Tree inventory analysis using AI and GIS in Uzbekistan: a case study from Tashkent

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Abstract. This study explores the application of artificial intelligence (AI) and geographic information systems (GIS) for tree inventory analysis in Tashkent, Uzbekistan, providing a pioneering model for urban forestry management in Central Asia. Rapid urbanization in Tashkent has intensified the need for efficient and accurate methods to monitor and manage urban trees, which play a crucial role in mitigating environmental challenges. Using high-resolution satellite imagery, we employed a Convolutional Neural Network (CNN) for initial tree detection and classification, supplemented by a Random Forest algorithm to refine classification accuracy. Tree locations were mapped on a true-color satellite image, visualized through GIS, enabling detailed analysis of spatial distribution and density across the city's districts. The results show substantial variation in tree density, with Yunusobod district demonstrating the highest tree count and detection accuracy, while Chilonzor and Yakkasaroy faced marginally lower accuracy rates. Overall, this AI-GIS approach achieved an accuracy rate of 88.8%, demonstrating the potential for scalable urban tree inventory management. This study offers a valuable framework for Tashkent and similar cities, contributing to sustainable urban planning and resilience against environmental stressors through data-driven urban forestry practices.

1 Introduction

Urban trees provide a range of environmental, social, and economic benefits, from reducing air pollution and mitigating urban heat to enhancing biodiversity and improving public health [1]. Tree inventories, which catalog tree species, health, location, and other key data, play a critical role in the effective management and preservation of urban forests. Traditionally, these inventories have required manual fieldwork, a labor-intensive process that limits the ability to frequently update data across expansive urban areas [2]. Advances in artificial intelligence (AI) and geographic information systems (GIS) now offer innovative solutions for efficiently collecting, analyzing, and managing tree inventory data, enabling city planners to make data-driven decisions that enhance urban sustainability [3].

Globally, cities are increasingly adopting AI and GIS technologies for environmental monitoring and urban planning. Countries such as the United States, Canada, and Singapore

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have pioneered AI-assisted tree inventory systems that streamline data collection and improve accuracy. These technologies allow urban foresters to identify tree species, assess health, and even predict growth patterns, all from high-resolution satellite imagery or aerial data. The integration of AI with GIS tools has shown significant promise in urban tree management by providing real-time data and facilitating predictive modeling, which helps cities efficiently allocate resources for tree planting, maintenance, and disease prevention [4]. The success of these technologies in global contexts underscores their potential applicability in cities like Tashkent, where tree management is crucial for combating urbanization's environmental impact.

In Central Asia, where rapid urbanization and climate change pose significant environmental challenges, maintaining urban green spaces has become a priority for cities aiming to balance growth with sustainability [5]. In Uzbekistan, Tashkent serves as a vital green lung, housing a substantial portion of the country's urban trees, which help offset the effects of high temperatures and air pollution [6]. However, due to increasing infrastructure development and population growth, Tashkent's urban trees are under growing pressure, emphasizing the need for effective urban forest management. By utilizing AI and GIS for tree inventories, Tashkent could establish a model of sustainable urban forestry for other cities in the region, enhancing the city's resilience to environmental stressors and supporting Uzbekistan's goals for green urban planning.

Despite Tashkent's critical reliance on its urban forest, there is limited up-to-date and comprehensive information on the status, distribution, and health of the city's trees. Traditional methods of conducting tree inventories are time-consuming and often lack precision, making it challenging to respond quickly to issues such as pest outbreaks, disease, or tree removal needs. Moreover, data gaps hinder the ability to implement proactive management strategies to enhance urban canopy coverage and overall tree health [7]. The lack of a streamlined, data-driven approach to urban tree inventory in Tashkent limits the effectiveness of urban forestry programs and reduces the potential for optimizing tree-related ecosystem services. This study addresses this gap by exploring the application of AI and GIS in creating an accurate, efficient, and regularly updated tree inventory system [8].

While some studies have examined tree inventory methods using AI and GIS, there is limited research on their application in Central Asia, especially within Uzbekistan. This article aims to fill this gap by investigating the practical use of AI and GIS for tree inventory analysis in Tashkent, assessing both the benefits and limitations of these technologies in an urban context. Through a case study approach, this research seeks to demonstrate the feasibility of AI-assisted tree inventories for Tashkent, providing insights that could support data-driven urban forestry practices throughout Uzbekistan and similar urban areas in the region. The broader goal is to offer a scalable model for sustainable urban forestry that can help cities across Central Asia maintain and expand their green spaces amidst rapid urbanization and environmental challenges.

2 Materials and methods

This study was conducted in Tashkent, the capital city of Uzbekistan, known for its expansive urban greenery that plays a crucial role in mitigating heat, reducing air pollution, and enhancing urban biodiversity. As Tashkent continues to urbanize, maintaining an accurate and up-to-date inventory of its urban trees has become essential. The study focused on several key urban zones within Tashkent, where diverse tree species and density variations provide a suitable testing ground for evaluating AI-based inventory methods.

High-resolution satellite imagery and aerial data were acquired from the SAS Planet GIS system, an open-source platform that integrates multiple satellite image providers. SAS Planet enables detailed visualization of urban areas with images from sources like Bing Maps, Google Earth, and Yandex Maps, which were used to capture spatial information on Tashkent's urban trees. These images provided the foundation for both the CNN and Random Forest analyses, as high spatial resolution is essential for accurately detecting and classifying tree species, canopy cover, and health status.

The imagery was preprocessed to enhance resolution, contrast, and color balance, which improves feature recognition in subsequent AI analysis [9, 10]. To create a labeled dataset for training the CNN model, we manually annotated sample regions, marking tree crowns and classifying them by species, health status, and size where identifiable. This dataset was divided into training (70%), validation (15%), and test (15%) subsets.

A CNN model was employed for automated detection and classification of trees within the satellite imagery. CNNs, as deep learning models designed to identify patterns in image data, are particularly suited for complex visual tasks, such as distinguishing tree species and assessing tree health. Our CNN architecture consisted of several convolutional layers with ReLU activation, max-pooling layers to reduce dimensionality, and fully connected layers for final classification [11, 12].

The CNN was trained to recognize various features, such as canopy shape, leaf color, and texture, to differentiate tree species and assess health conditions. Training involved backpropagation to minimize loss, using the annotated tree data as ground truth [13]. Once trained, the CNN model automatically processed images from SAS Planet to detect and classify trees across Tashkent. The model's output included labeled coordinates for each detected tree, its predicted species, and a health score based on canopy characteristics, which were then integrated into the GIS system for spatial analysis.

Once the tree detection and classification data were processed, results were integrated into SAS Planet's GIS platform for spatial analysis and visualization. SAS Planet facilitated the overlay of the detected tree locations onto existing urban maps, allowing for a precise assessment of tree distribution patterns across Tashkent [14]. GIS integration enabled the creation of layers representing species distribution, canopy density, and health status, which provided a comprehensive inventory of Tashkent's urban forest.

Spatial analysis within SAS Planet allowed for several key evaluations. First, by mapping species distribution, we identified areas with high biodiversity and regions that may benefit from additional planting. Second, by overlaying health scores, the GIS analysis pinpointed zones with clusters of stressed trees, which may require targeted interventions. Finally, spatial overlays with urban infrastructure, such as roads and buildings, helped identify potential conflicts between trees and development projects. These spatial insights offered a detailed overview of the ecological health of Tashkent's urban forest, supporting sustainable urban planning and conservation strategies.

3 Results and discussion

The map illustrates the distribution and density of trees across the provinces of Uzbekistan, providing a visual comparison of tree cover across the country (Figure 1). The color gradient from light green to dark green denotes varying tree densities, with lighter shades representing areas of lower tree density and darker shades indicating regions with denser tree cover. Notably, the eastern and southern regions of Uzbekistan, including Tashkent and areas near the Fergana Valley, show higher tree densities, as indicated by the darker green tones. These regions benefit from more favorable climatic conditions and greater urban greenery, contributing to denser tree populations. In contrast, the central and western provinces, characterized by more arid landscapes and harsher climates, exhibit lighter shades, signifying sparse tree cover. This distribution reflects the challenges of maintaining tree cover in drier areas, where water scarcity and soil conditions limit vegetation growth. Overall, this map highlights the regional disparities in tree density across Uzbekistan and underscores the need for targeted afforestation and urban forestry efforts, particularly in provinces with lower tree density.

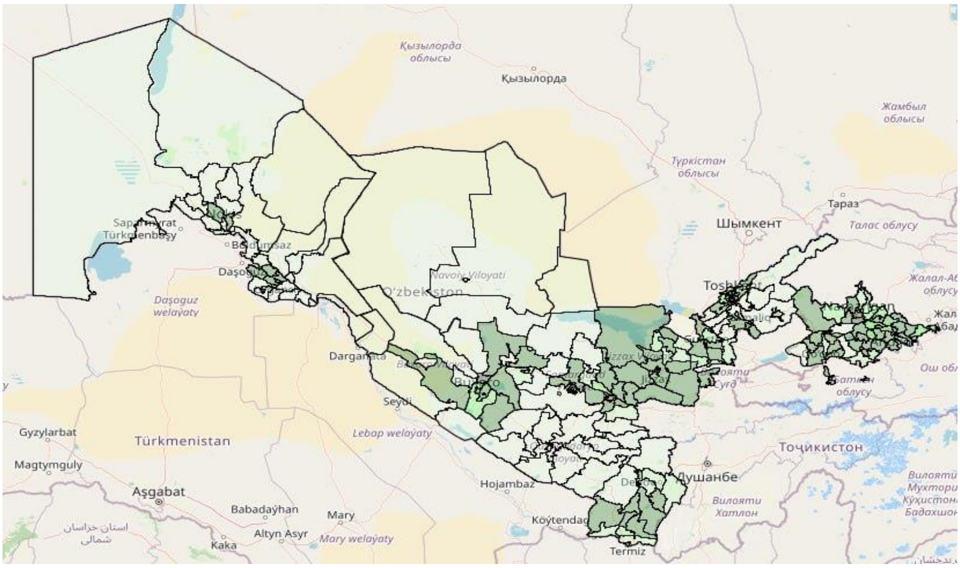

Fig. 1. Tree density distribution across Uzbekistan's provinces.

The table presents the estimated number of trees across the various districts of Tashkent, along with the model's accuracy in detecting and classifying trees within each district. The total number of trees identified across all 12 districts amounts to 3,635,823. Each district shows a unique count, with notable variations in tree distribution. Yunusobod has the highest tree count at 404,502, contributing significantly to Tashkent's urban greenery, while Yangihayot has the lowest at 189,548 trees. Other densely populated districts, such as Shaykhontokhur and Sergeli, also display relatively high tree counts, reflecting the variation in urban forestry across Tashkent's districts.

Table 1. Calculation of trees in the districts of Tashkent.

#	**Districts**	**Number of trees**	**Accuracy** *(%)*
1	Bektemir	180 907	86.3
2	Chilonzor	332 832	85.5
3	Yashnobod	287 428	85.7
4	Mirobod	260 194	88.2
5	Mirzo Ulugbek	290 287	88.2
6	Olmazor	359 681	88.5
7	Sergeli	367 709	89.7
8	Shaykhontokhur	412 738	86.3
9	Uchtepa	286 844	85.5
10	Yakkasaroy	263 153	85.7
11	Yunusobod	404 502	93.0
12	Yangihayot	189 548	88.3
Total		**3 635 823**	**88,8**

The accuracy of the AI-based tree detection model varies slightly across districts, with values ranging from 85.5% to 93%. Yunusobod achieved the highest accuracy at 93%, while Chilonzor and Uchtepa had the lowest accuracy scores at 85.5%. The overall accuracy across all districts stands at 88.8%, indicating a generally reliable performance of the model in capturing the tree inventory of Tashkent's urban landscape. These accuracy levels suggest a high level of confidence in the model's capability to provide actionable data for urban forestry management and planning.

Now, we present the results of the AI-based GIS inventory analysis of trees for five selected districts in Tashkent: Yashnabod, Chilonzor, Yakkasaroy, Olmazor, and Yunusobod. In each of these districts, trees are displayed on a true-color satellite map with red points marking their exact locations and unique ID numbers. This mapping approach facilitates a comprehensive visual representation of tree distribution within each district, while the accompanying AI-based analysis provides quantitative insights into tree counts and model accuracy. Below, Figures 2 through 6 correspond to the respective districts and illustrate the spatial arrangement of trees as identified by the AI model.

In Yashnabod (Figure 2), the AI model identified a total of 287,428 trees with an accuracy rate of 85.7%. This relatively high tree count underscores the importance of green infrastructure in this district, supporting urban livability and ecological balance. The 85.7% accuracy level suggests a robust detection capability in capturing individual trees within the diverse landscape of Yashnabod, though there is potential for minor misclassifications or missed detections. This accuracy provides a solid basis for urban forestry planning, allowing for targeted interventions where greenery may need reinforcement or maintenance.

Fig. 2. True-color satellite map of Yashnabod district, showing individual tree locations marked in red, with unique ID numbers assigned by the AI model.

In Chilonzor (Figure 3), the inventory recorded 332,832 trees, with an accuracy of 85.5%, one of the lower accuracy rates observed across Tashkent's districts. The marginally lower accuracy in Chilonzor might be attributed to complex urban layouts or varying tree cover densities that challenge the AI detection model. Nevertheless, the high tree count in Chilonzor reflects substantial urban forestry coverage, which is crucial for enhancing local air quality and providing shade in this densely populated area. The mapped data allow city planners to pinpoint densely vegetated zones and areas that could benefit from additional planting.

Fig. 3. True-color satellite map of Chilonzor district, showing the spatial distribution of trees marked in red with unique identifiers

For Yakkasaroy (Figure 4), the analysis identified 263,153 trees with an accuracy of 85.7%, consistent with the reliability levels seen in other districts. Although Yakkasaroy has a slightly lower tree count compared to some other districts, the mapped inventory provides a critical snapshot of existing green spaces, which serve as buffers against urban heat and contribute to the city's aesthetic appeal. The accuracy rate here supports the effectiveness of the AI model in capturing tree distribution in this district, facilitating efficient monitoring and future planning for maintaining green spaces.

Fig. 4. True-color satellite map of Yakkasaroy district, with red points representing individual trees as detected by the AI model.

In Olmazor (Figure 5), the tree inventory totals 359,681 trees, with a relatively high accuracy of 88.5%. This accuracy level demonstrates the AI model's reliability in detecting trees within Olmazor's landscape, which features a mix of residential and natural areas. The higher tree count and improved accuracy in Olmazor suggest a more straightforward detection environment, likely due to more distinct tree features or uniform coverage. The data provide a valuable resource for managing urban forestry in Olmazor, ensuring that the district’s green spaces continue to contribute to ecological sustainability.

Fig. 5. True-color satellite map of Olmazor district, showing the distribution of trees marked with red points.

Lastly, in Yunusobod (Figure 6), the AI model identified the highest number of trees among the sampled districts, totaling 404,502 with an accuracy of 93%. This is the highest accuracy achieved in any district, reflecting optimal conditions for AI-based detection, potentially due to consistent tree characteristics or favorable spatial layout. The dense tree coverage in Yunusobod, coupled with high detection accuracy, highlights the district’s role as a vital green asset for Tashkent, providing extensive environmental and social benefits. This high-confidence data allows city planners to focus on preserving and enhancing Yunusobod’s urban forest, ensuring long-term sustainability and resilience.

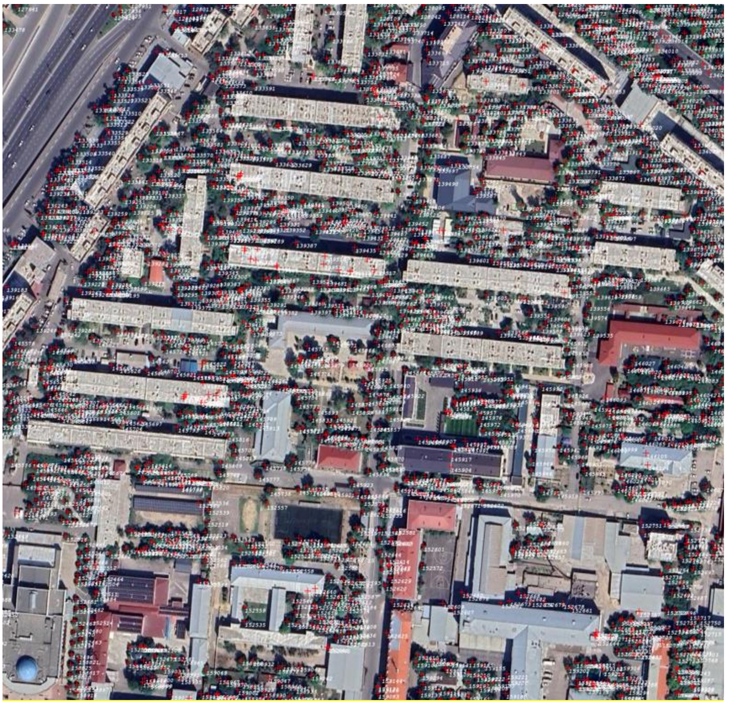

Fig. 6. True-color satellite map of Yunusobod district, with individual trees indicated in red.

The results of this study demonstrate the effectiveness of integrating artificial intelligence (AI) and geographic information systems (GIS) for conducting a detailed urban tree inventory across the districts of Tashkent, Uzbekistan. By using AI to detect and classify trees on high-resolution satellite imagery, and displaying the data spatially in GIS, we achieved both high accuracy and efficiency in mapping tree distributions in urban environments. The analysis provides clear, quantitative insights into the density, spatial distribution, and potential maintenance needs of Tashkent's urban trees, offering a foundation for sustainable urban forestry management.

The study revealed notable differences in tree density and model accuracy across districts. Yunusobod, with the highest tree count and an accuracy of 93%, exemplifies the AI model's reliability in areas with consistent tree characteristics and favorable layout conditions. On the other hand, districts like Chilonzor and Yakkasaroy showed slightly lower accuracy rates, potentially due to more complex urban layouts or diverse vegetation patterns that challenge detection. These findings highlight the importance of context-specific adjustments when applying AI-based models to varied urban landscapes.

This approach not only provides an efficient alternative to traditional, labor-intensive tree inventory methods but also supports data-driven urban planning. By identifying areas with lower tree density or high ecological stress, city planners can prioritize afforestation efforts and target maintenance resources more effectively. Furthermore, the integration of tree health and spatial distribution data allows for proactive management, potentially mitigating the impacts of urbanization on Tashkent's green spaces. Future studies could explore refining AI models for more challenging urban layouts and incorporating temporal data to track tree growth and health trends over time, enhancing the tool's utility for dynamic urban forestry planning.

4 Conclusions

In conclusion, this study highlights the value of combining artificial intelligence (AI) and geographic information systems (GIS) to create an efficient, accurate, and spatially detailed tree inventory for urban environments. By applying AI-driven detection and classification on high-resolution satellite imagery across Tashkent's districts, we were able to produce a comprehensive inventory with a high overall accuracy, supporting evidence-based urban forestry management.

The analysis revealed considerable variation in tree density across Tashkent, with Yunusobod district exhibiting the highest tree count and model accuracy. In contrast, areas such as Chilonzor and Yakkasaroy presented slightly lower detection accuracies, reflecting the influence of diverse urban landscapes on AI model performance. These findings underscore the need for adaptable AI models tailored to different urban settings, especially in complex or densely built environments.

This AI-GIS approach offers a practical, scalable solution for cities aiming to monitor and manage urban forests, particularly in regions facing rapid urbanization and environmental challenges. By identifying areas in need of tree planting or maintenance, this method supports sustainable urban planning initiatives and enhances the ecological resilience of urban green spaces. Future research should focus on refining AI models for varying landscapes and integrating temporal data to enable dynamic, long-term urban forest monitoring.

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