

PREDICTING GROUNDWATER LEVEL CHANGES USING AN ARTIFICIAL INTELLIGENCE MODEL

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Abstract. This study analyzes the annual dynamics of surface water bodies using multi-platform satellite remote sensing data and links these changes to the depletion of groundwater reserves. Among transformer-based architectures, the SegFormer model was selected and trained on surface water imagery from the period 2020–2025. The model identified a linear decreasing trend in surface water extent and predicted a further decline in groundwater storage by 2026. The results indicate that total water resources decrease by 19.6% over 2020–2025 and by 23.9% by 2026 relative to 2020, with an expected average annual reduction rate of approximately 3.9%.

Keywords: transformers, SegFormer, remote sensing imagery, geology, hydrology, hydrogeology.

ПРОГНОЗИРОВАНИЕ ИЗМЕНЕНИЙ УРОВНЯ ПОДЗЕМНЫХ ВОД С ИСПОЛЬЗОВАНИЕМ МОДЕЛИ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

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Аннотация. В данном исследовании анализируется ежегодная динамика поверхностных водоемов с использованием данных дистанционного зондирования со спутников на различных платформах и устанавливается связь этих изменений с истощением запасов подземных вод. Среди архитектур на основе трансформеров была выбрана модель SegFormer, обученная на изображениях поверхностных вод за период 2020–2025 годов. Модель выявила линейную тенденцию к уменьшению площади поверхностных вод и предсказала дальнейшее снижение запасов подземных вод к 2026 году. Результаты показывают, что общие водные ресурсы сократятся на 19,6% в период 2020–2025 годов и на 23,9% к 2026 году по сравнению с 2020 годом, при ожидаемом среднем ежегодном темпе сокращения примерно на 3,9%.

Ключевые слова: трансформаторы, SegFormer, данные дистанционного зондирования, геология, гидрология, гидрогеология.

Introduction. Groundwater remains a primary source of water in many parts of the world, enabling irrigation and supporting rural socio-economic activities. Serving as the lifeblood of numerous ecosystems, it plays a vital role in the lives of billions of people globally. Groundwater is essential for hydrological processes, water resource management, environmental sustainability, and adaptation to climate change. It has a particularly profound impact on the ecosystems of the regions under study, therefore necessitating a deep understanding of its dynamics.

The dynamics of changes in groundwater storage are of great significance in hydrology, as they affect the availability, quality, and sustainability of this resource. Furthermore, in the context of increasing anthropogenic activities and the impacts of climate change, an accurate and comprehensive assessment of groundwater storage variations is crucial for effective water resource management and climate adaptation strategies. Our research focus is the Tashkent region. In this study, groundwater monitoring is conducted based on hydrogeological images obtained through remote sensing methods, and recommendation systems are developed for the rational use of natural resources [4].

In recent years, Transformer architectures have demonstrated effective results in high-precision segmentation of natural environment imagery. Previous studies have primarily focused on the segmentation of surface water sources, while the correlation with changes in groundwater reserves has not been sufficiently explored [3]. Based on this, we first conduct an analysis of image segmentation models.

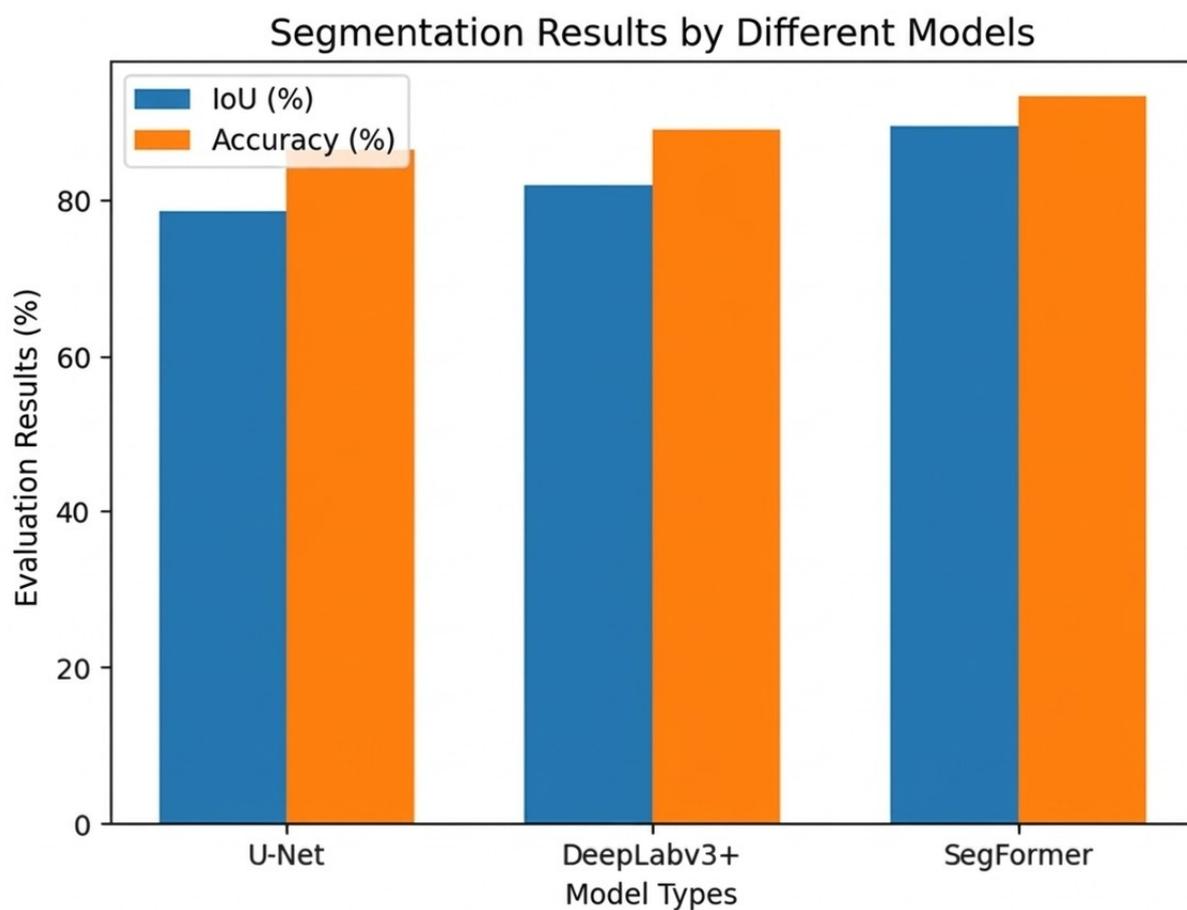


Figure 1. Comparative analysis of Transformer models

The obtained results show that the SegFormer model achieved higher accuracy in determining the volume of surface water reserves from remote sensing imagery compared to the U-Net and DeepLabv3+ models [1]. Based on the analysis of the models, as a result of analyzing the sharp decrease in surface water reserves using SegFormer-B0, it is possible to predict the depletion of groundwater in these and adjacent areas [5].

Table 1. Comparative analysis of Transformer models by accuracy

Model	IoU (%)	F1-score	Accuracy (%)
U-Net	76.5	0.81	83.2
DeepLabv3+	80.7	0.81	89.3
SegFormer-B0 (bizning)	87.3	0.89	93.2

In our research, based on the analytical results, we utilize the SegFormer model to achieve high accuracy in processing remote sensing imagery. The SegFormer (Segmentation Transformer) model is a neural network architecture primarily consisting of two parts, each with its own mathematical representation [2]. Its objective is to perform Semantic Segmentation, which involves assigning each pixel of an image to a corresponding class. The mathematical model of SegFormer is mainly represented through the functions of its two core modules: the Mix Transformer (MiT) Encoder (Hierarchical Transformer Encoder) and the Lightweight All-MLP Decoder (Multi-Layer Perceptron Decoder). The encoder divides the image into 4 x 4 overlapping patches [6]. This process can be implemented using Convolution.

$$P_i = \text{Norm}(\text{Conv}(I_i)) \quad (1)$$

Here, P_i is the image patch at stage i , and $f(K=7, S=4)$ is the function with kernel size $K=7$ and stride $S=4$. As a result, a sequence of tokens is generated. In other transformers, the computational complexity of the Self-Attention mechanism is very high, specifically $O(N^2C)$. Here, N is the number of tokens and C is the channel dimension. To reduce complexity, SegFormer utilizes a special mechanism that shortens the sequence length of the K (Key) and V (Value) matrices (Sequence Reduction):

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_{\text{head}}}}\right)V \quad (2)$$

Efficient Self-Attention (SRA) in SegFormer: The K and V matrices are reduced to K' and V' , where R is the reduction ratio:

$$K' = \text{Linear}(\text{Reshape}(K, R)) \quad (3)$$

The $\text{Reshape}(K, R)$ function transforms K into a new sequence with a length of N/R (or this can be implemented using 2D convolution). Thus, SRA is calculated as follows:

$$\text{SRA}(Q, K, V) = \text{Softmax}\left(\frac{Q(K' \dots T)}{\sqrt{d_{\text{head}}}}\right)V' \quad (4)$$

This reduces the computational complexity to $O(N^2C/R)$. In the next stage, the Mix-FFN (Mix Feed-Forward Network) is implemented. The Mix-FFN in SegFormer does not use Positional Encoding. Instead, to process positional information, it introduces a 3x3 Depthwise Convolution into the standard FFN (Feed-Forward Network) layer:

$$F_{out} = MLP(DW Conv_{3 \times 3}(GELU(MLP(F_i)))) + F_i \quad (5)$$

Here, F_{in} is the input feature, MLP is the Multi-Layer Perceptron (Linear Layers), GELU is the activation function, and DWConv 3x3 is the 3x3 depthwise convolution. Using the results obtained from the expressions above, the decoding process is performed. The purpose of the Decoder is to combine features of various scales obtained from the encoder and produce a segmentation mask at the pixel level. In the next stage, Feature Alignment and Upsampling are carried out. Features at each scale, F_i , are first projected to a common channel dimension C , and then all features are brought to the same size as the highest-resolution feature (i.e., $H/4 \times W/4$). In Channel Projection, each feature F_i is transformed to the common channel dimension C .

$$\hat{F}_i = Linear_{C_i \rightarrow C}(F_i), \forall i \in \{1, 2, 3, 4\} \quad (6)$$

Upsampling: All new features are brought to the same spatial dimension as \hat{F}_1 (i.e., $\frac{H}{4} \times \frac{W}{4}$) bilan bir xil fazoviy o'lchamga keltiriladi.

$$\hat{F}_i^{up} = Upsample_{\frac{H}{4} \times \frac{W}{4}}(\hat{F}_i), \forall i \in \{2, 3, 4\} \quad (7)$$

In the above formula, \hat{F}_1^{up} is equal to \hat{F}_1 . After the alignment and upsampling stage, we perform Feature Fusion to combine the features. All upsampled features are concatenated and filtered through another Linear Layer [8]:

$$F = Linear_{4C \rightarrow C}(Concat(\hat{F}_1^{up}, \hat{F}_2^{up}, \hat{F}_3^{up}, \hat{F}_4^{up})) \quad (8)$$

In the next stage, we perform Segmentation Mask Prediction. The final fused feature F is transformed into a channel dimension of N_{cls} (Number of classes) through another linear projection. This function provides the class probabilities for each pixel:

$$M = Linear_{C \rightarrow N_{cls}}(F) \quad (9)$$

Here, $M \in R^{\frac{H}{4} \times \frac{W}{4} \times N_{cls}}$ represents the mask. Based on the segmentation model, the S(.) function produces the segmentation mask M based on the input image I :

$$M = Decoder(Encoder(I)) \quad (10)$$

To obtain the final segmentation mask, after applying the Softmax function, the spatial dimension of M is upsampled to the original image size $H \times W$ using Bilinear/Nearest-Neighbor Interpolation.

$$M_{final} = Upsample_{H \times W}(M)$$

In the formula above, M_{final} is equal to $S(\cdot)$.

1. Selected model architecture.

Transformers were originally created to solve Sequence2Sequence problems such as text generation and translation. The Transformer model, which utilizes self-attention together with encoder and decoder blocks, is a new generation approach developed to transform sequences into other sequences [9].

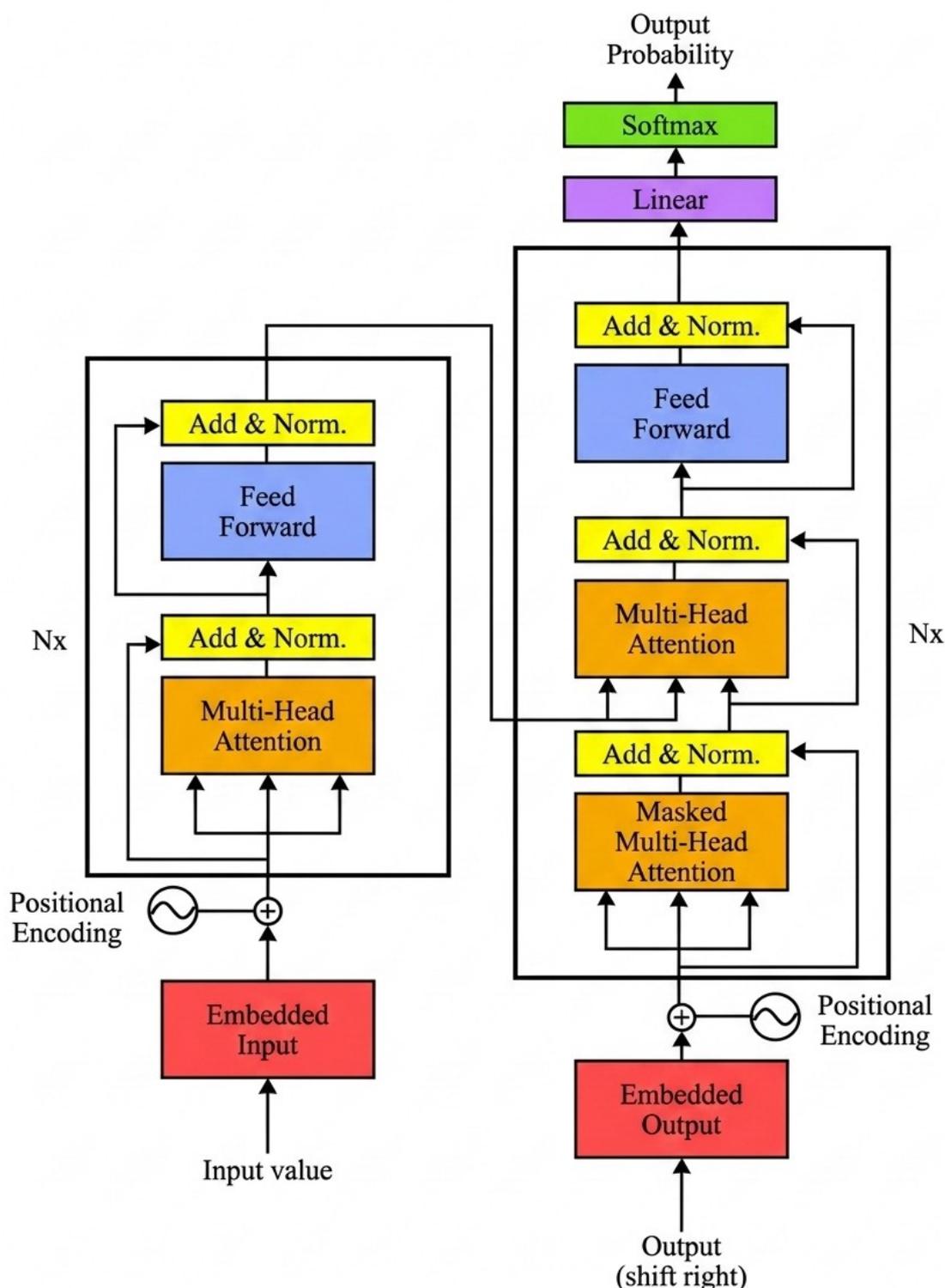


Figure 2. General architecture of Transformers

Based on this architecture, we will construct the SegFormer architecture. This represents a modern architecture designed to transform one sequence into another using an encoder and decoder, integrated with the self-attention mechanism.

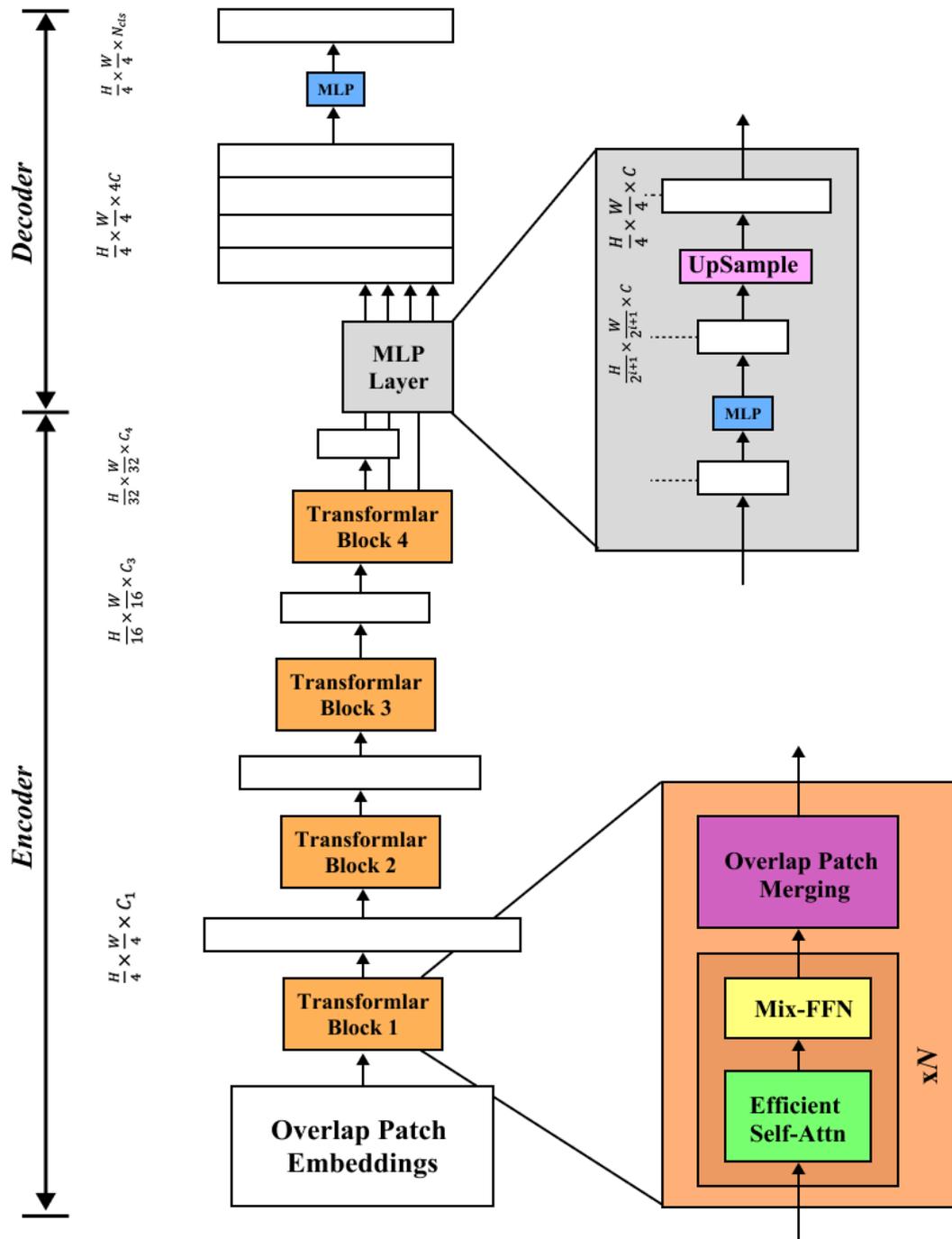


Figure 3. SegFormer architecture

Its architecture has the appearance shown above (Figure 3). The architecture is based on a transformer architecture with Encoder-Decoder heads, where the encoder utilizes Self-Attention.

1. Results obtained based on the model.

Based on the results of the analysis, it can be seen that the accuracy of the SegFormer model is high. Therefore, using the SegFormer model, we will perform the prediction of groundwater changes based on images of surface water reserves. In the research work, the parameters of the transformer model are configured to obtain results. In this process, we use 3200 images obtained from the Tashkent region, and in the first stage, we separate suitable images as a result of image processing.

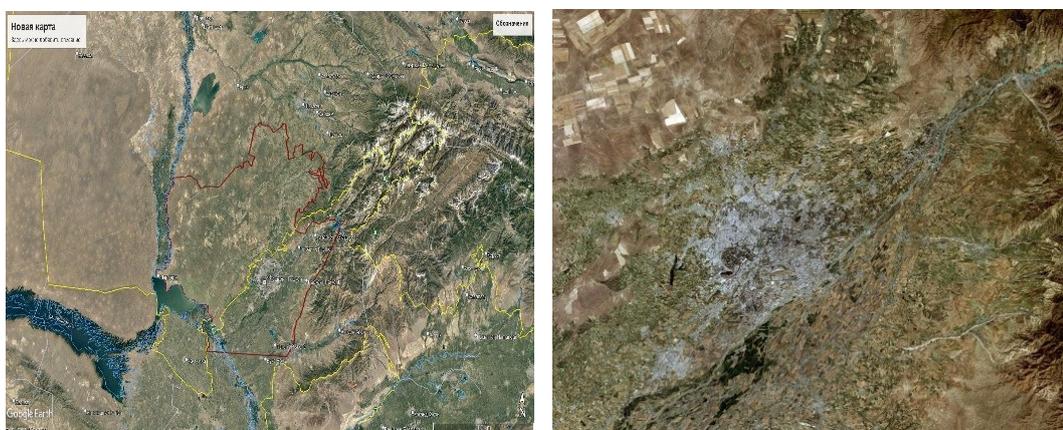


Figure 4. Remote sensing imagery of the areas around Tashkent (dataset)

Based on the images above, images of surface water reserves and the volume of flowing water have been obtained across several years. Using this data, the decrease in water reserves from year to year is analyzed, and its impact on groundwater is predicted. For this purpose, we utilize the aforementioned SegFormer model. The model parameters are configured as follows: to optimize the model, we use the AdamW Optimizer; for error evaluation, CrossEntropyLoss; with a Batch size of 8 and Epoch of 100. The evaluation metrics are F1-score and Accuracy [12].

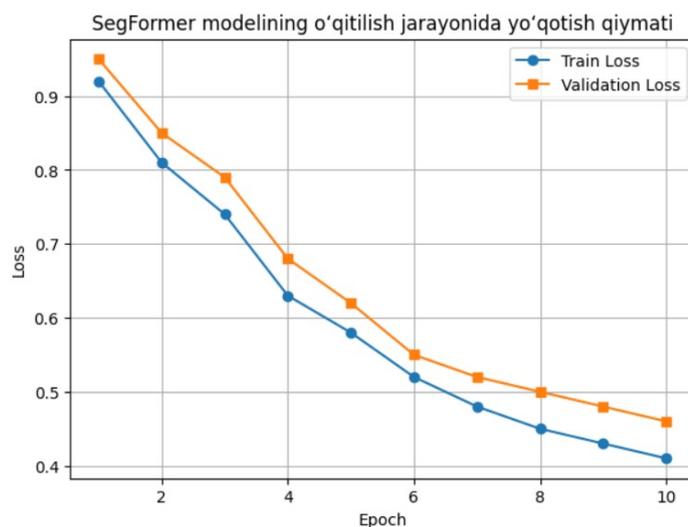


Figure 5. Image training losses

As can be seen from the graph, the loss values during the training and validation processes are steadily decreasing. This indicates that the convergence of the model is good. The results show that the areas where water layers are located have been accurately segmented. Based on the trained model, we predict the state and impact of the changes in surface water body images across various years on the levels of groundwater.

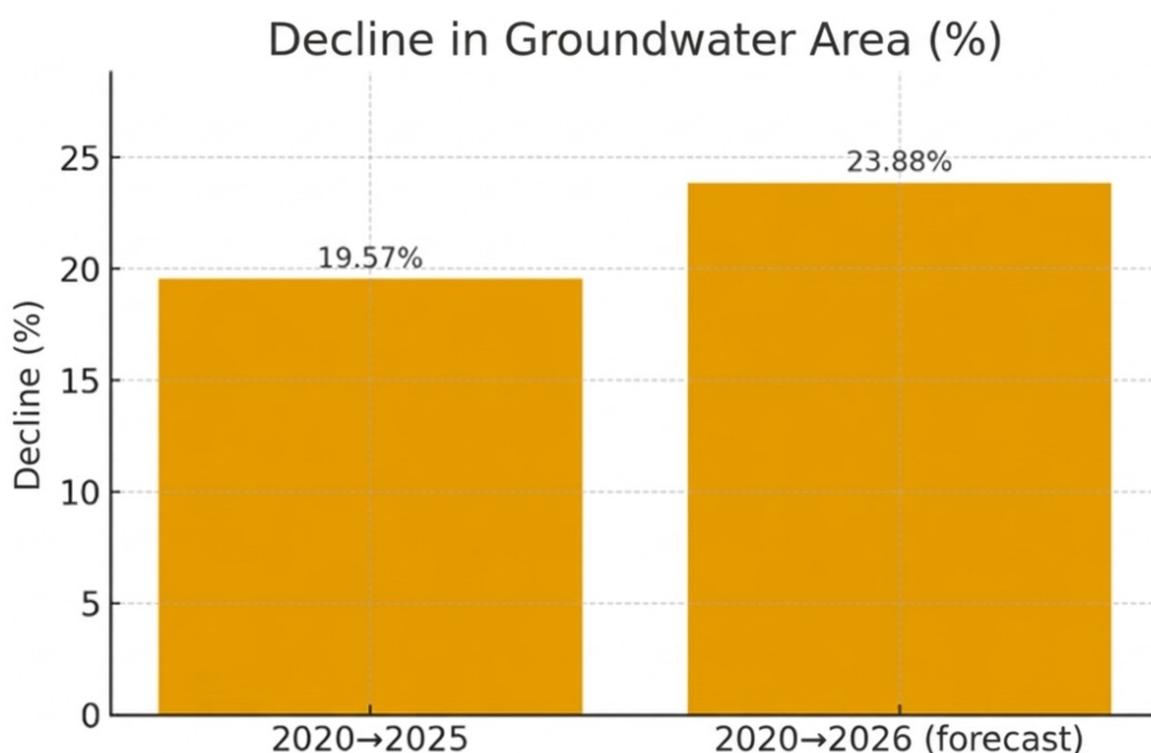


Figure 6. Predicting the decline of groundwater over several years (%)

The following results were achieved through forecasting. In 2022, the water area amounted to 512.4 km², and in 2025, the water area will be 412.1km². Based on these results, we perform a SegFormer-based prediction for the year 2026 for 390.05 km², and calculate the total decrease between 2020 and 2025. In this case, a decrease of 19.57 % can be observed. The total decrease in 2020-2026 is equal to 23.88 %. The average annual decrease might correspond to 3.915 %.

Conclusion. In this research, determining the state of groundwater resources and forecasting for future years was carried out by analyzing images obtained through remote sensing based on the SegFormer model. During the research, images between the years 2020 and 2025 were analyzed, a linear trend of water area changes was determined, and the decrease of groundwater reserves for the year 2026 was predicted. In 2020, the area of the water-covered region amounted to 512.4km², and in 2025, it was 412.1 km². According to the SegFormer model's linear forecast for the year 2026, the area is predicted to decrease to 390.05 km². These results show a decrease of 19.6% between 2020 and 2025, and 23.9% until 2020-2026. The average annual decrease rate is around 3.9%. In them, a significant reduction in water-filled zones was observed in the transition from 2025 to 2026, with an increase in land area. This situation is probably related to the decrease in the amount of precipitation, the increase in temperature, and the disruption of the natural balance of groundwater. The obtained results indicate that the SegFormer model has high potential for application in geological, hydrological, and hydrogeological monitoring systems.

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