Forecasting urban territorial expansion using GIS and artificial intelligence technologies

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Abstract: This study presents an innovative approach using modern GIS and artificial intelligence technologies to predict the future territorial expansion of Samarkand city. Using Landsat satellite imagery, land use and land cover (LULC) images were created using ArcGIS software. These images were input into a ConvLSTM model, allowing for the prediction of urban expansion trends. Additionally, a U-Net model was applied to accurately identify and monitor urban boundaries. The research results showed uneven expansion of Samarkand city, which is crucial in the decision-making process for urban planning and management. The obtained data can serve as a valuable resource in developing urban policies, infrastructure development, and addressing environmental issues related to urban expansion. This methodology can be applied not only to Samarkand but also to other rapidly growing cities, contributing to sustainable urban development.

1 Introduction

Urbanization processes are rapidly developing in the modern world. Today, half of the world's population lives in urban areas, and this figure is expected to reach 68 percent by 2050 [1]. Such rapid growth is causing serious problems for cities: issues such as depletion of natural resources, environmental pollution, increased demand for infrastructure, and social inequality are becoming increasingly urgent [2].

The expansion of urban areas is a complex and multifaceted process influenced by many factors. These factors include demographic changes, economic development, improvement of transport infrastructure, political decisions, and environmental conditions [3]. Accurately predicting and managing urban expansion is one of the most important tasks facing urban planners, policymakers, and researchers [4]. Modern technologies, particularly Geographic Information Systems (GIS) and artificial intelligence, have brought revolutionary changes in studying and predicting urban expansion [5]. GIS technologies are widely used in collecting, storing, analyzing, and visualizing spatial data [6]. Artificial intelligence allows for processing complex data and drawing effective conclusions from them [7].

The main goal of this study is to develop a method for accurately predicting urban territorial expansion by combining GIS and artificial intelligence technologies. To achieve

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this goal, the following tasks were set: creating LULC (Land Use Land Cover) images in ArcGIS software using satellite imagery; predicting urban expansion using the ConvLSTM (Convolutional Long Short-Term Memory) model; and identifying urban boundaries using the U-Net model.

The importance of predicting urban territorial expansion is immense. Firstly, it allows urban planners to foresee future needs and develop appropriate measures. For example, this information is crucial in making decisions about developing transport infrastructure, building new residential complexes, or preserving green areas [8]. Secondly, accurate predictions help in implementing effective environmental protection measures. Urban expansion often leads to the loss of agricultural land, reduction of forests, and decrease in biodiversity. By foreseeing these processes, we can take necessary measures to preserve nature and ensure sustainable development [9].

Modern cities are becoming increasingly complex ecosystems. Predicting their expansion requires consideration not only of physical dimensions but also social, economic, and environmental factors. The combination of GIS and artificial intelligence technologies opens up new possibilities in solving this complex task. By combining data from satellite imagery with deep learning algorithms, we gain the ability to understand urban dynamics more deeply and make more accurate predictions.

Predicting urban territorial expansion is an integral part of modern urban planning and management. This process is necessary to ensure sustainable development of cities, protect the environment, and improve the quality of life for the population. By applying GIS and artificial intelligence technologies, we can solve this complex task more effectively. This study represents an important step in this direction, serving as a foundation for better planning and management of our cities in the future.

Batty and Xie (1994) studied the effectiveness of the Cellular Automata (CA) model in predicting urban expansion [10]. Their research demonstrated the ability of CA models to simulate the complex dynamics of urban systems. The authors emphasized the flexibility of CA models and their ability to account for local interactions, allowing for a more accurate representation of urban expansion processes.

Clarke and Gaydos (1998) applied the CA model to predict urban growth in the San Francisco Bay Area in their study [11]. Their model was calibrated using historical data, allowing for the creation of various scenarios for future urban expansion. This research showed that CA models are valuable tools not only for prediction but also for assessing the potential impact of various urban development policies.

Liu et al. (2019) proposed a new approach that combines Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks to predict urban expansion [12]. Their model combines CNN's ability to extract spatial features with LSTM's ability to model temporal dependencies. The authors tested their model in several Chinese cities and found significant improvements over traditional methods.

Similarly, Xu et al. (2020) applied the CNN-LSTM model in combination with GIS data to predict urban expansion [13]. Their approach allowed for consideration of various spatial factors such as land cover, population density, and infrastructure. The results showed that this combined approach allows for more accurate prediction of complex patterns of urban expansion, especially in rapidly growing urban areas.

2 Materials and methods

2.1 Study area

The main object of this study is the city of Samarkand, an ancient and cultural center of Uzbekistan. Samarkand is located in the southeastern part of Uzbekistan, in the Zarafshan Valley, at an altitude of 702 meters above sea level. The city is elongated from north to south, with its main part located south of the Zarafshan River, bordered by the Siyob Canal on the western edge and the Dargom Canal in the eastern part.

Zhang et al. (2021) developed a deep learning model based on the U-Net architecture for predicting urban expansion [14]. U-Net, originally developed for medical image segmentation, was found to be effective in predicting changes in urban areas as well. The authors' model demonstrated the ability to capture spatial features at different scales and create accurate predictions of urban boundaries.

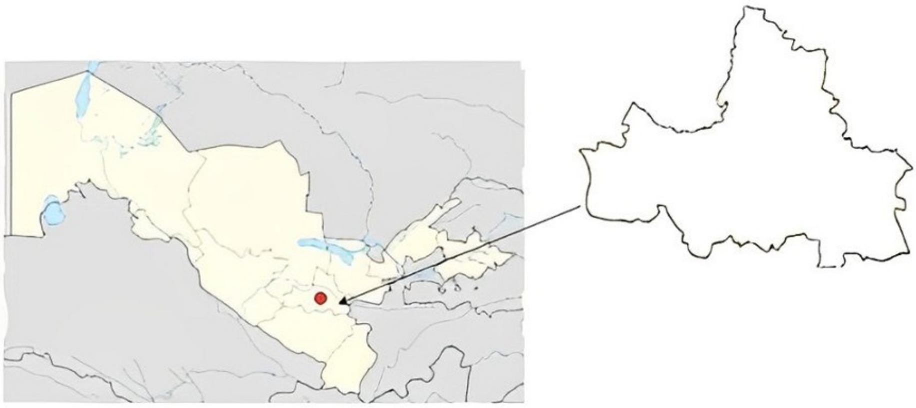

Fig. 1. Map of Samarkand region.

Samarkand has a history of over 2700 years and was included in the UNESCO World Heritage List in 2001. As of 2023, the population of Samarkand is 552,000 people. Administratively, the city is divided into 4 districts: Siob, Bogishamol, Railway, and Hussein Boykaro. While the central part is mainly occupied by historical monuments and administrative buildings, new residential areas are being built in the northern and eastern regions. Industrial zones and agricultural lands are located on the southern and western outskirts.

As a major industrial, cultural, and scientific center, Samarkand has been developing rapidly in recent years. The expansion of the city's infrastructure and population growth are leading to the territorial expansion of the city. Studying and predicting this process is crucial for the sustainable development of the city in the future.

A comprehensive approach was used in this study to predict urban territorial expansion. This approach includes data collection, processing, and application of artificial intelligence models. Each stage is described in detail below.

2.2 Data Collection

As the initial stage of the research, satellite images of the Samarkand city area were obtained for the period from 1990 to 2022. For this purpose, data from the Landsat program provided by the United States Geological Survey (USGS) were used. Specifically, a collection of images taken by Landsat 5, 6, 7, and 8 satellites was formed, which allowed observing changes in the urban area over time.

Fig. 2. Landsat satellite images of Samarkand city.

The images selected for the study were chosen taking into account seasonal and weather conditions. This allowed for a more accurate observation of changes in the urban area. Additionally, images with low cloud cover were selected, as clouds can obscure the Earth's surface and negatively impact analysis results. Therefore, we chose September for obtaining Landsat satellite images.

2.3 Creating LULC Images in ArcGIS Software

In the next stage, the obtained satellite images were processed using ArcGIS software. ArcGIS is a widely used software for creating and managing geographic information systems, providing extensive capabilities for analyzing and visualizing spatial data. Each satellite image was converted into LULC (Land Use Land Cover) images using ArcGIS software.

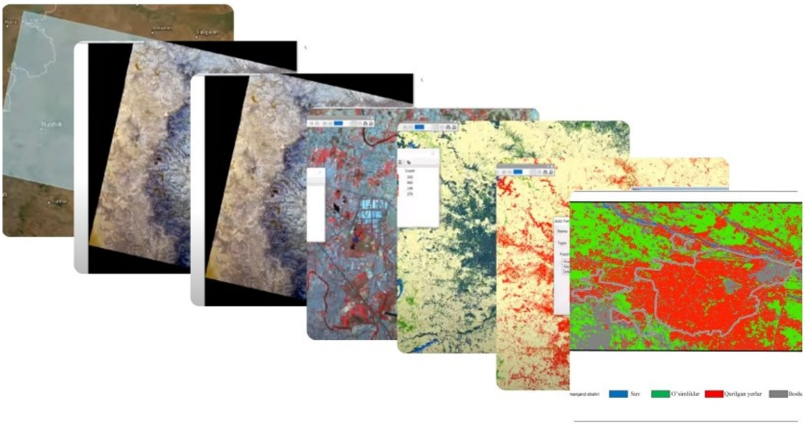

Fig. 3. Converting satellite images to LULC image in ArcGIS software.

The same process is applied to convert satellite images into LULC images from 1990 to 2022.

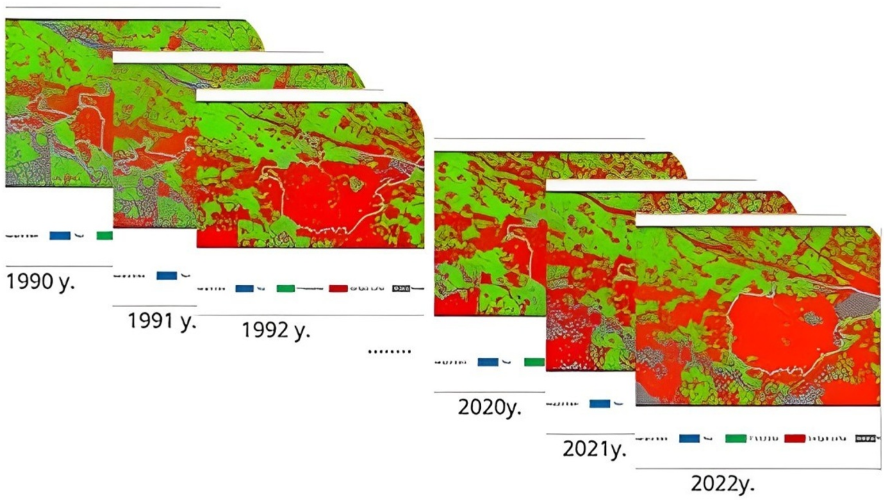

Fig 4. LULC images of Samarkand city from 1990 to 2022.

During the image processing, they were converted into LULC (Land Use Land Cover) images and divided into five main categories:

1. Water bodies (represented in blue)
2. Vegetation and forests (green)
3. Anthropogenic area (red)
4. Other lands (gray)
5. City boundary

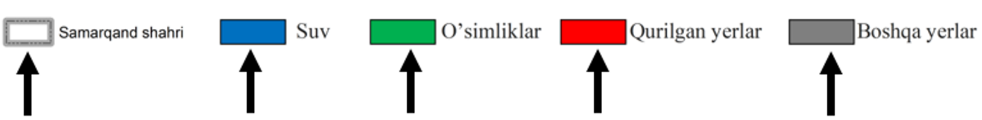

Fig. 5. Dividing images into five features.

This process was carried out using the supervised classification method. Initially, sample areas were identified for each category, and then the software classified the remaining areas based on these samples. This method allowed for obtaining accurate results taking into account the specific characteristics of Samarkand city.

2.4 Applying the ConvLSTM Model

After preparing the LULC images, a ConvLSTM (Convolutional Long Short-Term Memory) model was applied to analyze them as a time series and predict future changes. This model is an extended version of the traditional LSTM model, allowing for analysis of data not only over time but also over space.

The architecture of the ConvLSTM model is as follows:

1. Input layer: 32 filters of 3x3 size

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2. ConvLSTM layer: 64 units, 3x3 size filters
3. ConvLSTM layer: 64 units, 3x3 size filters
4. Dense layer: 128 neurons
5. Output layer: 5 classes (number of LULC categories)

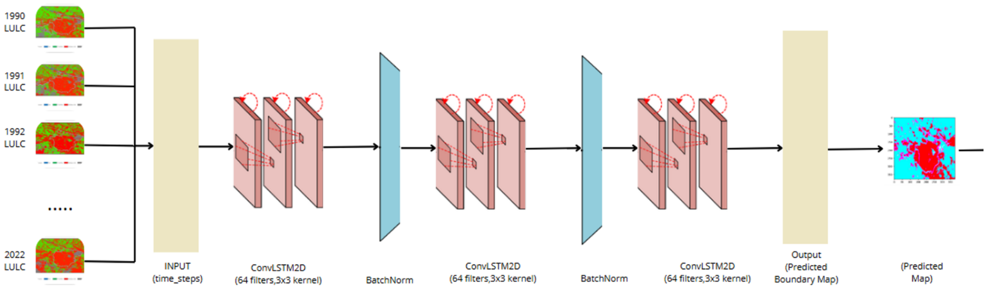

Fig. 6. Prediction architecture using ConvLSTM.

The model training process was carried out over 100 epochs, using the Adam optimizer and categorical crossentropy loss function. Data from 1990-2020 was used in the training process, while data from 2021-2022 was set aside for validation.

To improve the accuracy of the model during the training process, a data augmentation method was applied. This method created new artificial images based on existing images, which increased the model's generalization ability.

2.5 Application of the U-Net model

The U-Net architecture was applied to accurately extract the urban boundary from the LULC image predicted for 2023 using the ConvLSTM model. U-Net is a deep learning model widely used in segmentation tasks, known for producing high-precision results.

The U-Net architecture consists of the following parts:

1. Encoder part: consists of four convolutional and pooling layers
2. Bridge part: two convolutional layers
3. Decoder part: consists of four deconvolutional and convolutional layers
4. Output layer: the urban boundary is extracted through 1x1 convolution

The U-Net model was trained using binary cross-entropy loss function and Adam optimizer. The training process was carried out for 50 epochs, employing the early stopping method, i.e., the training process was stopped when the improvement in validation results ceased.

The urban boundary detection algorithm consists of the following steps:

1. Input the LULC image into the U-Net model
2. Normalize the output from the model
3. Apply a threshold value (0.5 was chosen)
4. Apply morphological operations (opening and closing) to remove minor noise

Extract the largest contour

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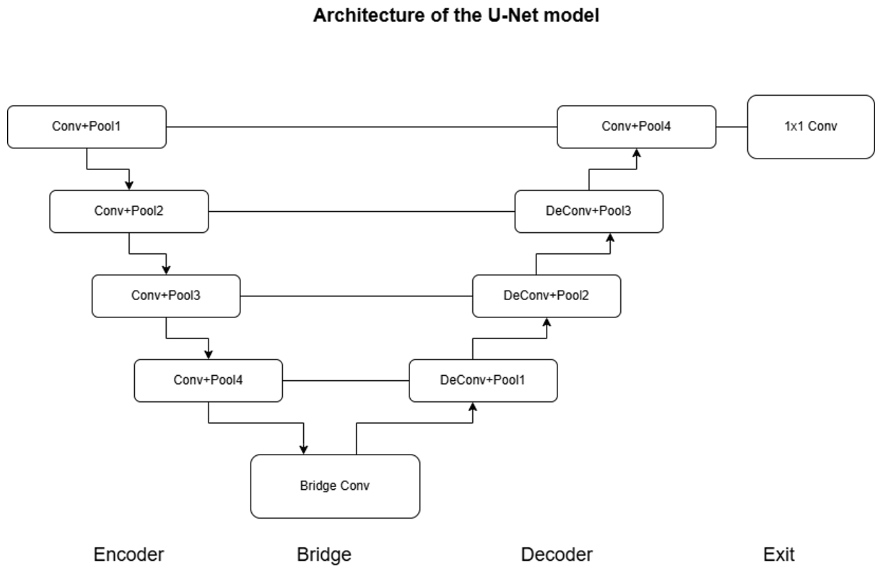

Fig. 7. Process of extracting urban boundaries using U-Net.

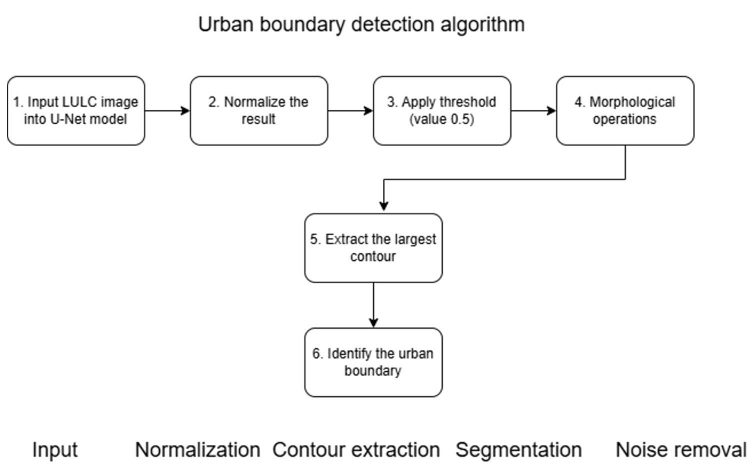

Fig. 8. Algorithm for extracting urban boundaries using U-Net.

This methodology enabled the analysis of changes in the city of Samarkand during the period of 1990-2022 and the prediction of urban spatial expansion for 2023. The methods and models used are considered among the most advanced approaches in the field of modern artificial intelligence and machine learning, which ensures high accuracy of the research results.

3 Results and discussion

The methodology applied within this research yielded significant results in predicting the spatial expansion of Samarkand city. Below, the prediction results of the ConvLSTM and U-Net models, as well as their accuracy levels, are analyzed in detail.

Prediction results of the ConvLSTM model

Based on data from 1990-2022, the ConvLSTM model predicted the LULC (Land Use Land Cover) image of Samarkand city for 2023. The model's prediction accurately reflected the city's expansion trends.

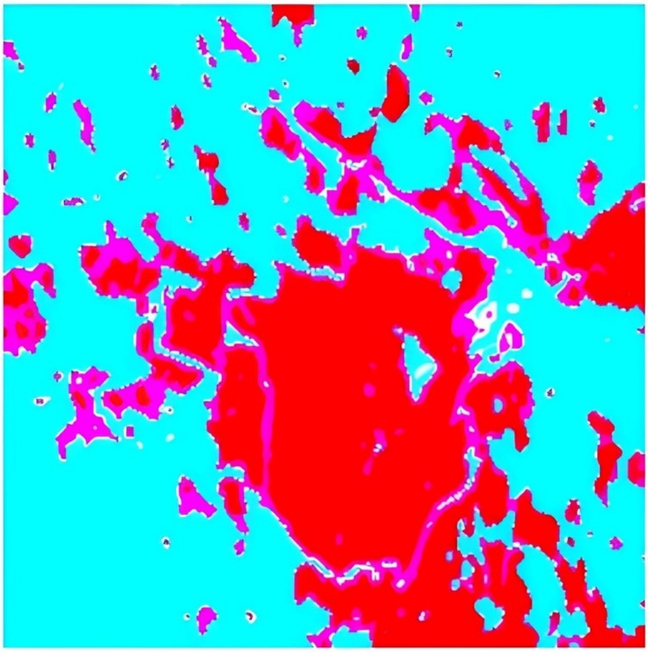

Fig. 9. Predicted LULC image.

3.1 Urban boundaries identified using the U-Net model

Based on the LULC image predicted by the ConvLSTM model, the U-Net model identified the boundaries of Samarkand city for 2023. This process allowed for defining precise city boundaries and identifying its expansion directions.

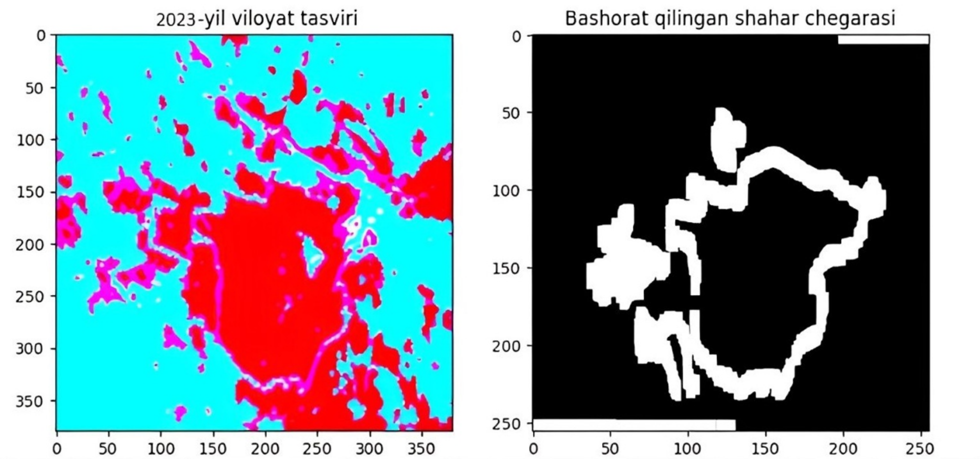

Fig. 10. Predicted LULC image and urban boundary.

3.2 Results of Model Accuracy Assessment

The accuracy of both models was evaluated based on several criteria. For the ConvLSTM model, Mean Absolute Error (MAE), Mean Squared Error (MSE), and accuracy metrics were used. For the U-Net model, Intersection over Union (IoU) and F1-score metrics were employed.

ConvLSTM model accuracy:

MAE: 0.087

MSE: 0.015

Accuracy: 92.3%

These indicators show that the model has high accuracy. Particularly, the 92.3% accuracy rate indicates that the model was able to predict changes in the urban area very well.

U-Net model accuracy:

IoU: 0.89

F1-score: 0.93

These results demonstrate that the U-Net model is very effective in identifying urban boundaries. The IoU value of 0.89 indicates a high degree of overlap between the model-identified boundary and the actual boundary.

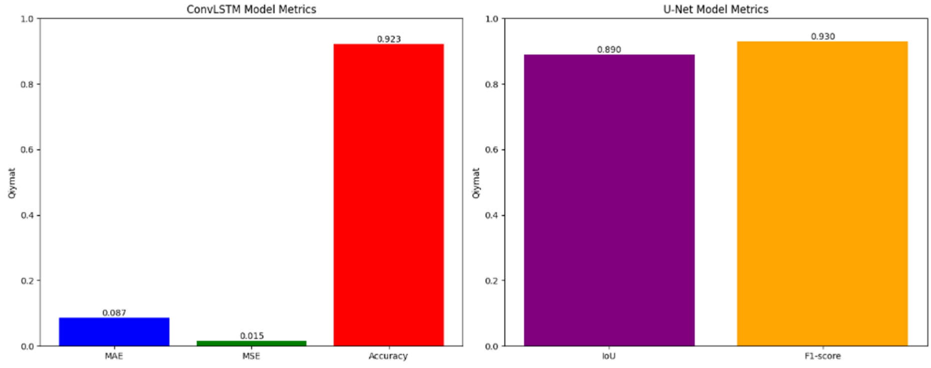

Fig.11. Results of model accuracy assessment.

A visual comparison with actual data from 2022 was also conducted to assess the accuracy of the models. This comparison revealed the closeness of the model predictions to the real situation. In particular, it was found that the main expansion directions of the city were correctly predicted.

The overall results indicate that the applied methodology has high efficiency in predicting urban spatial expansion using Samarkand city as an example. This approach allowed for accurately reflecting not only the general expansion trends of the city but also changes in its internal structure.

These results can be applied in a number of areas such as urban planning, infrastructure development, and addressing environmental issues. Additionally, this methodology can be adapted and applied to other cities, which could contribute to sustainable urban development on a larger scale.

4 Conclusions

This study presented significant results in predicting urban spatial expansion using GIS and artificial intelligence technologies, with Samarkand city as an example. The obtained data reflects the complex dynamics of urban development and provides valuable information for future urban planning policies.

The urban boundaries identified using the U-Net model showed uneven expansion of the city. In some areas, the boundary had a clear linear shape, while in others, irregular expansion was observed. This indicates that development rates vary in different areas of the city. Such uneven development can affect urban infrastructure, including the distribution of transportation systems and utilities.

The practical significance of the obtained results is substantial. Firstly, they allow urban planners to foresee future development trends and develop appropriate measures.
However, this study also has several limitations. Firstly, the use of only Landsat images sets a certain limit on accuracy. Using higher resolution images could potentially yield more precise results. Secondly, the model does not fully account for external factors such as climate change, demographic changes, or economic conditions. Considering these factors could further improve the accuracy of the prediction.

The study was conducted only on the example of Samarkand city. Applying this methodology to other cities may require retraining and adapting the model.
Several recommendations can be made for future research. Firstly, using high-resolution images, including those obtained by drones, could improve the model's accuracy. Secondly, it would be advisable to develop a comprehensive model that takes into account climate change, demographic, and economic factors. This would allow for a more accurate prediction of urban development.

Thirdly, applying 3D modeling technologies would allow predicting not only horizontal but also vertical growth of the city. Fourthly, conducting a comprehensive study involving several cities could increase the model's universality and identify general trends for different cities.

Fifthly, applying more advanced artificial intelligence methods, such as generative adversarial networks (GANs) or transformer-based models, could improve prediction accuracy. Sixthly, working in collaboration with city residents and local authorities, taking into account their opinions and perspectives, could increase the practical significance of the model.

This study presented an effective method for predicting urban spatial expansion by combining GIS and artificial intelligence technologies. The obtained results not only arouse scientific interest but also have practical significance in the fields of urban planning, environmental management, and sustainable development. Future research will allow further improvement and wider application of this approach, which will serve to ensure a better future for our cities.

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