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APPLICATION OF REMOTE SENSING DATA IN THE STUDY OF URBANIZATION PROCESSES

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Abstract: Today, as the population continues to grow, the process of urbanization is also rapidly developing. The use of remote sensing data in the study of urbanization processes is considered highly effective and convenient.
In this article, maps of cities in the Tashkent region were created based on classification methods. Considering the relatively coarse spatial resolution of the Landsat satellite, samples were taken from raster data. A flowchart of processes using machine learning techniques in remote sensing data analysis was developed.
The results of the study show that changes in Tashkent indicate an active increase in urbanization. Open lands have significantly decreased, suggesting the construction of new buildings and infrastructure. At the same time, less attention has been paid to the preservation or expansion of green areas, reflecting limited efforts to improve the city's ecology. Moreover, the expansion of the capital's territory represents a higher level of urbanization, while the total area of green zones has markedly declined. The proportion of tree-covered areas decreased from 19% to 15% over the past 30 years, which in turn indicates a growing scarcity of greenery in the city.
Keywords: Urban, remote sensing, machine learning, classify, satellite images, Tashkent, Angren, forest, agriculture, barren soil, developed land, water.

Introduction

The process of urbanization reflects the multifaceted development of a population within a specific region. The concept of urbanization can be interpreted through several aspects, including population growth, expansion of urban areas, an increase in the number of buildings, vertical development (the rise in the number of floors), and the advancement of infrastructure.
The continuous expansion of urban territories has become a typical indicator of modern development. This phenomenon is primarily driven by population growth, improved living standards, and infrastructural development. Remote sensing data have become one of the most in-demand sources of information in the 21st century. Such data are collected through various sensors installed on satellites, drones, aircraft, or other platforms. These sensors operate across different ranges of the electromagnetic spectrum (e.g., optical, infrared, microwave) and make it possible to analyze numerous features such as surface characteristics, atmospheric conditions, and vegetation cover.
Remote sensing data acquisition can be classified into two main types:
Passive sensors-measure energy emitted from the Sun or the Earth's own thermal radiation. Examples include satellite imagery from "Landsat" and "Sentinel-2".
Active sensors-emit electromagnetic waves from their own sources (such as radar or lidar) and record the reflected signals. Examples include "Sentinel-1" and "ICESat" satellites, which employ active remote sensing technology.

Methodology

Areas classified as *bare land* included unusable surfaces within riverbeds and barren soils located near the airport runway. These areas were used as training samples for the machine learning model. To identify *forest or tree-covered areas*, clear satellite images and the infrared bands of the Landsat data were utilized. Large parks, urban recreational zones, and botanical gardens were selected as representative samples and uploaded to the model for training.

Agricultural lands were identified around the city, characterized by rectangular, rhomboid, and trapezoidal shapes. When visualized in the infrared spectrum, these fields appeared in shades of red, light red, and brown. Several training samples from these regions were digitized and saved as shapefiles.

After creating the training samples, they were stored in memory as shapefiles. The machine learning process was then executed, and the classification analysis was performed using the trained samples [3], [4].

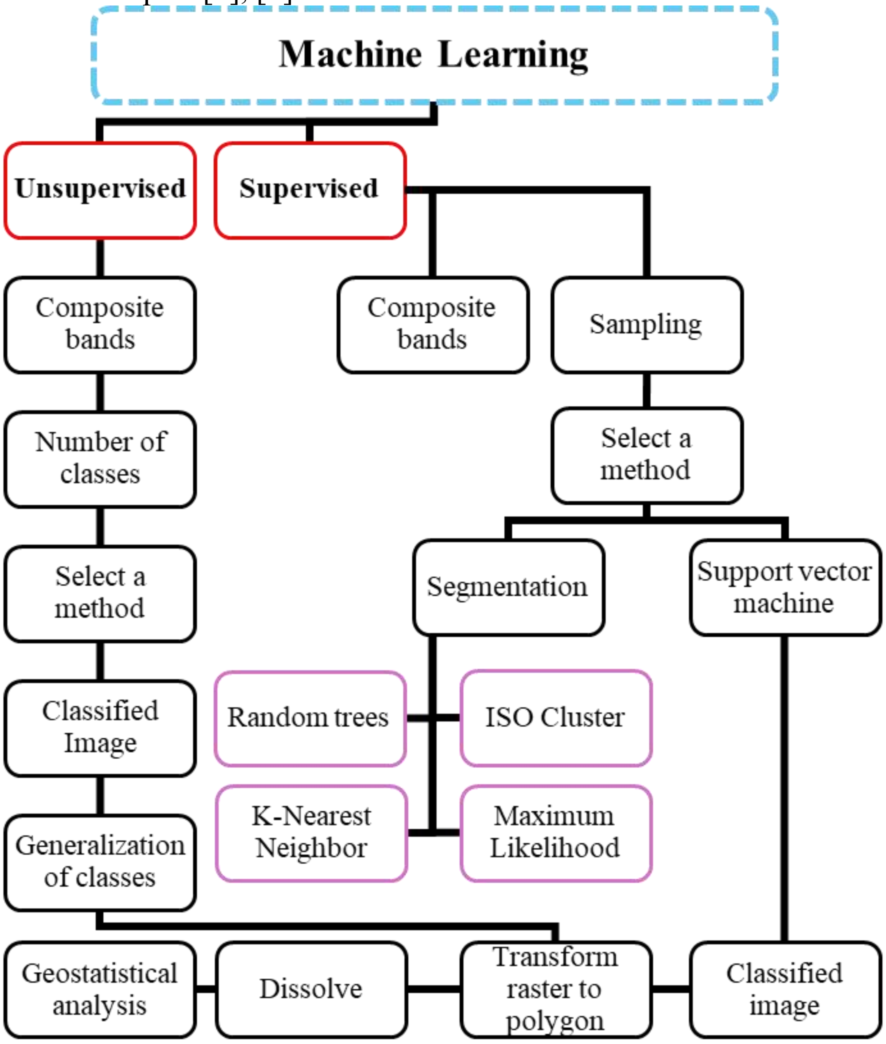

Figure 1. Flowchart of Machine Learning Techniques on Remote Sensing Data

Once these processes were completed, several satellite images were sequentially processed (Figure 2). Based on the results obtained from the performed tasks, it became possible to observe the unique characteristics and dynamics of each city.

Remote sensing provides multiple methods for detecting urbanization. For instance, it allows for the identification of land use and land cover (LULC) changes, analysis of urban heat island effects, monitoring of air quality, and assessment of urban ecological infrastructure. Through machine learning, it is possible to classify different land use types to support these analyses. Remote sensing data are also effectively utilized for identifying thermal islands, studying atmospheric quality using advanced space-based sensors, and monitoring vegetation or green cover distribution in urban environments [1], [2].

Remote sensing data offer accurate and rapid means for conducting environmental monitoring; however, several limitations should be considered:

• High-level technical knowledge and advanced computer processing capabilities are required for effective data analysis.

• Optical sensors cannot capture imagery through cloud cover, which necessitates the use of radar sensors.

• High-resolution satellite imagery can be costly.

Despite these challenges, remote sensing remains one of the most efficient tools for in-depth analysis of urbanization and environmental conditions. It provides a scientific foundation for decision-making and facilitates the visualization of spatial and ecological changes.

The urbanization process is characterized by an increase in population, industrial expansion, and the conversion of land for non-agricultural purposes. Consequently, cities experience growth in total land area or shifts in land categories over time. To examine these processes, a machine learning (ML) approach was employed, integrating multiple analytical stages. This method was used to perform land use and land cover analysis for the years 1994 and 2024.

Landsat satellite imagery corresponding to the summer months of 1994 was used in the analysis. The territory of Tashkent region, including its seven cities and the city of Tashkent, was covered using three satellite image tiles.

The land cover classification process is inherently complex and begins with the composition of spectral bands across different ranges. This process involves combining monochromatic images from multiple spectral bands into a single color composite image. On top of the composite imagery, training samples were delineated to initialize the machine learning classification process (Figure 1).

Figure 2. List of terrain types selected for machine learning

The samples were delineated based on the pixel structure, considering the relatively coarse spatial resolution of the Landsat satellite imagery. *Water bodies* were identified using pixels corresponding to large reservoirs and river sections visible in different parts of the satellite images. *Built-up areas* were represented by pixels covering large settlements, industrial and factory rooftops, multi-story residential buildings, and quarry zones.

Results

Angren City Condition in 1994, the total area of Angren covered approximately 19,790 hectares. At that time, the boundaries of the city were not yet precisely defined. Angren, as a settlement, possessed favorable environmental and infrastructural conditions. Despite being an industrial city located near mountainous areas, its natural environment remained in good condition. The city had adequate water resources and a significant amount of vacant land, which served as reserves for future construction. Although Angren was recognized primarily as an industrial center, it still maintained notable areas of agricultural fields and tree-covered zones (Figure 11).

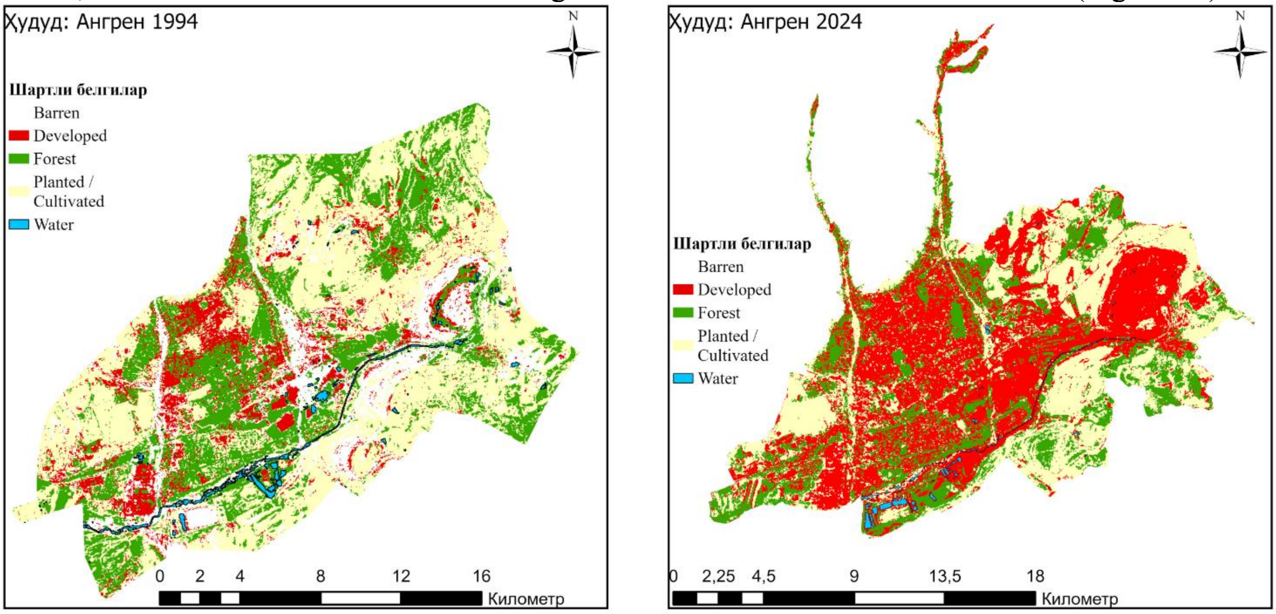

Figure 3. Classification of land types in Angren city in 1994 and 2024

Status as of today, the total area of Angren has increased to 14,846 hectares. During this time, the city's borders have changed dramatically.

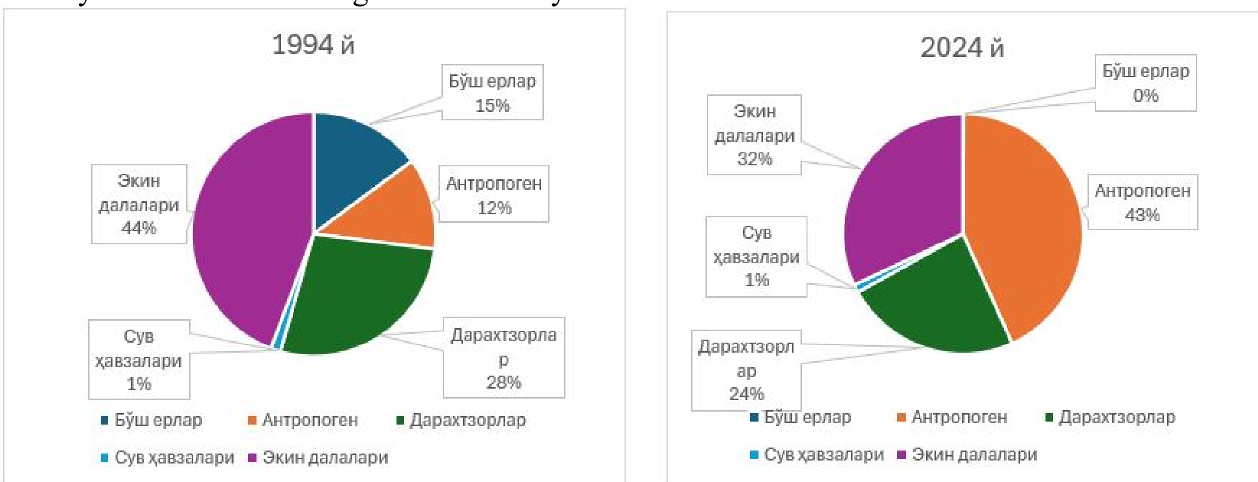

Figure 4. Land type classification indicators in Angren city in 1994 and 2024

The total area has decreased due to the definition of boundaries. Highlands and mountainous areas have been excluded from the urban structure. The share of land used by the population for residential and industrial purposes has increased significantly. The population has grown. There is a problem of shortage of water resources. Forests and arable land have decreased. Vacant lands have been eliminated. Large-scale quarrying has had its impact.

Discussion

According to the results of the statistical analysis, over the past 30 years, the area occupied by urban and industrial development has increased by approximately 3.5 times. The extent of tree-covered areas has partially decreased, while the main expansion occurred at the expense of agricultural lands and pastures. Although the proportion of water bodies did not show a significant decline, their relative share slightly decreased due to the overall reduction in the total land
area.

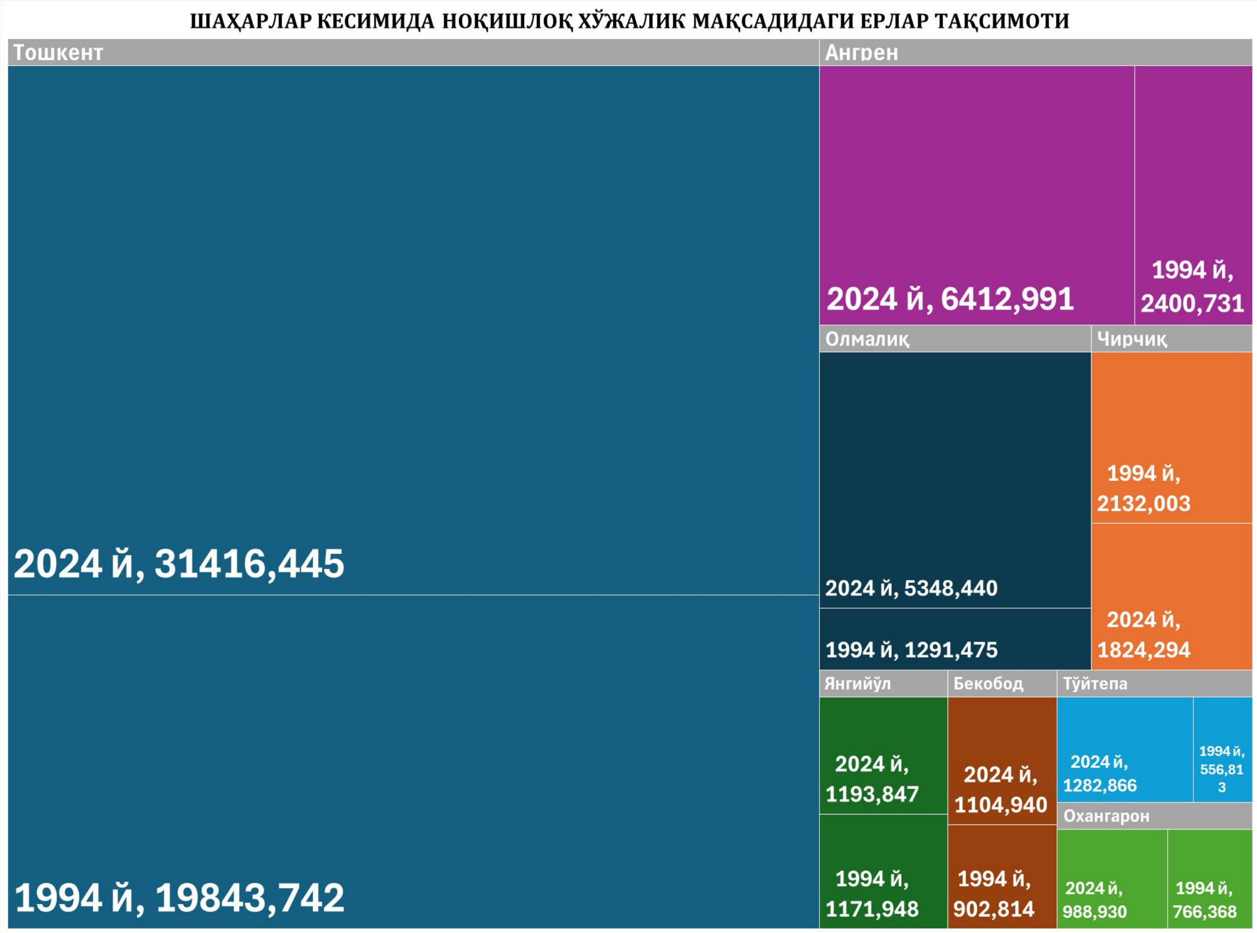

Figure 5. Infographic of built-up areas in cities and towns in Tashkent region and Tashkent city

Across the cities of Tashkent region and Tashkent city, the area covered by buildings and structures has increased sharply over the past 30 years (1994–2024). In 1994, built-up areas covered more than 29,000 hectares, whereas today this figure has reached approximately 49,500 hectares (Figure 19).

The zones occupied by buildings and infrastructure are marked as “red zones”, indicating areas with potential environmental risks associated with residential and industrial activities. In contrast, green zones are designated as areas that provide oxygen, shade, and help reduce surface heat, thereby improving the local microclimate.

Water bodies were analyzed as key resources supporting vegetation growth and reflecting the availability of water resources within the study area during the research period. The remaining areas—bare lands and agricultural lands—were classified as zones with minimal environmental impact on the microclimate. Bare lands were considered neutral areas that neither significantly improve nor worsen urban climatic conditions. Agricultural fields, on the other hand, can contribute to dust generation, but during the growing season, they compensate for this effect through oxygen production by vegetation [5].

Conclusion

1. According to the conducted analysis, from 1994 to 2024, the urban infrastructure of Tashkent region and Tashkent city has developed significantly.

2. The development has mainly occurred due to industrial expansion, which has led to the disruption of ecological balance.

3. The area of forested lands has decreased, especially within residential zones, where the proportion of green areas has declined sharply.

4. The reduction of vacant and agricultural lands is associated with industrialization processes, resulting in the loss of natural landscapes.

5. Measures taken to ensure environmental sustainability (if any) have not been sufficiently effective, leading to a deterioration in the state of the environment.

6. Tashkent city accounts for the largest proportion of built-up areas, representing approximately 63% of the total urbanized land.

7. Ohangaron city, on the other hand, has the smallest proportion of built-up areas among the analyzed cities

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