *ArcGIS Blog*. <https://www.esri.com/arcgis-blog/products/arcgis/imagery/pretrained-land-cover-models>.
- Gargiulo, C., & Zucaro, F. (2023). A method proposal to adapt urban open-built and green spaces to climate change. *Sustainability*, 15(10), 8111. <https://doi.org/10.3390/su15108111>.

- Green, R.A. (2008). Unauthorised development and seismic hazard vulnerability: A study of squatters and engineers in İstanbul, Turkey. *Disasters*, 32(3), 358–376. <https://doi.org/10.1111/j.1467-7717.2008.01044.x>.
- Gündoğan, A.Z. (2021). Rethinking centrality: Extended urbanization in İstanbul. *City*, 25(1–2), 46–66. <https://doi.org/10.1080/13604813.2021.1890955>.
- Hao, Y., Wu, Y., Wang, L., & Huang, J. (2018). Re-examine environmental Kuznets curve in China: Spatial estimations using environmental quality index. *Sustainable Cities and Society*, 42, 498–511. <https://doi.org/10.1016/j.scs.2018.08.014>.
- Hayır Kanat, M. (2017). Suburbanization and post-suburbanization urbanization in İstanbul. *International Journal of Social Science Research*, 6(2), 31–45.
- Helber, P., Bischke, B., Dengel, A., & Borth, D. (2018). Introducing EuroSAT: A novel dataset and deep learning benchmark for land use and land cover classification. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium* (pp. 204–207). IEEE.
- Hennig, E.I., Schwick, C., Soukup, T., Orlitová, E., Kienast, F., & Jaeger, J.A.G. (2015). Multi-scale analysis of urban sprawl in Europe: Towards a European de-sprawling strategy. *Land Use Policy*, 49, 483–498. <https://doi.org/10.1016/j.landusepol.2015.08.001>.
- IBM. (2024). *What is deep learning?* <https://www.ibm.com/think/topics/deep-learning#:~:text=Deep%20learning%20is%20a%20subset,self%2Ddriving%20cars%20and%20robotics>.
- Jones, R.N., Dettmann, P., Park, G., Rogers, M., & White, T. (2007). The relationship between adaptation and mitigation in managing climate change risks. *Mitigation and Adaptation Strategies for Global Change*, 12, 685–712. <https://doi.org/10.1007/s11027-007-9094-5>.
- Jorge, O.J., Yongtao, T., & Qian, Q.K. (2018). Learning from best practices in sustainable urbanization. *Habitat International*, 78, 83–95. <https://doi.org/10.1016/j.habitatint.2018.05.013>.
- Kaya, Y. (2018). Urban vulnerability to climate change: An assessment for İstanbul. *International Journal of Social Inquiry*, 11(2), 219–257.
- Kızıldaş, M.Ç., & Kültür, Ö.F. (2023). Examination of high-capacity rail systems and solutions for İstanbul traffic. *European Journal of Science and Technology*, (50), 97–104. <https://doi.org/10.31590/ejosat.1141943>.
- Klein, R.J.T., Saleemul, H., Fatima, D., Downing, T.E., Richels, R.G., Robinson, J.B., & Toth, F.L. (2007). Inter-relationships between adaptation and mitigation. In *Climate change 2007: Impacts, adaptation and vulnerability* (pp. 745–778). Cambridge University Press.
- Küçükmehtetoğlu, M., & Geymen, A. (2009). Urban sprawl factors in the surface water resource basins of İstanbul. *Land Use Policy*, 26, 569–579. <https://doi.org/10.1016/j.landusepol.2008.08.007>.
- Kurt, S., Karaburun, A., & Demirci, A. (2010). Coastline changes in İstanbul between 1987 and 2007. *Scientific Research and Essays*, 5(19), 3009–3017.
- Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*, 14(5), 778–782. <https://doi.org/10.1109/LGRS.2017.2681128>.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>.

- Mutlu, A. (2013). Law No. 6360 on metropolitan municipality: A rural perspective. *Turkish Journal of Politics and Culture*, (21), 7–24.
- Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., & Wulder, M.A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, 148, 42–57. <https://doi.org/10.1016/j.rse.2014.02.015>.
- Öncel, H., & Levend, S. (2023). The effects of urban growth on natural areas. *Environmental Monitoring and Assessment*, 195(7), 816. <https://doi.org/10.1007/s10661-023-11383-7>.
- Oueslati, W., Alvanides, S., & Garrod, G. (2015). Determinants of urban sprawl in European cities. *Urban Studies*, 52(9), 1594–1614. <https://doi.org/10.1177/0042098015577773>.
- Peker, E., & Ataöv, A. (2024). Challenges in local climate action. *Planning*, 34(1), 22–35. <https://doi.org/10.14744/planlama.2024.88319>.
- Pontius, R.G., & Millones, M. (2011). Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing*, 32(15), 4407–4429. <https://doi.org/10.1080/01431161.2011.552923>.
- Regulation No. 6360. (2015, June 5). *Official Newspaper*.
- Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234–241). Cham: Springer international publishing. https://doi.org/10.1007/978-3-319-24574-4_28.
- Şahin, C. (2015). Spatial development of Istanbul during the Republican era. In *Great Istanbul History Encyclopedia* (Vol. 1). Istanbul Kültür AŞ Publications.
- Schober, P., Boer, C., & Schwarte, L.A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & analgesia*, 126(5), 1763–1768. <https://doi.org/10.1213/ane.0000000000002864>.
- Scott, A.J. (2011). Emerging cities of the third wave. *City*, 15(3–4), 289–321. <https://doi.org/10.1080/13604813.2011.595569>.
- Scott, A.J. (Ed.). (2001). *Global city-regions: Trends, theory, policy*. Oxford University Press.
- Solórzano, J.V., Mas, J.F., Gao, Y., & Gallardo-Cruz, J.A. (2021). Land use land cover classification with U-Net. *Remote Sensing*, 13(18), 3600. <https://doi.org/10.3390/rs13183600>.
- Soltani, A., & Karimzadeh, D. (2013). The spatio-temporal modeling of urban growth. *TeMA – Journal of Land Use, Mobility and Environment*, 2, 189–200. <https://doi.org/10.6092/1970-9870/1547>.
- Sun, L., Chen, J., Li, Q., & Huang, D. (2020). Dramatic uneven urbanization. *Nature Communications*, 11(1), 5366. <https://doi.org/10.1038/s41467-020-19158-1>.
- Talib, M.N.A., Hashmi, S.H., Aamir, M., & Khan, M.A. (2022). Testing non-linear effect of urbanization. *Frontiers in Environmental Science*, 10, 971394. <https://doi.org/10.3389/fenvs.2022.971394>.
- Tekeli, İ. (2015). On the Representation Issues and Demographic Implications Arising from the Changing Settlement Patterns Worldwide. *Journal of Demography*, (37–38), 65–78.
- Toros, H., Abbasnia, M., Sağdıç, M., & Tayanç, M. (2017). Long-term variations of temperature. *Advances in Meteorology*, 1–14. <https://doi.org/10.1155/2017/6519856>

- Turkey, Ministry of Agriculture and Forestry, General Directorate of Forestry. (2015). *Turkey's forest assets*.
- Turkish State Meteorological Service. (2023). *Official statistics*. <https://mgm.gov.tr/veridegerlendirme/il-ve-ilceler-istatistik.aspx>.
- Turkish Statistical Institute. (2023). *Address-based population registration system*. <https://www.tuik.gov.tr>.
- Turkish Statistical Institute. (2025). *International migration statistics, 2024* [Data set]. <https://data.tuik.gov.tr/Bulten/Index?p=Uluslararası-Göç-İstatistikleri-2024-54083>.
- Tyukavina, A., Stehman, S.V., Pickens, A.H., Potapov, P., & Hansen, M.C. (2025). Practical global sampling methods. *Remote Sensing of Environment*, 324, 114714. <https://doi.org/10.1016/j.rse.2025.114714>.
- Ulmas, P., & Liiv, I. (2020). Segmentation of satellite imagery using U-Net models. *arXiv Preprint*. <https://doi.org/10.48550/arXiv.2003.02899>.
- Yan, M., Ge, H., Zhang, L., Chen, X., Yang, X., Liu, F., et al. (2022). Long-term PM_{2.5} exposure. *Ecotoxicology and Environmental Safety*, 244, 114025. <https://doi.org/10.1016/j.ecoenv.2022.114025>.
- Yao, J., Xu, P., & Huang, Z. (2021). Impact of urbanization. *Ecological Indicators*, 129, 107827. <https://doi.org/10.1016/j.ecolind.2021.107827>.
- Yılmaz, H., & Saler, S. (2023). The silent cry for help from our seas. *Journal of Biological Sciences and Health*, 1(2), 38–55. <https://jobish.com.tr/index.php/j/article/view/19>.