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Research Article

ADVANCING FOREST LAND MONITORING IN ISTANBUL REGIONAL DIRECTORATE OF FORESTRY: INTEGRATING U-NET DEEP LEARNING

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Abstract

This study presents a comprehensive analysis of land use and land cover change within the Istanbul Regional Directorate of Forestry (RDF) utilizing semantic segmentation referred to as pixel-based classification. Focusing particularly on forest land dynamics, Sentinel-2 satellite imagery spanning five years from 2019 to 2023 was processed using a U-Net architecture. The study area encompasses diverse forest ecosystems, urban/built-up areas, water bodies, rangelands, wetlands, and agricultural lands. Through the application of advanced remote sensing techniques, significant changes in forest and rangeland were identified and quantified, 15.250 and 13.226 hectares of area decreased in five years, shedding light on the drivers and implications of land use transformations in this critical region. Controversially, built area and agricultural lands were increased by 13.878 and 15.953 hectares over 5 years. The findings contribute to a deeper understanding of forest dynamics and inform sustainable management strategies for preserving the ecological integrity and socio-economic value of forested landscapes within the Istanbul RDF. Additionally, the results reveal the average F1-score for each land cover class is approximately 90% for each year, with forested areas achieving an average F1-score of about 92%, demonstrating the robustness and accuracy of the classification approach.

Keywords: Forest management, remote sensing, deep learning, Istanbul, U-Net

Araştırma Makalesi

İSTANBUL ORMAN BÖLGE MÜDÜRLÜĞÜ'NDE ORMAN ALANLARININ İZLENMESİNDE YENİ YAKLAŞIM: U-NET DERİN ÖĞRENME YÖNTEMİNİN ENTEGRASYONU

Özet

Bu çalışma, İstanbul Orman Bölge Müdürlüğü (OBM) sınırları içerisinde arazi kullanım ve örtüsündeki değişimlerin kapsamlı bir analizini sunmakta olup, piksel tabanlı sınıflandırma olarak bilinen semantik segmentasyon yöntemi kullanılmıştır. Özellikle orman alanlarındaki dinamiklere odaklanılan çalışmada, 2019–2023 yılları arasındaki beş yıllık dönemi kapsayan Sentinel-2 uydu görüntüleri U-Net mimarisi ile işlenmiştir. Çalışma alanı; çeşitli orman ekosistemlerini, kentsel/yerleşim alanlarını, su kütlelerini, mera alanlarını, sulak alanları ve tarım arazilerini içermektedir. Gelişmiş uzaktan algılama tekniklerinin uygulanmasıyla, orman ve mera alanlarında sırasıyla 15.250 hektar ve 13.226 hektarlık bir azalma belirlenmiş ve nicel olarak ortaya konmuştur. Bu durum, söz konusu bölgede arazi kullanımındaki dönüşümleri etkileyen unsurları ve sonuçlarını ortaya koymaktadır. Buna karşılık, yerleşim ve tarım alanlarında ise beş yıllık süreçte sırasıyla 13.878 hektar ve 15.953 hektar artış tespit edilmiştir. Elde edilen bulgular, orman dinamiklerine ilişkin daha derin bir anlayış kazandırmakta ve İstanbul OBM sınırları içerisindeki ormanlık alanların ekolojik bütünlüğünü ve sosyo-ekonomik değerini korumaya yönelik sürdürülebilir yönetim stratejilerinin geliştirilmesine katkı sağlamaktadır. Ayrıca, her bir arazi örtüsü sınıfı için ortalama F1-skorunun her yıl yaklaşık %90 düzeyinde olduğu, ormanlık alanlarda ise ortalama F1-skorunun yaklaşık %92 olarak gerçekleştiği tespit edilmiştir. Bu durum, kullanılan sınıflandırma yönteminin sağlamlığını ve doğruluğunu ortaya koymaktadır.

Anahtar kelimeler: Orman amenajmanı, uzaktan algılama, derin öğrenme, İstanbul, U-Net

1. INTRODUCTION

Monitoring land use and land use change is vital for a range of areas, including environmental sustainability, urban planning, agricultural management, and natural resource conservation. This monitoring helps us understand how natural and human-induced factors alter the landscape and aids in developing suitable policies and practices. Remote sensing techniques play a critical role in this monitoring process (Jensen & Lulla, 1987). Remote sensing platforms, including satellites and aircraft, can identify land use and changes across extensive areas. High-resolution imagery can be used to identify different land types and uses. "Additionally, changes over time can be identified through multiple image acquisitions and time series analyses (Hame, 1986). Remote sensing is valuable for the objective and comprehensive data it provides for monitoring land use change. These techniques support the monitoring, assessment, and management of land to achieve sustainable land use goals (Green et al., 1994).

Türkiye has increasingly recognized the importance of Land Use, Land Use Change, and Forestry (LULUCF) regulation as a crucial component of sustainable development and environmental conservation efforts in recent decades (Schlamadinger et al., 2007). Within the context of LULUCF classification, Türkiye has made significant strides in adopting standardized methodologies and classification systems to effectively monitor and manage its diverse landscape (Zengin et al., 2013). These efforts involve the integration of remote sensing data, geographic information systems (GIS), and ground-based surveys to delineate and classify various land cover types. Understanding Türkiye's land use and land cover dynamics is crucial for assessing environmental changes and informing policies that promote sustainable land management, biodiversity conservation, and climate change mitigation strategies (Atalay et al., 2014).

The Marmara region in Türkiye experiences continuous land use changes due to urbanization, agricultural expansion, and environmental factors (Bozkurt et al., 2023). Monitoring these changes is essential for sustainable development and informed decision-making by local authorities and policymakers. Traditional methods of land use classification often rely on manual interpretation of satellite imagery, which can be time-consuming and subjective. Forest land is among the most important, vulnerable, and pressured land classes, crucial for ecological balance, biodiversity, and essential ecosystem services (Atmis & Cil, 2013). However, these valuable ecosystems face increasing threats from deforestation, land degradation, and climate change. Effective forest management and conservation efforts require accurate and timely information on forest extent, distribution, and dynamics (Gunşen & Atmis, 2019). Traditional forest mapping and monitoring methods are often labour-intensive, time-consuming, and limited in spatial and temporal resolution. Forest ecosystems are globally significant natural resources, making their sustainable management and protection crucial.

In the 21st century, sustainable forest management has become increasingly important, and it emphasizes the need to continuously monitor the changes caused by natural factors or human impacts on forest assets at regional, national, and international levels (Watson et al., 2000). To enable international assessments and comparisons, this monitoring should be based on inventory information collected according to certain norms and standards. Forest inventory does not only mean stand measurements based on sample areas in a small region but also includes all the measurement, observation, counting, and evaluation works carried out to determine the physical existence of forest areas that can reach thousands of hectares in size. It also involves the products and services spontaneously formed within these forests, together with factors that play a role in their formation, by using all data sources, including data processing and storage methods based on remote sensing technologies and GIS (Jensen & Lulla, 1987).

In the context of the Istanbul RDF overseeing extensive forested areas in a dynamic urban landscape, the need for efficient and reliable forest mapping and monitoring tools is particularly acute. Rapid urbanization, infrastructure development, and land-use change pose significant challenges to forest conservation and management efforts in the region (Akyurek et al., 2018). Therefore, adopting advanced technologies is essential to enhance forest monitoring and management. Remote sensing technologies are particularly valuable for continuous monitoring, as traditional methods are costly and time-consuming for extensive areas.

Over recent years, the intersection of remote sensing technologies and artificial intelligence has brought about a transformative shift in forest monitoring methodologies. With the advent of sophisticated algorithms and advanced image processing techniques, the field has witnessed remarkable progress in the accurate and efficient analysis of forest ecosystems (Green et al., 1994). Semantic segmentation, also known as pixel-based classification, plays a fundamental role in remote sensing, similar to traditional image classification methods (Yuan et al., 2021). Semantic segmentation assigns labels to each pixel in a raster image, providing an understanding of pixel class membership, unlike traditional classification methods such as random forest and maximum likelihood classifiers. Semantic segmentation is a critical

technique that requires two primary inputs, namely a raster image comprising multiple bands and a corresponding label image that contains pixel-level annotations. There are several algorithms available for performing semantic segmentation, including U-Net, Mask R-CNN, and Feature Pyramid Network. These algorithms have been developed and proven to be efficient in the task of semantic segmentation. Among these, U-Net stands out as a prominent choice, renowned for its effectiveness in segmenting images (Ronneberger et al., 2015). This guide primarily focuses on U-Net because of its wide recognition and similarities to other segmentation algorithms, providing comprehensive insights into semantic segmentation in remote sensing. Deep learning algorithms, U-Net architecture, have shown promise in automating the process of forest mapping and change detection using satellite imagery (Diakogiannis et al., 2020). By leveraging large volumes of high-resolution imagery and ground-truth data, these algorithms can accurately delineate forested areas and track changes over time with unprecedented speed and accuracy (Xie et al., 2019).
A study proposed using the U-Net algorithm with Sentinel-2 imagery to monitor land use and its changes over five years within the Istanbul RDF. This algorithm is known for its effectiveness in image segmentation tasks and offers a promising approach to accurately classify various land use categories such as water, forest, snow/ice, pasture/grassland, wetland, agriculture, cloud, settlement, and open space. By utilizing high-resolution satellite imagery, this study aims to provide detailed and up-to-date information on land cover dynamics in the region.

The primary aim of this study is threefold. Firstly, (1) it endeavours to develop an automated land use classification system utilizing the U-Net deep learning algorithm. Through the training of the model on annotated satellite imagery, the objective is to achieve precise classification of various land use categories. Additionally, (2) the study seeks to detect and quantify land use changes over time within the boundaries of the Istanbul RDF. Through the analysis of temporal variations in land cover, the aim is to discern trends and patterns associated with urban expansion, deforestation, agricultural intensification, and other pertinent land use dynamics. Finally, (3) the study aims to evaluate the performance of the developed classification model using quantitative metrics, including overall accuracy, precision, recall, and F1 score. The model's validation will be conducted using ground-truth datasets to assess its proficiency in accurately classifying land use categories and detecting changes over time.

2. MATERIALS AND METHODS

2.1 Study Site

The Istanbul RDF encompasses a variety of ecosystems, ranging from forests and water bodies to urban areas, which are continuously affected by land use changes due to urbanization, agriculture, and environmental factors. The geographical coordinates of the Istanbul RDF are 26019'48" and 29057'31" east longitudes and 40048'38" and 42006'21" north latitudes, covering an area of approximately two million hectares. The RDF spans six provinces - Istanbul, Adapazarı, İzmit, Edirne, Kırklareli, and Tekirdağ - and includes ten forestry operation directorates: Bahcekoy, Catalca, Demirkoy, Edirne, Istanbul, Kanlica, Kirklareli, Sile, Tekirdag, and Vize. There are no significant mountains within the boundaries of the RDF (General Directorate of Forestry 2021) (Figure 1).

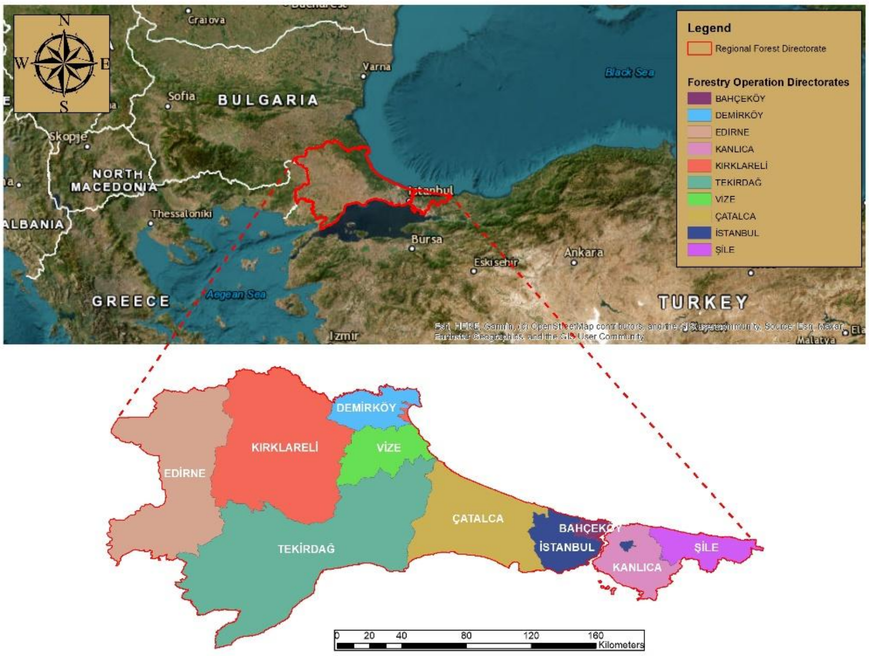

Figure 1. Geospatial overview of Istanbul RDF and subdivisional boundaries.

2.2. Workflow

The workflow for this study encompassed four key stages aimed at robustly monitoring land cover changes within the Istanbul RDF through the integration of U-Net deep learning architecture with satellite imagery. Firstly, the process began with data acquisition and preprocessing, involving the retrieval of Sentinel-2 satellite imagery covering the study area and ground-truth data. These data underwent preprocessing to mitigate noise, correct atmospheric effects, and ensure spatial alignment, facilitating subsequent analysis. Labeled masks were also generated through an image segmentation platform. Secondly, the U-Net architecture and implementation phase focused on implementing the U-Net deep learning model, renowned for its efficacy in semantic segmentation tasks. This involved training the model with the preprocessed satellite images and corresponding ground-truth data, with further optimization and fine-tuning to adapt to the unique characteristics of the study area. Postprocessing techniques were then applied to refine the classification results, addressing artifacts and enhancing spatial coherence. Lastly, validation and model evaluation formed the final stage, where the accuracy of land cover classifications was validated against ground-truth data. The model's performance was evaluated using metrics such as precision, recall, and F1-score for each land cover class. Overall accuracy and reliability were assessed through comprehensive validation and evaluation processes, ensuring the integrity and effectiveness of the classification model in monitoring land cover changes within the Istanbul RDF.

2.2.1. Data Acquisition and Preprocessing

Sentinel-2 imagery was obtained from the Copernicus Open Access Hub (ESA, 2019) in this study. The geographic area of interest was defined using coordinates or by drawing a bounding box on the platform's map interface. The imagery was selected for a specific period from the beginning of June until the end of September within the 5-year interval from 2019 to 2023. Filters were also applied to select scenes with minimal cloud cover to ensure the quality of the imagery. A maximum threshold for cloud cover, typically set to 5%, was specified to prioritize images with clear visibility and minimal atmospheric interference. Additional filters, such as sensor mode (e.g., MSI Level-1C) and acquisition type (e.g., Level-2A processed data), were applied as needed to refine the selection of Sentinel-2 imagery. The selected imagery underwent a preview process to visually inspect the scenes for cloud cover and overall clarity. Only images meeting the quality criteria were included in the final selection for download and analysis.

We acquired the dataset comprising 15,056 images, each with dimensions of 256x256 pixels and belonging to 8 classes and we preprocessed the dataset by standardizing the pixel values, handling some missing data, and augmenting the dataset if necessary to increase diversity. Data acquisition and preprocessing of the Sentinel-2 imagery was firstly conducted by Google Earth Engine and secondly manipulated by R 4.2.2 to ensure data consistency and accuracy (R Core Team 2013).

The process of creating labelled masks is often meticulous and time-consuming. It entails delineating regions within each image that correspond to predefined land cover classes (Voelsen et al., 2020). To streamline this task, we utilized the image segmentation platform segments.ai. Initially, we converted Sentinel-2 RGB images, obtained from Google Earth Engine, into .png format for compatibility with the segmentation platform. Subsequently, utilizing the platform, we conducted image segmentation and identified regions to be masked for each image within our dataset. Upon labelling the masks, the platform generated a .json file containing the URLs for downloading the binary images. This approach facilitated efficient and systematic annotation of land cover classes across the imagery dataset.

The preprocessed satellite imagery is divided into training, validation, and test sets. From these sets, training patches or tiles are extracted, each containing a portion of the satellite image along with its corresponding ground truth labels. To enhance the diversity of the training dataset, data augmentation techniques such as rotation, flipping, and scaling are applied. This increases the variability of the training samples and improves the robustness of the trained model. Data have split the dataset into a training set containing 75% of the images and a validation set containing the remaining 25%. This ensures a portion of the data is held out for evaluation during model training. The data for each year has been evaluated and processed separately.

2.2.2. U-Net Architecture and Implementation

U-Net, a novel architecture composed of convolutional neural network layers, offers a more successful approach to pixel-based image segmentation than classical models, even with a limited number of training images. The presentation of this architecture is based on biomedical images (Ronneberger et al., 2015).

Conventionally, in a convolutional neural network model, down-sampling operations, such as pooling layers employing different approaches like maximum, average, or median pooling are applied throughout the model, followed by up-sampling in the latter half of the model (Diakogiannis et al., 2020). These layers aim to increase the resolution of the output. For localization, high-resolution features sampled throughout the model are combined, and subsequent convolutional layers aim to produce a more precise output based on this information. U-Net derives its name from its architecture, resembling the letter "U" where input images are obtained as segmented output maps in Figure 2. A distinctive aspect of its architecture is the absence of fully connected layers; only convolutional layers are utilized, with each standard convolution operation being activated by a rectified linear unit (ReLU). To ensure seamless segmentation of images, pixels at the boundary are symmetrically added around the image, facilitating complete segmentation.

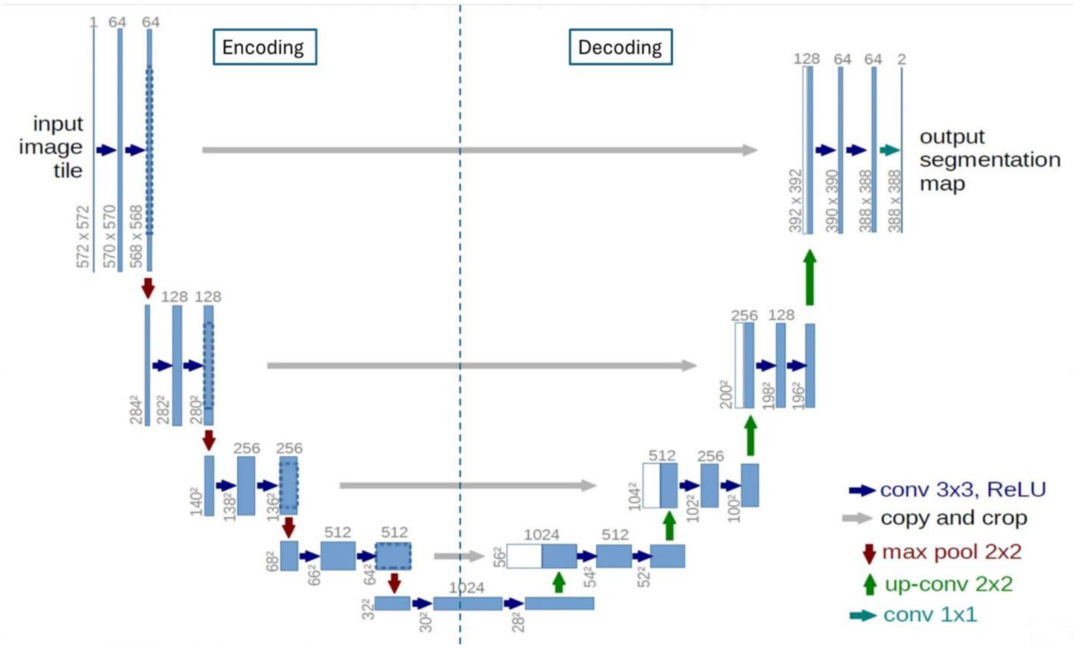

Figure 2. Schematic diagram of U-net convolutional network architecture for image segmentation.

To ensure seamless segmentation of images using the U-Net model, pixels are symmetrically added around the image perimeter. This strategy expands the segmentation area, enabling the model to handle large images without compromising resolution or accuracy due to GPU memory limitations. This approach enhances the scalability and applicability of the U-Net architecture for various image analysis tasks, such as satellite imagery or medical imaging (Farmer et al., 2013).

In this study, we firstly utilized a 3x3 filter with a Smoothed ReLU activation function, secondly employed a 2x2 filter with max pooling for size reduction helping to down-sample the feature maps, capturing the most important information, thirdly applied a 2x2 filter for classification used as the output layer activation function for multi-class classification problems and providing probabilities for each class, fourthly, a default stride value of 1 and padding value of 0 were used. This configuration ensures that the feature map generated by the convolutional layers remains the same size as the input image, and finally, the training process was set to run for 50 epochs referring to one complete pass through the entire training dataset during the training process. All steps were carried out in R for training the model, with TensorFlow as the backend for Keras.

2.2.3. Postprocessing

To apply the trained U-Net model to new remote sensing images for inference and generate thematic maps illustrating the distribution of different land cover classes across the study area, we first loaded the new images into the model. Through inference, the model predicted land cover classes at each pixel, generating probability distributions for each class. Subsequently, we refined the segmentation results through post-processing techniques, including the removal of small, isolated regions and smoothing of boundaries using morphological operations and filters like Gaussian blur (Maragos & Pessoa, 1999).

Following post-processing, we assigned land cover classes to each pixel based on the highest predicted probability obtained from the inference step. Thematic maps were then generated, where the pixel-wise predictions were converted into raster format and overlaid onto a base map. By interpreting these maps, patterns, trends, and anomalies in land cover distribution were identified. Comparison with ground truth data or expert knowledge helped assess the accuracy and reliability of the model predictions. Further analysis, such as area statistics calculation or spatial queries, was performed to extract meaningful insights and inform decision-making processes based on the generated thematic maps.

2.2.4. Validation and Model Evaluation

Initially, the Sentinel-2 imagery was overlaid with the current forest management plan and cadastral data to verify the accuracy of land class assignments along the borders of Istanbul RDF for each year. This step ensured alignment with existing land management boundaries and administrative divisions within the Istanbul RDF. The accuracy of the land use and land cover classifications, particularly in forested areas, was mainly assessed by comparing them with data from the National Forest Inventory (NFI). This validation step provided a comprehensive evaluation of the classification results against ground-truth information collected through ground surveys and field measurements. Subsequently, the classification outputs were further validated by local experts using high-resolution Google Earth images for each year within the 5-year interval (2019-2023). This qualitative assessment enabled the identification of any discrepancies or inaccuracies in the classification results, particularly in areas where ground conditions may have changed over time.

The NFI has provided us with an essential database for this study in terms of the exact identification of forest lands. Briefly, the NFI in Türkiye is typically conducted at 5-year intervals to track changes in forest resources over time and inform forest management and conservation strategies. The NFI is designed to operate on a 5-year cycle, with permanent sample plots covering a total of 825 designated locations (Figure 3). These plots are primarily determined based on the prevailing land use patterns validated by NFI experts each year.

The performance evaluation of the proposed method for land cover classification was conducted using a range of evaluation metrics, with a focus on the precision and recall measured over consecutive years. The accuracy rate, serving as a fundamental metric, gauges the classifier's overall correctness in predictions. Precision, another key metric, quantifies the accuracy of class predictions, indicating the proportion of correctly predicted instances among all instances identified as positive. A high precision value signifies fewer false positives, essential for reliable land cover classification (Macleod & Congalton, 1998).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

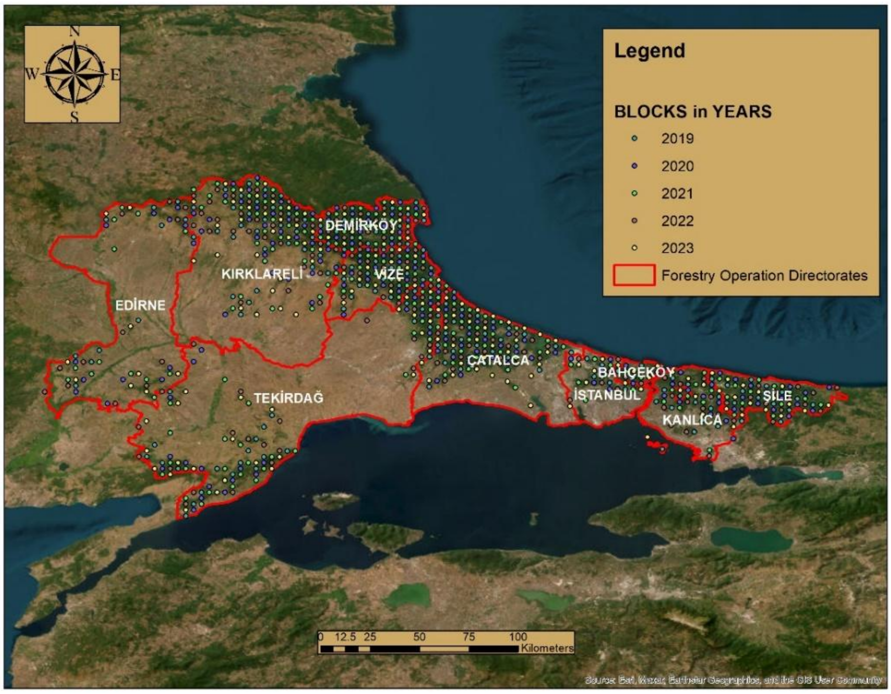

Figure 3. Distribution of national forest inventory sample plots across the Istanbul RDF.

The F1-score, calculated as the harmonic mean of precision and recall, offers a balanced assessment of classifier performance. It is particularly valuable when dealing with imbalanced datasets or when both false positives and false negatives are significant.

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

By analyzing the average F1-score over multiple years, the method's consistency and reliability in land cover classification can be thoroughly assessed, enabling effective monitoring of land cover changes, and facilitating comparisons with alternative classification techniques.

3. RESULTS AND DISCUSSION

3.1 Results

The application of the U-Net algorithm to satellite imagery enables accurate segmentation of land use categories within the Istanbul RDF. By analyzing temporal changes in land cover over 5 years, we could make inferences about trends and patterns associated with urban expansion, deforestation, agricultural intensification, and other land use dynamics. Quantitative metrics such as precision, recall, and F1-score are computed to assess the performance of the classification model and validate the consistency of the results. The class maps generated through the land cover classification process provided detailed insights into the spatial distribution of various land cover classes within the study area. Each land cover class, including water, forest, wetland, agricultural land, built-up areas, bare ground, snow/ice, clouds, and rangeland, was accurately delineated and visualized on the maps.

The analysis of land use changes from 2019 to 2023 encompasses both spatial mapping (Figure 4.) and quantitative assessment (Table 1.) for precision and recall metrics were assessed across various land cover classes.

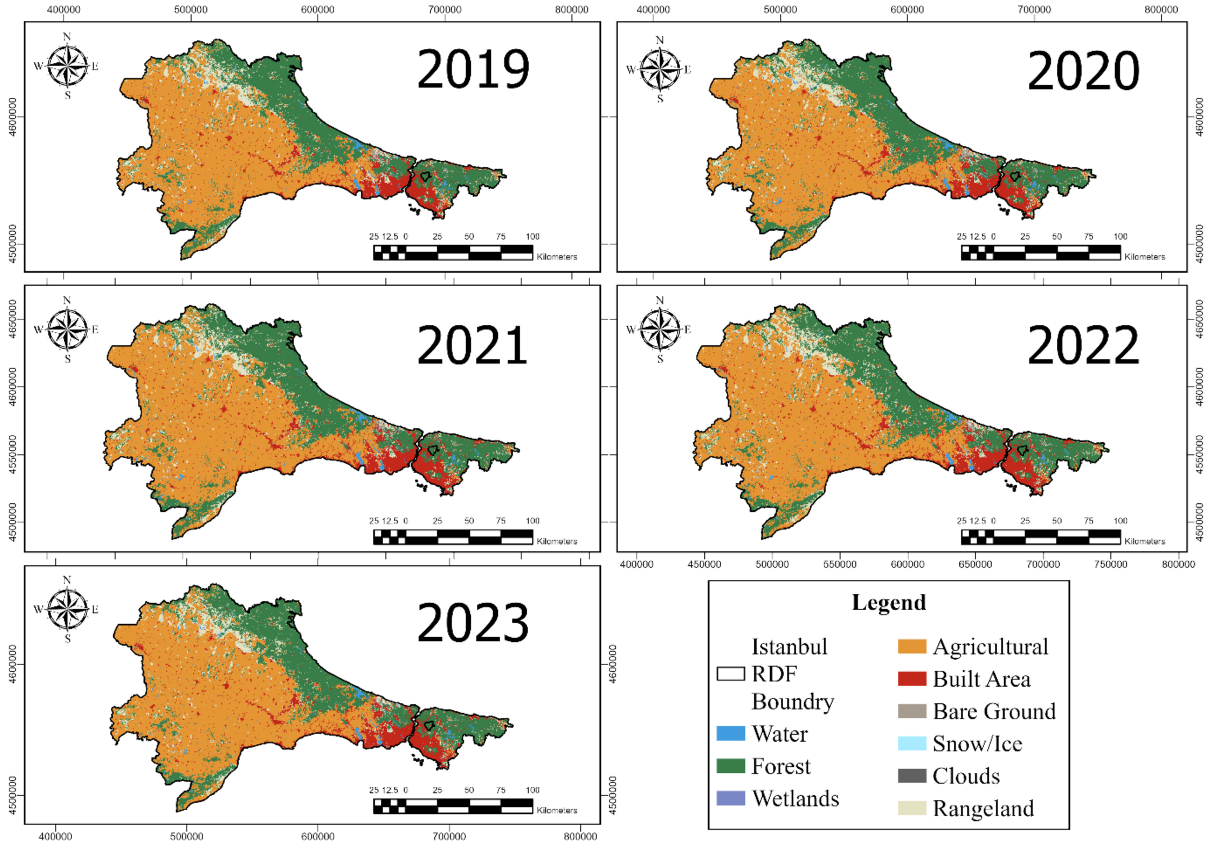

Figure 4. Thematic land cover map of the Istanbul RDF, 2019 to 2023.

These maps serve as valuable tools for identifying changes in land cover patterns, such as deforestation, urban expansion, or agricultural encroachment, over the specified period. Additionally, numerical analysis techniques are employed to quantify the extent and magnitude of land use changes, providing statistical insights into the rates of change and the relative contributions of different land use categories to overall landscape dynamics. By integrating both map-wise and numerical approaches, a comprehensive understanding of land use changes from 2019 to 2023 is achieved, facilitating informed decision-making and land management strategies within the study area.

Table 1. Annual land cover classification accuracy and F1-scores from 2019 to 2023

Year	Classes	Area (ha)	Precision	Recall	F1-Score	Overall F1-Score
	Water	23,76	0.83	0.98	89.9	
	Forest	599,31	0.93	0.94	93.5	
	Wetland	350,00	0.62	0.68	64.9	
	Agricultural	1,192,377	0.91	0.9	90.5	
2019	Built Area	194,61	0.96	0.79	86.7	91.54
	Bare Ground	11,02	0.84	0.87	85.5	
	Snow/Ice	1,00	0.96	0.97	96.5	
	Clouds	12,00	0.98	0.96	97.0	
	Rangeland	177,25	0.74	0.55	63.1	
	Water	27,48	0.85	0.91	87.9	
	Forest	603,17	0.91	0.95	93.0	
	Wetland	364,00	0.58	0.62	59.9	
	Agricultural	1,192,674	0.88	0.91	89.5	
2020	Built Area	198,71	0.97	0.8	87.7	92.21
	Bare Ground	12,04	0.78	0.88	82.7	
	Snow/Ice	1,00	0.99	0.97	98.0	
	Clouds	42,00	0.97	0.95	96.0	
	Rangeland	164,20	0.89	0.56	68.7	
	Water	26,34	0.86	0.92	88.9	
	Forest	603,72	0.92	0.89	90.5	
	Wetland	300,00	0.48	0.66	55.6	
	Agricultural	1,190,590	0.9	0.88	89.0	
2021	Built Area	203,40	0.89	0.79	83.7	89.47
	Bare Ground	10,59	0.59	0.77	66.8	
	Snow/Ice	2,00	0.98	0.98	98.0	
	Clouds	16,00	0.96	0.95	95.5	
	Rangeland	163,73	0.89	0.59	71.0	
	Water	22,30	0.84	0.96	89.6	
	Forest	575,28	0.93	0.91	92.0	
	Wetland	214,00	0.68	0.72	69.9	
	Agricultural	1,197,516	0.92	0.9	91.0	
2022	Built Area	207,72	0.94	0.89	91.4	92.89
	Bare Ground	10,09	0.68	0.81	73.9	
	Snow/Ice	1,00	0.97	0.96	96.5	
	Clouds	11,00	0.96	0.97	96.5	
	Rangeland	185,54	0.82	0.51	62.9	
	Water	25,23	0.91	0.94	92.5	
	Forest	584,06	0.88	0.92	90.0	
	Wetland	261,00	0.58	0.67	62.2	
	Agricultural	1,208,330	0.89	0.92	90.5	
2023	Built Area	208,49	0.95	0.81	87.4	90.36
	Bare Ground	8,27	0.66	0.83	73.5	
	Snow/Ice	1,00	0.96	0.94	95.0	
	Clouds	15,00	0.92	0.94	93.0	
	Rangeland	164,03	0.78	0.48	59.4	

In 2019, the precision scores ranged from 0.62 to 0.98, while recall scores varied between 0.55 and 0.98 in Table 1. The highest precision score of 0.98 was achieved for the agricultural class, indicating a high proportion of correctly predicted positive instances among all instances predicted as positive on a proportional basis in terms of the area it covers. Conversely, the rangeland class exhibited the lowest recall score of 0.55, suggesting that the model missed a considerable proportion of actual positive instances within this land cover category. It is noteworthy that the overall F1-score, calculated as the harmonic mean of precision and recall, attained a commendable value of 91.54%. The precision score for the forest class is at an impressive 0.93, indicating a high level of accuracy in correctly identifying forested areas among all instances predicted as positive. Similarly, the recall score for the forest class is notably high at 0.94, signifying the model's effectiveness in capturing the most actual forested areas within the study region.

In 2020, precision scores ranged from 0.58 to 0.99, while recall scores varied between 0.56 and 0.95. The forest class attained the highest precision score of 0.91, indicating a high proportion of correctly predicted positive instances among all instances predicted as positive. Conversely, the wetland class exhibited the lowest precision score of 0.58, suggesting potential misclassification of non-wetland areas as wetlands. Notably, the forest class demonstrated exceptional performance with a recall score of 0.95, indicating the model's effectiveness in capturing most actual forested areas within the study region. Overall, the classification model achieved an impressive F1-score of 92.21%, highlighting its accuracy and reliability in delineating land cover classes for the year 2020.

In 2021, precision scores spanned from 0.48 to 0.98, with recall scores ranging between 0.59 and 0.92. The agricultural class notably achieved the highest precision score of 0.92, indicating a significant proportion of accurately predicted positive instances relative to its area coverage. Conversely, the wetland class yielded the lowest precision score of 0.48. Interestingly, the forest class displayed a slightly diminished recall score of 0.89 compared to previous assessments, suggesting a minor decline in the model's capability to identify all genuine forested areas within the study vicinity. Overall, the classification model garnered an F1-score of 89.47%, underscoring its efficacy in delineating land cover classes for the year 2021.

In 2022, precision scores ranged from 0.68 to 0.97, while recall scores varied between 0.51 and 0.9. The highest precision score of 0.97 was achieved for the built area class, signifying a notable accuracy in correctly identifying built areas among all instances predicted as positive, especially considering the considerable area it covers. Specifically, the forest class demonstrated a precision score of 0.93 and a recall score of 0.91, underscoring the model's capability in accurately delineating forested areas. Overall, the classification model attained an impressive F1-score of 92.89%, indicative of its robust performance in delineating land cover classes for the year 2022.

In 2023, precision scores ranged from 0.58 to 0.96, while recall scores varied between 0.48 and 0.94. Particularly, the water class achieved the highest precision score of 0.91, indicating a high proportion of correctly predicted positive instances among all instances predicted as positive. In terms of recall, the built area class demonstrated the highest score of 0.81, indicating the model's effectiveness in capturing many actual built-up areas within the study region. Additionally, the forest class exhibited respectable precision and recall scores of 0.88 and 0.92, respectively, underscoring the model's accuracy in identifying forested areas. The overall F1-score for the classification model in 2023 was 92.89%, reflecting its robust performance in delineating land cover classes.

Over the 5 years under study, notable changes in land cover dynamics were observed, particularly concerning forest, rangeland, agricultural, and built-up areas. The analysis revealed a decrease of approximately 16 ha. in forested areas and a corresponding decline of approximately 14 ha. in rangeland areas. In contrast, agricultural and built-up areas experienced an increase of approximately 16 and 14 ha., respectively. These findings underscore the dynamic nature of land cover changes within the study area and highlight the ongoing urbanization and agricultural expansion trends. The observed decrease in forest and rangeland areas signals potential environmental concerns, such as habitat loss and ecosystem degradation, while the expansion of agricultural and built-up areas reflects the growing human footprint and land use intensification.

In a Sentinel-2 satellite image of 2023 in Figure 5, a detailed comparison will be conducted with the finer scale prediction results obtained from 2019 to 2023 years within the same area. This comparative analysis aims to elucidate any discrepancies or classification challenges encountered in the land cover classification process. Notable emphasis will be placed on identifying areas where the classification model exhibits inconsistencies or inaccuracies in predicting specific land cover classes. It is observed that rangeland areas often exhibit characteristics that may lead to misclassification, appearing as buffer or transition zones between forested and agricultural areas. However, upon closer validation, it becomes evident that these transitions are not gradual but rather abrupt. This discrepancy highlights a significant classification problem wherein rangeland areas are inaccurately represented within the classification model. Such misclassifications can distort the understanding of land cover dynamics and hinder effective land management strategies. Thus, addressing this issue is imperative for enhancing the accuracy and reliability of land cover classification techniques within the study area. This observation underscores the importance of rigorous validation procedures and continual refinement of classification methodologies to ensure an accurate depiction of land cover types and transitions.

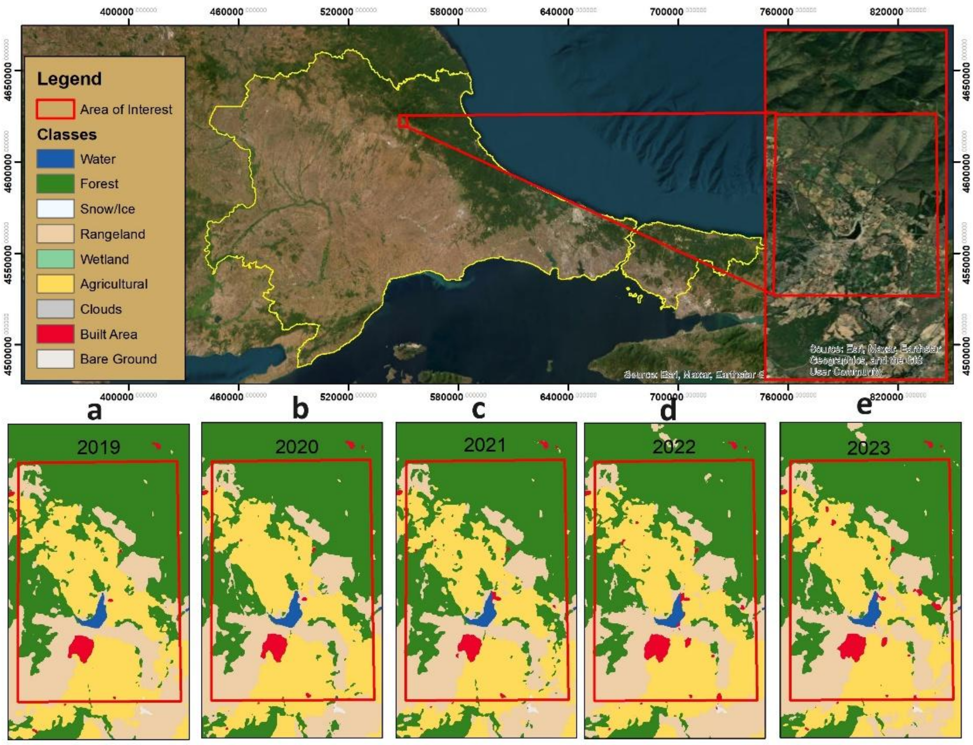

Figure 5. Comparative analysis of land cover classifications from 2019 to 2023 in the Istanbul RDF, with a specific focus on the highlighted area of interest (red boundary). Within highlighted area, built-up land expanded by approximately 7% between 2019 and 2023, while forested regions decreased by about 3%, and rangeland exhibited variable annual fluctuations.

For this reason, despite rangeland accuracy yielding the highest precision, it consistently registers the lowest accuracy rates. This discrepancy underscores the complexity and challenges associated with accurately classifying rangeland areas within the land cover classification model. The observed discrepancy between precision and accuracy highlights the inherent difficulty in precisely delineating rangeland boundaries and distinguishing them from adjacent land cover types. Such challenges may arise due to the heterogeneous nature of rangeland landscapes, characterized by diverse vegetation types and land use practices. Additionally, the abrupt transitions between rangeland, forested, and agricultural areas further compound classification difficulties. Consequently, despite achieving high precision, the classification model struggles to accurately capture the true extent and distribution of rangeland areas, resulting in lower overall accuracy rates. Addressing this inconsistency requires a concerted effort to refine classification methodologies, incorporate additional contextual information, and improve validation procedures to enhance the accuracy of rangeland classification within the study area.

3.2 Discussion

The comprehensive analysis of land cover classification results spanning from 2019 to 2023 sheds light on the efficacy and challenges associated with remote sensing techniques and the U-Net algorithm, particularly in the context of the Istanbul RDF. Precision and recall metrics were utilized to evaluate the performance of the classification model across various land cover classes, including water bodies, forests, wetlands, agricultural areas, built-up areas, bare ground, snow/ice, clouds, and rangeland. Especially, precision and recall scores exhibited considerable variability across different land cover classes and years, indicating the complexity of accurately delineating land cover types within the study area.

Comparisons between land cover and land use change patterns observed in Istanbul RDF and other major global cities highlight shared urbanization-driven transformations. Istanbul, similar to European cities such as London and Paris, has experienced rapid urbanization and population growth, significantly transforming its landscape (Bozkurt et al., 2023). Bozkurt et al. (2023) documented significant urban expansion in Istanbul between 1990 and 2018, resulting in a 3.02% decrease in agricultural areas and a 6.66% decrease in forested areas, while urban areas expanded by 9.69%. Projections suggest that this trend will continue until 2030, emphasizing the urgent need for sustainable urban development plans to mitigate further natural area conversion.

The use of U-Net enhanced the efficiency and accuracy of forest inventory and monitoring processes within the RDF. Traditional methods of forest inventory, which rely on manual interpretation of satellite imagery or field surveys, are often time-consuming, labour-intensive, and prone to errors. In contrast, U-Net offered a more automated and scalable approach to land cover classification, allowing for the rapid analysis of large-scale imagery datasets with high spatial resolution (Solórzano et al., 2021). This enabled forestry authorities to make informed decisions based on up-to-date and reliable information, leading to more effective resource allocation and management planning. By providing accurate and timely information on forest cover dynamics, the U-Net model assisted policymakers and stakeholders in formulating targeted interventions to address deforestation, mitigate the impacts of climate change, and promote biodiversity conservation. Additionally, by integrating remote sensing technology and deep learning algorithms into forestry management workflows, the RDF enhanced its capacity for data-driven decision-making and adaptive management in the face of environmental challenges.

The thematic maps generated through this study (Figure 4) served as crucial foundational resources for future NFI in Türkiye initiatives and detailed international reporting of forested areas. These maps provide essential data for assessing the extent and distribution of forest cover in Türkiye, forming the basis for national and international reporting obligations regarding total forest area. Particularly in Türkiye, where land use and change exhibit year-to-year variability, RDF assessments, especially in metropolitan regions, hold significant importance (Tolunay et al., 2011). The implementation of U-Net automation within the RDF study area has yielded results with consistently high average accuracy rates. This high level of accuracy can be attributed to several factors, including precise masking of trained datasets and optimization of the U-Net algorithm. Moreover, the validation process involved rigorous cross-referencing with forest management maps, cadastral data, NFI ground measurements, and manual observation using Google Earth. These meticulous validation procedures have bolstered the reliability and high accuracy of the study's findings.

Despite promising results, spatial heterogeneity within land cover types remains a major challenge in remote sensing-based classification. Variations in vegetation structure, topography, and land management practices can result in mixed pixels, particularly at the boundaries between distinct land cover types. This ambiguity contributes to classification errors, especially in transitional zones. Scientific evidence suggests that model accuracy is strongly influenced by the quality, diversity, and representativeness of training datasets (Foody, 2002; Belgiu & Drăguţ, 2016). Insufficient or imbalanced training data that fail to capture intra-class variability—particularly for complex classes like rangeland and forest—can limit the generalizability and predictive capacity of classification models. To address these limitations, future research should prioritize refining deep learning architectures with enhanced spatial-contextual modeling (e.g., attention mechanisms), improving data quality through active learning and data augmentation techniques, and adopting advanced preprocessing methods such as radiometric correction and terrain normalization. Moreover, integrating ancillary data sources—including vegetation indices like NDVI and EVI, texture metrics, and topographic parameters such as slope and aspect—has been shown to markedly improve class separability. For example, Jin et al. (2018) combined core spectral bands with ancillary variables—multi-temporal vegetation indices (NDVI, EVI), GLCM-derived texture measures, and DEM-based slope and elevation—in a Random Forest framework and increased overall accuracy to approximately 89 %; summer NDVI, a near-infrared band, elevation, and texture statistics were identified as the most influential predictors. Finally, ensemble or hybrid approaches that combine multiple classifiers (e.g., U-Net with Random Forest or CNN-LSTM architectures) can leverage the complementary strengths of different models, often resulting in higher classification accuracy and robustness in complex landscapes (Zhu et al., 2017).

Furthermore, it was observed that rangeland areas often appeared as buffer zones between forested and agricultural areas, not only leading to misclassifications but also resulting in a decline in prediction accuracy, which can be attributed to several underlying factors. Upon closer validation, it became evident that these transitions were not gradual but rather abrupt, highlighting a significant classification problem within the model. Another significant contributor is the inherent similarity in spectral signatures exhibited by these land cover types, particularly in areas where forest edges blend into open grasslands or where sparse tree cover characterizes the landscape (Kilic et al., 2006). This spectral resemblance poses a challenge for the classification algorithm, hindering its ability to accurately discriminate between rangeland and forest land pixels.

In Türkiye, approximately 99% of forests are state-owned, managed for diverse economic, ecological, and socio-cultural purposes, while privately-owned forests present unique management challenges. Enhanced regulatory measures and policy interventions are needed to address complexities related to land ownership, management practices, and land cover dynamics (Zengin et al., 2013). Discrepancies between forest area data reported by the General Directorate of Forestry and actual measurements highlight limitations in current forest management plan data. Specifically, polygon logic methods used in management plans often misclassify bare ground, rangeland, or agricultural lands as forest areas. Furthermore, privately-owned urban forests are frequently misclassified as built-up areas. Addressing illegal logging, deforestation, improving data collection and monitoring systems, and refining cadastral and forest management plans will be crucial for achieving accurate forest assessments and sustainable management within Istanbul RDF and beyond (Atmis & Cil, 2013).

4. CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates the effectiveness of the U-Net deep-learning architecture for automating land-use and land-cover (LULC) monitoring in the Istanbul RDF. Leveraging high-resolution Sentinel-2 imagery, the model achieved consistently high classification accuracy across five successive years (2019–2023), thereby providing reliable, up-to-date information for environmental management and spatial planning.

To facilitate transparent dissemination and stakeholder engagement, all annual LULC maps, accuracy tables, and code have been deployed in an interactive R Shiny application that can be accessed at *https://ergin.shinyapps.io/LULC/*. Users can visualise class-level changes, download geospatial layers, and explore precision-recall metrics, making the workflow fully reproducible and policy-relevant.

Future research should focus on scaling the methodology to larger regions and incorporating complementary data sources—such as LiDAR-derived canopy metrics, multi-temporal SAR backscatter, and high-resolution DEM derivatives—to further improve class separability in heterogeneous landscapes. Methodological advances such as attention-augmented U-Net variants, adversarial training, and active-learning sample selection could also mitigate class imbalance and data-scarcity issues. Finally, ensemble or hybrid architectures (e.g., U-Net features combined with Random Forest or Transformer backbones) deserve exploration, as recent studies report consistent gains of 3 to 7 percentage points in overall accuracy when such combinations are applied to complex LULC tasks.

In summary, by uniting deep-learning image segmentation with an open, web-based delivery platform, this work provides a scalable blueprint for near-real-time forest-land monitoring in Türkiye and sets the stage for broader adoption of AI-driven decision-support tools in the forestry sector.

AUTHOR CONTRIBUTIONS

Ergin Çağatay ÇANKAYA: Conceptualization, methodology, formal analysis, investigation, data curation, writing - original draft preparation, writing - review and editing, visualization and supervision, **Burhan GENCAL**: Writing, review and editing, **Turan SÖNMEZ**: Review and editing. All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

ETHICS COMMITTEE APPROVAL

This study does not require any ethics committee approval.

REFERENCES

Adepoju, M. O., Millington, A. C., & Tansey, K. T. (2006). Land use/land cover change detection in metropolitan Lagos (Nigeria): 1984–2002. P 1-5 in ASPRS 2006 Annual Conference Reno, Nevada May.

Atalay, I., Efe, R., & Öztürk, M. (2014). Ecology and classification of forests in Türkiye. *Procedia-Social and Behavioral Sciences, 120*, 788-805. https://doi.org/10.1016/j.sbspro.2014.02.163

Atmis, E., Günsen, B. H., Yücedağ, C., & Lise, W. (2012). Status, use and management of urban forests in Türkiye. *South-east European Forestry: SEEFOR, 3*(2), 69-78. https://doi.org/10.15177/seefor.12-08

Atmis, E., & Cil, A. (2013). Sustainable forestry in Türkiye. *Journal of Sustainable Forestry, 32*(4), 354-364. https://doi.org/10.1080/10549811.2013.767210

Bagan, H., & Yamagata, Y. (2012). Landsat analysis of urban growth: How Tokyo became the world's largest megacity during the last 40 years. *Remote Sensing of Environment, 127*, 210-222. https://doi.org/10.1016/j.rse.2012.09.011

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing*, 114, 24-31.

Bozkurt, S. G., Kuşak, L., & Akkemik, Ü. (2023). Investigation of land cover (LC)/land use (LU) change affecting forest and seminatural ecosystems in Istanbul (Türkiye) metropolitan area between 1990 and 2018. *Environmental Monitoring and Assessment, 195*(1), 196. https://doi.org/10.1007/s10661-023-10975-7

Cui, L., & Shi, J. (2012). Urbanization and its environmental effects in Shanghai, China. *Urban Climate, 2*, 1-15. https://doi.org/10.1016/j.uclim.2012.10.008

Diakogiannis, F. I., Waldner, F., Caccetta, P., & Wu, C. (2020). ResUNet-a: A deep learning framework for semantic segmentation of remotely sensed data. *ISPRS Journal of Photogrammetry and Remote Sensing, 162*, 94-114. https://doi.org/10.1016/j.isprsjprs.2020.01.013

ESA. (2023, June). *Copernicus Open Access Hub*. https://scihub.copernicus.eu/dhus/#/home

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote sensing of environment*, 80(1), 185-201.

Farmer, E., Jones, S., Clarke, M., Buxton, L., Soto-Berelov, M., Page, S., Mellor, A., & Haywood, A. (2013). Creating a large area landcover dataset for public land monitoring and reporting. In *Geospatial Science Research Symposium* (pp. 116-132), Melbourne, Australia.

General Directorate of Forestry. (2021). *Türkiye Orman Varlığı (Forest Assets of Türkiye)*. General Directorate of Forestry, Ministry of Environment and Forest, Ankara, Türkiye.

Gökburun, İ. (2017). İstanbul'da Nüfusun Gelişimi ve İlçelere Dağılımı (1950–2015). *Journal of Anatolian Cultural Research (JANCR), 1*(3), 110-130. https://ankad.org/index.php/ankad/article/view/27

Green, K., Kempka, D., & Lackey, L. (1994). Using remote sensing to detect and monitor land-cover and land-use change. *Photogrammetric Engineering and Remote Sensing, 60*(3), 331-337.

Günsen, H. B., & Atmiş, E. (2019). Analysis of forest change and deforestation in Türkiye. *International Forestry Review, 21*(2), 182-194. https://doi.org/10.1505/146554819826606577

Hame, T. H. (1986). Satellite image aided change detection. *Remote Sensing-Aided Forest Inventory, Research Notes, 19*, 47-60.

Hayati, Z., Yeşil, A., Asan, U., Bettinger, P., Cieszewski, C., & Siry, J. P. (2013). Evolution of modern forest management planning in the Republic of Türkiye. *Journal of Forestry, 111*(4), 239-248. https://doi.org/10.5849/jof.11-103

Jensen, J. R., & Lulla, K. (1987). Introductory digital image processing: A remote sensing perspective. *Geocarto International, 2*(1), 65. https://doi.org/10.1080/10106048709354084

Jin, Y., Liu, X., Chen, Y., & Liang, X. (2018). *Land-cover mapping using Random Forest classification and incorporating NDVI time-series and texture: A case study of central Shandong*. International journal of remote sensing, 39(23), 8703-8723.

Kilic, S., Evrendilek, F., Berberoglu, S., & Demirkesen, A. (2006). Environmental monitoring of land-use and land-cover changes in a Mediterranean region of Türkiye. *Environmental Monitoring and Assessment, 114*, 157-168. https://doi.org/10.1007/s10661-006-2525-z

Macleod, R. D., & Congalton, R. G. (1998). A quantitative comparison of change-detection algorithms for monitoring eelgrass from remotely sensed data. *Photogrammetric Engineering and Remote Sensing, 64*(3), 207-216.

Maragos, P., & Pessoa, L. (1999). Morphological filtering for image enhancement and detection. In *The Image and Video Processing Handbook* (pp. 135-156).

R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015: 18th International Conference Proceedings* (pp. 234-241). Springer International Publishing.

Ruiz-Luna, A., & Berlanga-Robles, C. A. (2003). Land use, land cover changes and coastal lagoon surface reduction associated with urban growth in northwest Mexico. *Landscape Ecology, 18*(2), 159-171. https://doi.org/10.1023/A:1024461215456

Schlamadinger, B., Bird, N., Johns, T., Ward, M., & Yamagata, Y. (2007). A synopsis of land use, land-use change and forestry (LULUCF) under the Kyoto Protocol and Marrakech Accords. *Environmental Science & Policy, 10*(4), 271-282. https://doi.org/10.1016/j.envsci.2006.11.002

Solórzano, J. V., Mas, J. F., Gao, Y., & Gallardo-Cruz, J. A. (2021). Land use land cover classification with U-Net: Advantages of combining Sentinel-1 and Sentinel-2 imagery. *Remote Sensing, 13*(18), 3600. https://doi.org/10.3390/rs13183600

Tolunay, D., Karabiyik, B., & Temerit, A. (2011). First results of a nation-wide systematic forest condition survey in Türkiye. *iForest-Biogeosciences and Forestry, 4*(3), 145. https://doi.org/10.3832/ifor0567-004

Voelsen, M., Bostelmann, J., Maas, A., Rottensteiner, F., & Heipke, C. (2020). Automatically generated training data for land cover classification with CNNs using Sentinel-2 images. *ISPRS Archives, 43*(B3), 767-774. https://doi.org/10.15488/10821

Watson, R., Noble, I. R., Bolin, B., Ravindranath, N. H., Verardo, D. J., & Dokken, D. J. (2000). *Land Use, Land-Use Change, and Forestry: A Special Report*. Cambridge University Press.

Xie, S., Liu, L., Zhang, X., Yang, J., Chen, X., & Gao, Y. (2019). Automatic land-cover mapping using Landsat time-series data based on Google Earth Engine. *Remote Sensing, 11*(24), 3023. https://doi.org/10.3390/rs11243023

Yin, J., Zhong, H., Xu, S., Hu, X., Wang, J., & Wu, J. (2011). Monitoring urban expansion and land use/land cover changes of Shanghai metropolitan area during the transitional economy (1979–2009) in China. *Environmental Monitoring and Assessment, 177*, 609-621. https://doi.org/10.1007/s10661-010-1660-8

Yuan, X., Shi, J., & Gu, L. (2021). A review of deep learning methods for semantic segmentation of remote sensing imagery. *Expert Systems with Applications, 169*, 114417. https://doi.org/10.1016/j.eswa.2020.114417

Zengin, H., Yeşil, A., Asan, U., Bettinger, P., Cieszewski, C., & Siry, J. P. (2013). Evolution of modern forest management planning in the Republic of Turkey. *Journal of Forestry, 111*, 239-248.

Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE geoscience and remote sensing magazine*, 5(4), 8-36.