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DELINEATION OF AGRICULTURAL FIELD BOUNDARIES USING MACHINE LEARNING: BASED ON THE CASE OF THE ZHETYSAI DISTRICT, KAZAKHSTAN

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Abstract: Accurate delineation of agricultural field boundaries is essential for agro-production monitoring, irrigation management, and sustainable land use planning. Manual digitization is labour-intensive and poorly scalable, while conventional segmentation algorithms are sensitive to spectral heterogeneity and weak inter-field contrast. The Zhetysai district of southern Kazakhstan – where approximately 45-50% of irrigated farmland exhibits salinization – exemplifies the urgent demand for automated field mapping. This study evaluates the Meta AI Segment Anything Model (SAM) with Low-Rank Adaptation (LoRA) fine-tuning as a parameter-efficient, scalable approach to automated field boundary delineation. High-resolution Esri World Imagery served as the primary data source. A training dataset of 705 manually digitized field polygons was prepared in ArcGIS Pro and exported as classified tiles. SAM – pre-trained on over one billion masks – was fine-tuned via the SAMLoRA architecture, which freezes the Vision Transformer encoder and trains only lightweight adapter layers, enabling efficient domain adaptation from limited annotations. The model was trained on a CUDA GPU with early stopping, then applied district-wide to generate a pixel classification raster, which was vectorized into closed field polygons and validated through expert visual inspection. Fine-tuning achieved 91% overall pixel accuracy on the validation subset. Applied to the full study area, the model delineated 4,060 field polygons covering 809.76 km^2. Expert verification confirmed high boundary correspondence and negligible false positives. The results demonstrate that a foundation model can be effectively adapted to a new agrolandscape with minimal labelled data, yielding a reproducible and scalable geospatial workflow suitable for precision irrigation management, sown area assessment, and land resource governance across irrigated regions.

Keywords: field boundary delineating, segmentation, deep learning, satellite images, Segment Anything Model, pre-trained models

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INTRODUCTION

Delineating the boundaries of agricultural fields is a crucial task for monitoring agro-production, resource planning and ensuring food security (Zhang et al., 2021). Accurate field contours are necessary for calculating sowing areas, forecasting yields and managing reclamation efforts. In various applied tasks (for example, subsidy accounting and land management), the presence of reliable field boundaries serves as a primary condition. However, automatic segmentation of agricultural land into individual fields faces significant challenges. Firstly, manual digitization of fields from satellite images is labor-intensive and time-consuming (García-Pedrero et al., 2017). Secondly, heterogeneity of the spectral characteristics within a single field and the weak contrast between neighboring crops complicates the algorithmic delineation of boundaries (Zhang et al., 2021). Nevertheless, spatial analysis based on geoinformation technologies enables objective monitoring of large territories. Modern remote sensing (RS) tools and machine learning (ML) open up possibilities for regularly updating field maps and observing their condition in near real-time (Wang et al., 2022). This is especially relevant given the increasing demands for precise land use and control over agricultural resources.

Traditional and modern field segmentation methods. The task of automatically delineating field boundaries has been addressed using both classical image processing techniques and machine learning algorithms. Traditional approaches include boundary detection methods (such as Sobel, Canny operators, etc.) and image segmentation algorithms (for example, multi-scale segmentation, SLIC superpixels, watershed). These methods allow for the formation of field contours without the need for training on labelled data, but they require careful parameter tuning and are sensitive to noise - excessive "false" edges often degrade the accuracy of field delineation. Therefore, in recent years, greater

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attention has been paid to deep learning methods based on convolutional neural networks, capable of automatically extracting field features from satellite images (Wang et al., 2022). For example, García-Pedrero et al. (2017) proposed an agglomerative segmentation approach based on superpixels. The image is first divided into small homogeneous superpixels, after which the algorithm sequentially merges neighboring superpixels based on a classifier, effectively transforming the boundary segmentation task into a problem of determining which superpixels belong to the same field. Visual inspection has shown promising results for such automated field delineation in high-resolution satellite images of fragmented agro-landscapes (Zhang et al., 2021), confirming the potential of machine learning approaches for these tasks.

Segmentation of fields using deep neural networks. Modern research actively employs convolutional neural networks such as U-Net for semantic segmentation of fields in satellite data. Zhang et al. (2021) developed a comprehensive approach to automatic boundary delineation of fields using a modified U-Net architecture with recurrent residual blocks (R2U-Net). A key feature of their method was the automated generation of training data: instead of manual annotation of fields, a combination of edge detection (Canny operator) and watershed segmentation was used to quickly obtain field contours from the original image. This automation significantly reduced the labor costs associated with data preparation compared to traditional manual vectorization. The resulting semi-automatically generated labels were then used to train a deep segmentation network (recurrent residual U-Net) with the extraction of both low-level and high-level features of the fields. Additionally, a stage of post-processing of the network results was introduced to connect fragmented boundary segments. The proposed algorithm was tested on Sentinel-2 images of agricultural lands belonging to small farmers in Heilongjiang province (China) and demonstrated an improvement in accuracy compared to the basic U-Net and object-based image analysis: the overall accuracy reached 89.3%, and the kappa coefficient was 0.85. These results exceeded the accuracy of classical methods (standard U-Net 82%, OBIA 82%) and confirm the versatility of the R2U-Net model for boundary delineation of fields across different agro-landscapes (Zhang et al., 2021).

Other studies extend the capabilities of field segmentation by incorporating temporal and multispectral data. For example, Wang et al. (2022) used combined Sentinel-1 and Sentinel-2 data for mapping rice fields. They proposed a two-stage approach: first, high-resolution optical images are processed with a segmentation model U-Net (with a ResNet34 encoder) to extract the boundaries of agricultural fields, and then, using time series of radar images from Sentinel-1, they perform per-pixel classification of the delineated fields (identifying rice crops). The approach combines the advantages of spatial segmentation and pixel classification. According to the results, using the U-Net neural network with ResNet34 as the backbone architecture gave the best metrics: the Intersection over Union (IoU) for the field masks reached approximately 0.80, surpassing a simpler U-Net model. Ultimately, combining the field maps with a rice classification model allowed for the generation of a refined rice field map with an IoU of about 0.95, significantly improving accuracy compared to a purely pixel-based approach. In addition to the mentioned works, numerous other methods based on deep learning have emerged, aimed at improving the accuracy of boundary delineation.

For example, multi-task segmentation networks have been developed that simultaneously learn to segment the areas themselves and their boundaries. Long et al. (2022) proposed a lightweight BsiNet model with a single encoder-decoder, demonstrating high efficiency and quality (F1-score ~0.86). Li et al. (2023) introduced the SEANet architecture, which considers both the field mask and its boundary mask (the so-called approach of highlighting the «parcel edge of interest»), achieving an F1 score of approximately 0.85. A promising solution is also the ResUNet-a network with a conditional multi-task learning mechanism: this model simultaneously predicts multiple maps (the overall field mask, the boundary mask, the distance map) and reconstructs the original image, allowing for more accurate contour closure of fields by leveraging the interrelation between the predicted layers. To enhance focus on boundaries, attention mechanisms are also incorporated. In particular, integrating modules into the U-Net structure enables the highlighting of significant regions in the image, thereby improving the accuracy of contour segmentation (Awad & Erer, 2023).

The practical application of deep learning methods for delineating agricultural field boundaries is significantly simplified by using pre-trained models integrated into ArcGIS environment. Such models are trained on heterogeneous geospatial data and enable the automation of object segmentation without the need for a full neural network training cycle, providing ready-made GIS layers (Esri, 2025a). A promising direction is the use of general-purpose foundation segmentation models, in particular Segment Anything Model (SAM), capable of transferring knowledge to new agro-landscapes with minimal annotation effort. This makes possible rapid and scalable mapping of agricultural lands for applied agro-monitoring and land use tasks. Specifically, SAM – a deep learning model by Meta AI, initially trained on over one billion masks – can be fine-tuned for field delineation using efficient parameter adaptation methods (Esri, 2025b).

Accurate delineation of agricultural field boundaries is particularly important in irrigated arid regions, where precise spatial data on land use are essential not only for agro-production monitoring but also for managing water resources and controlling soil salinization (Aldazhanova et al., 2022). The Zhetysai district of southern Kazakhstan represents one of the most agriculturally intensive and water-stressed areas in the country.

According to Kaimuldinova et al. (2026), approximately 45-50% of irrigated lands in this district exhibit signs of salinization, including 15-20% classified as moderately to strongly saline soils. Their integrated assessment revealed that the water delivery coefficient in the district ranged from 0.61 to 0.68, reflecting significant conveyance losses within irrigation canal networks. Furthermore, areas with high soil salinity demonstrated Normalized Difference Vegetation Index (NDVI) values reduced by 10-25%, directly indicating declining agricultural productivity.

These findings underscore the urgent need for automated and spatially accurate field boundary mapping to support precision irrigation management and sustainable land use planning in such conditions. Large-scale digitalization of crop field boundaries provides vital information for smart agriculture applications, yet effective and budget-friendly solutions

for extracting closed agricultural field boundaries at regional scale remain scarce (Ha et al., 2026). The emergence of foundation segmentation models such as SAM opens new possibilities for scalable field mapping with minimal labeling effort, including the application of parameter-efficient fine-tuning strategies such as LoRA, which have demonstrated strong performance in agricultural image segmentation tasks (Mao et al., 2026; Kirillov et al., 2023).

The present study aims to address this gap by applying SAM with LoRA adaptation to automatically delineate agricultural field boundaries in the Zhetysai district, demonstrating the practical utility of this approach for regions where both land and water resource management are critical priorities.

MATERIALS AND METHODS

Study Area

The Zhetysai district is located in the southern part of the Republic of Kazakhstan, within Turkestan region, and is characterized by a high level of agricultural land development (Figure 1).

The district is one of the key agricultural areas in the region, primarily specializing in irrigated farming. Long-term climate trends in the Turkestan region – rising temperatures and declining precipitation – further increase the pressure on irrigated agriculture (Mustafayev et al., 2023). According to data from the district agricultural department, a significant portion of the land fund consists of arable lands, with irrigated agricultural lands predominating.

The area of irrigated arable land is approximately 80,000 hectares and is used by about 10,000 peasant and farming households, reflecting a high level of land resource utilization in agricultural turnover (Department of Agriculture and Land Relations of the Zhetysai District, 2025; Inbusiness.kz, 2021).

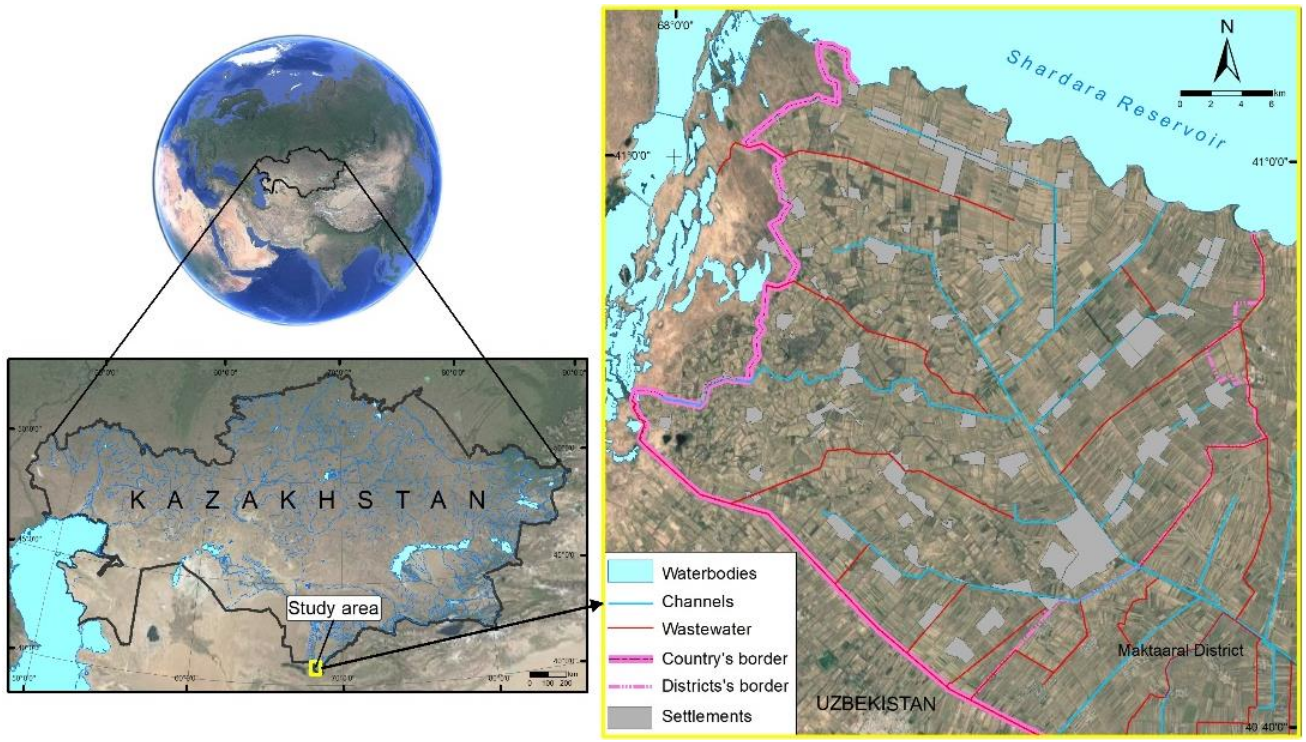


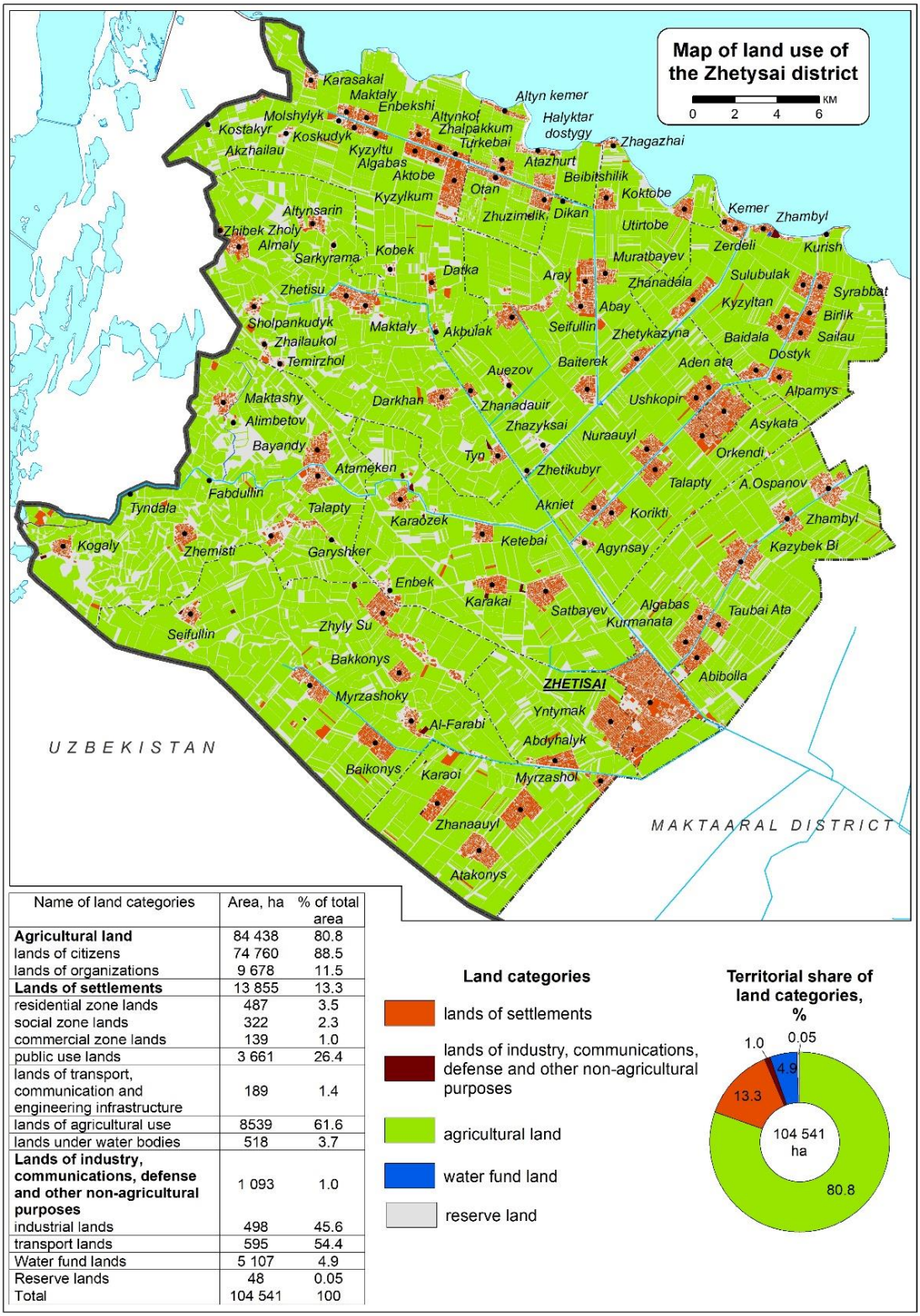
Figure 1. Overview schematic map of the Zhetysai district location (Source: Authors, 2025)

In accordance with their designated purpose, the land fund of the Zhetysai district is subdivided into the following categories: agricultural lands; lands of populated areas (cities, towns and rural settlements); lands for industry, communications, defense and other non-agricultural purposes; water fund lands; and reserve lands.

Lands belonging to categories of specially protected natural areas and forest fund are absent within the district, which emphasizes the predominantly agricultural nature of land use. The total area of land resources in the Zhetysai district is 1,045.41 km^2, which is approximately 0.9% of the territory of the Turkestan region. In terms of size, the district is among the smaller administrative districts of the region. The land fund is predominantly composed of agricultural lands, which account for 80.8% of the total area of the district. A significant portion of these lands is in the possession of citizens, indicating the development of farming and peasant land use. The land of settlements occupies 13.3% of the district's territory and is primarily represented by agricultural land within settlement boundaries, as well as public use lands. The share of land used for industry, transportation and other non-agricultural activities is insignificant, amounting to about 1.0%. Water fund lands cover 4.9% of the district's area, reflecting the role of irrigation and water management facilities in supporting agricultural production. Reserve lands occupy a minimal share -0.05%, indicating that the territory of the district is almost fully engaged in economic activities (Table 1, Figure 2).

The agricultural sector provides employment and income for a significant portion of the population: approximately 40,000 residents of the district directly depend on the volume of agricultural crop production (Inbusiness.kz, 2021).

The Zhetysai district is one of the centers of intensive farming, with the well-established land use structure where arable lands occupy a large percentage of the territory.



Name of land categories	Area, ha	% of total area
Agricultural land	84 438	80.8
lands of citizens	74 760	88.5
lands of organizations	9 678	11.5
Lands of settlements	13 855	13.3
residential zone lands	487	3.5
social zone lands	322	2.3
commercial zone lands	139	1.0
public use lands	3 661	26.4
lands of transport, communication and engineering infrastructure	189	1.4
lands of agricultural use	8539	61.6
lands under water bodies	518	3.7
Lands of industry, communications, defense and other non-agricultural purposes	1 093	1.0
industrial lands	498	45.6
transport lands	595	54.4
Water fund lands	5 107	4.9
Reserve lands	48	0.05
Total	104 541	100

Figure 2. Map of land use of the Zhetysai district (Source: Authors, 2025)

A feature of the district is the widespread use of irrigation and the associated vulnerability to water resource shortages. The Zhetysai district is located in the lower course of the Syrdariya River, and its irrigation network is fed by the transboundary Dostyk canal. During the summer growing season, water shortages for irrigation are regularly observed: due to limited capacity and other factors, not all the necessary amount of moisture reaches the distant fields. According to local authorities, every summer there is a problem with water scarcity on the fields, which forces emergency measures (pumping water from the Shardara reservoir) to save the crops (Inbusiness.kz, 2021).

In the conditions of increasing water resource shortages, automation of field monitoring is becoming particularly relevant. Traditional methods of accounting for sowing areas and controlling irrigation do not provide sufficient timeliness and accuracy for such a large agricultural area.

Table 1. Land fund of the Zhetysai district by land categories in 2025
(Source: Department of Agriculture and Land Relations of the Zhetysai District, 2025)

Name of land categories	Area, ha	% of total area
Agricultural land	84 438	80.8
including:		
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Reserve lands	48	0.05
TOTAL LAND	104 541	100.0

Here, Geographic Information Systems (GIS) and machine learning methods come to the rescue, enabling automatic detection of each field's boundaries and monitoring their condition. Automatic delineation of field contours on satellite images of the Zhetysai district will allow for precise assessment of sown areas, timely identification of non-irrigated sections or stress zones, and optimization of water distribution among farms.

This is especially important in the context of irrigated agriculture: accurate field boundaries obtained through segmentation will enable the implementation of targeted irrigation and soil moisture control systems for each plot. Furthermore, automated GIS data on land use structure will facilitate decision-making at the district level.

Considering the high percentage of arable land and water dependence of agricultural production in the Zhetysai district, the introduction of machine learning methods for delineating field boundaries is a timely and justified step.

Such an approach will contribute to increasing the efficiency of agriculture in the region through digital land resource monitoring and more rational use of limited water resources.

METHODS

In this study, an automated boundary extraction method for agricultural fields from satellite images was employed using deep learning technologies. The baseline algorithm selected was the Segment Anything Model (SAM), developed by Meta AI, which is a universal segmentation model capable of delineating objects in images without additional training on each new class. SAM is trained on the Segment Anything 1-Billion mask (SA-1B) dataset, which includes a collection of 11 million images and over one billion masks.

This makes the model highly reliable in defining object boundaries and distinguishing various objects across different domains, even if the model has never encountered such objects before (Esri, 2025c). This potential was utilized through fine-tuning the SAM model specifically for the segmentation of agricultural lands in the conditions of the Zhetysai district. The work was implemented within the ArcGIS Pro GIS environment (with the Image Analyst module), which provides tools for deep learning and integration of pre-trained models.

Initial data and annotation

The initial data consisted of satellite images from the global Esri World Imagery database, characterized by high spatial resolution (Esri, 2026). Within the study area, the basemap consists of WorldView-3 (WV03) satellite imagery (Vivid Standard product, provider Vantor, formerly Maxar Technologies) acquired on 21 and 28 April 2025, with a spatial resolution of 0.31 m and a stated positional accuracy of 5 m. The study area covers agricultural lands of the Zhetysai district in the Turkestan region of Kazakhstan. To create the training dataset, polygonal contours of 705 fields (agricultural plots) were manually digitized based on the specified images. Annotation was performed in ArcGIS Pro through visual interpretation of the images and creation of polygons that encompass the areas of the cultivated fields.

Each such polygon was assigned the class attribute “field” (value 1), while the background (outside the polygons) was classified as class 0 (not a field). This manually annotated sample served as the basis for training the model (Figure 3).

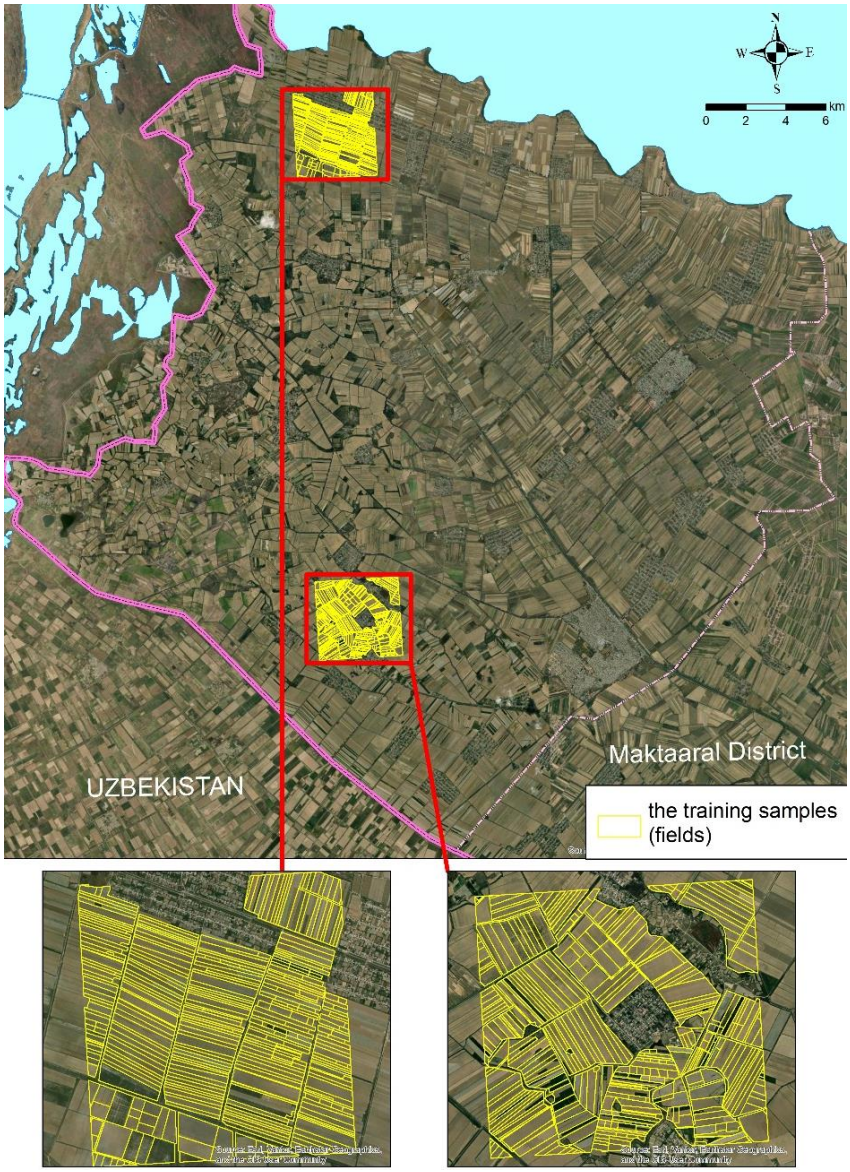


Figure 3. Spatial distribution of the training samples used for model training
(Source: Authors, 2025; base imagery: Esri World Imagery, WorldView-3, April 2025)

Data preparation for training

After the annotation stage, the initial data was converted into a format suitable for training a neural network using the ArcGIS Export Training Data For Deep Learning tool. This tool slices the original raster layer and the corresponding vector labels into a set of training tiles (fragments) of a specified size with a certain overlap. In our experimental settings, the tiles were formed with a pixel size of 2 meters (by setting the Cell Size parameter equal to 2) to reduce the level of detail to an optimal scale for model training.

Each tile was generated along with a class map of the same size: pixels within the field contours were assigned a value of 1, while other pixels were assigned 0. The metadata format selected during export was “Classified Tiles”, designed for pixel-wise classification tasks (Esri, 2025b). This format involves saving a separate raster mask for each tile, where object classes are encoded without additional textual annotations (Esri, 2025d).

To ensure sufficient coverage of data variability, the entire digitized set of 705 polygons was used; during tile generation, overlap between neighboring cutouts was applied so that object boundaries appeared in different training samples, which improves the model's robustness to boundary effects (Figure 4).

Model and training parameters

The model training was conducted using the ArcGIS Train Deep Learning Model tool. The chosen model architecture is based on the SAM algorithm scheme with adaptation using the Low-Rank Adaptation (LoRA) method. The use of SAM+LoRA (implemented in ArcGIS Pro as the SAMLoRA model type) allowed for fine-tuning the pre-trained SAM model for our specific task with a relatively small amount of training data (Esri, 2025e).

The LoRA technique involves freezing the original weights of the large image encoder and training only additional layers with a small number of parameters, integrated into the model architecture (Esri, 2025f).

Thus, pre-trained SAM weights (loaded via ArcGIS Living Atlas as a .dlpk model file) were used in combination with new trainable parameters specific to field segmentation. During training, the main layers of the Vision Transformer encoder of SAM remained unchanged, preserving the model's generalization capabilities, while the training focused on adapting the model to recognize the "field" class. The training dataset was divided into training and validation subsets; during training, an early stopping strategy was used: the process automatically terminated when the validation metric stopped improving (Esri, 2025e). The controlled metric selected was the overall segmentation accuracy on the validation data, although precision and Intersection over Union (IoU) metrics for the "field" class were also evaluated on the validation set. Training was conducted on a GPU supporting CUDA; for the SAM model, at least 8 GB of video memory was required (Esri, 2025c). Several dozen training epochs were performed, after which the model reached convergence.

Upon completion of training, the model demonstrated high accuracy: according to the ArcGIS report, an overall pixel accuracy of approximately 91% was achieved on the validation data, indicating the model's suitability for reliably recognizing field boundaries in the studied area.

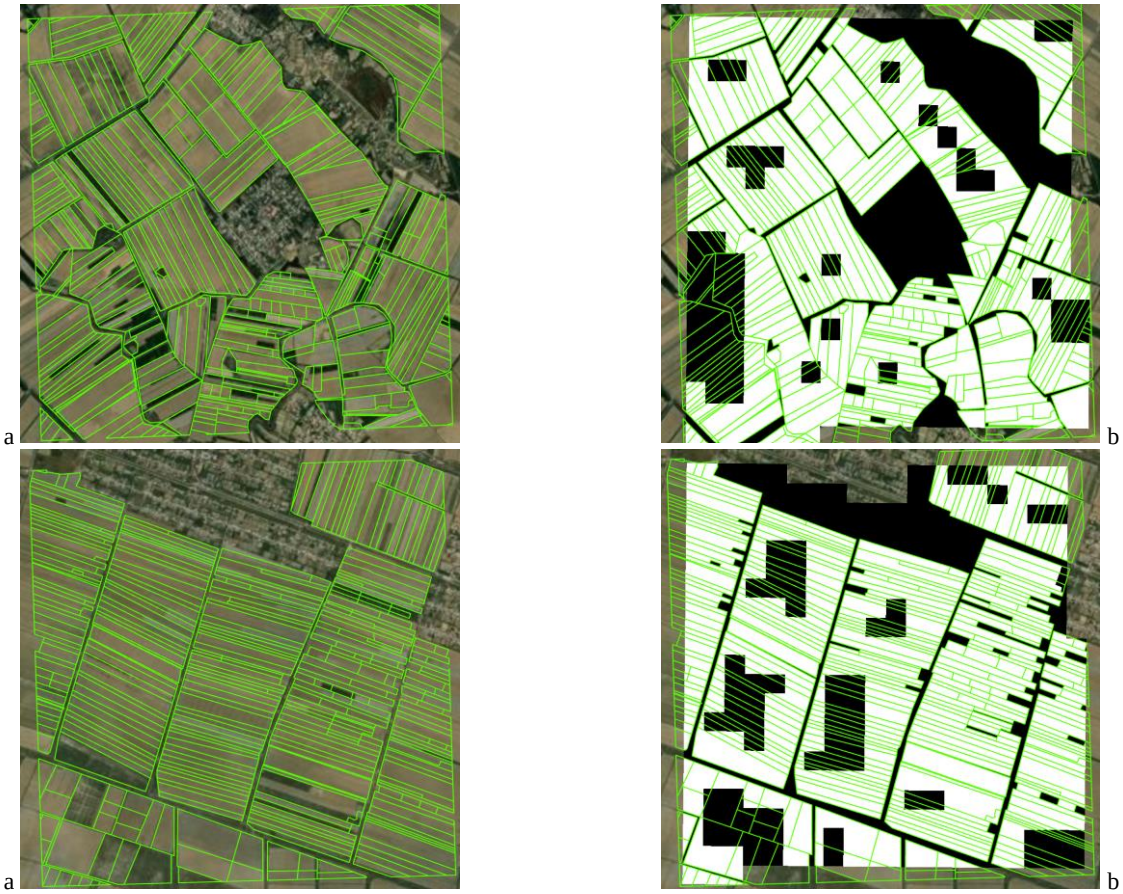


Figure 4. Generated tiles: a – training set; b – mask of the training data, where the sowing fields are marked in white (Source: Authors, 2025; base imagery: Esri World Imagery, WorldView-3, April 2025)

RESULTS AND DISCUSSION

The trained neural network was applied to segment a broader area of the Zhetysai district. Automatic image classification was performed using the ArcGIS Classify Pixels Using Deep Learning tool, which allows generating a raster class map from an input satellite image based on the trained model. The result of the model's work was a thematic image in which pixels corresponding to agricultural fields were labeled as the "field" class.

Subsequently, this raster segmentation was converted into a vector format for easier boundary analysis. A built-in post-processing script was used for the conversion, transforming clusters of connected pixels of the "field" class into closed polygons. As a result, a total of 4,060 agricultural field polygons covering approximately 809.76 km² were automatically delineated across the entire study area. In the western part of the district, adjacent fields separated by narrow field roads and irrigation ditches were partly merged into larger contiguous polygons; therefore, the number of polygons underestimates the actual number of individual fields. The obtained polygons represent the contours of individual fields corresponding to various agricultural plots detected by the model in satellite images (Figure 5).

Despite the different nature of the landscape, this transfer learning model was able to identify most of the fields with high accuracy; although some omissions were observed, the overall quality was considered high.

Additional fine-tuning of the model on a small labeled dataset specific to the study area helped to eliminate gaps and significantly improve the results. This approach confirms that large pre-trained models can be effectively fine-tuned for precise delineation of field boundaries in new regions with minimal data labeling efforts.

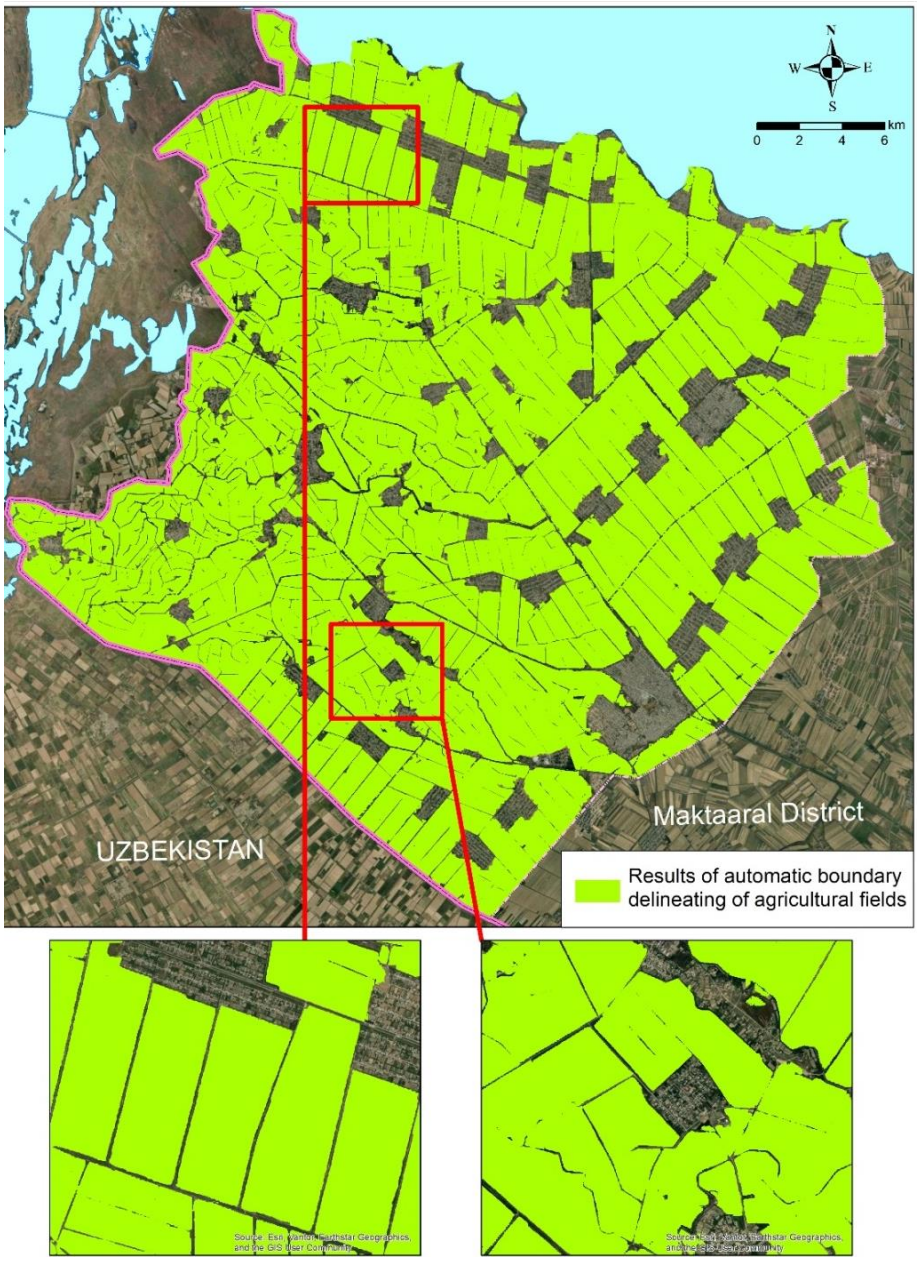


Figure 5. Results of automatic boundary delineating of agricultural fields using the SAM model (Source: Authors, 2025; base imagery: Esri World Imagery, WorldView-3, April 2025)

Quality control of results

To ensure the reliability and topological correctness of the delineated objects, an additional quality control step was carried out. Firstly, artifact filtering algorithms were applied to the resulting polygon dataset: objects with deliberately small areas, arising as segmentation noise, were removed, and possible overlaps or mismatches between polygons were eliminated. Secondly, boundary smoothing and, if necessary, merging of close or intersecting polygons were performed, if such issues were caused by the model's characteristics. These operations were carried out semi-automatically using a script launched from ArcGIS Pro (Esri, 2025f; Ralouta, 2025). The script analyzed the classification raster layer and generated an updated vector layer, in which each field polygon had attributes such as ID, class “field” and calculated area.

After this step, the final layer of fields was checked by an expert through visual comparison with the original images: in sampled zones, the model's results were found to be correct - the field boundaries matched the visible boundaries on the images, and false positives (e.g., areas identified that were not actually fields) were practically absent.

Thus, the quality of the automatic field delineation was confirmed to be high.

The proposed methodology is based on publicly available data and tools, making it reproducible and potentially scalable. All stages – from data annotation to training the neural network and spatial analysis of the results – are carried out using standard GIS tools and are described in enough detail for another researcher to replicate.

Moreover, the approach of training a pre-trained model on local data can be easily adapted to new territories. It is sufficient to gather a relatively small set of training polygons in the region of interest and perform a similar process of data export, model training, and application to the images of that area.

The versatility of the SAM model means that it can segment images of various types and regions (Esri, 2025c), so transferring and adapting the model to different conditions does not require building an architecture from scratch or collecting large datasets. Thus, the developed workflow for delineating agricultural field boundaries using deep learning can be reproduced and applied to different geographic areas, provided that appropriate initial satellite data and a small amount of labeled examples for fine-tuning the model are available.

CONCLUSION

The conducted study demonstrates the effectiveness of deep learning approaches for automated delineation of agricultural field boundaries based on high-resolution satellite imagery. The application of the Segment Anything Model combined with the LoRA technique enabled efficient adaptation of a pre-trained segmentation architecture to the agro-landscape conditions of the Zhetysai district using a relatively limited training dataset.

The model trained on manually digitized field contours achieved a segmentation accuracy of approximately 91%, confirming its reliability for automated spatial mapping tasks.

Application of the trained model to the entire study area resulted in the automatic identification of more than four thousand agricultural fields, forming an up-to-date geospatial dataset of land-use structure. The obtained results highlight the strong potential of foundation segmentation models for geospatial analysis of agricultural landscapes.

The proposed workflow is reproducible and scalable and can be adapted for monitoring agricultural territories in other regions, supporting the development of digital tools for land and water resource management.

This study has several limitations that should be considered when interpreting its findings. The workflow was tested solely in the Zhetysai district – an irrigated, structurally homogeneous agricultural area.

Whether the 91% segmentation accuracy holds in landscapes with irregular field geometries, complex relief, or diverse cropping systems remains an open question. Regional validation elsewhere is a necessary next step.

The training set of 705 manually digitized polygons was adequate for fine-tuning SAM via LoRA, yet it captures only a fraction of the field diversity found across the district. Manual digitization also introduces human inconsistency: field edges near drainage channels or adjacent plots with similar spectral response are difficult to trace consistently, and different operators may draw the same boundary differently.

The study depended entirely on Esri World Imagery – a mosaic composite in which acquisition dates vary between areas and cannot be selected by the user. Clouds, shadows, and off-season capture dates embedded in the mosaic cannot be controlled for. Accuracy was reported as overall pixel accuracy (~91%), a metric known to behave poorly under class imbalance – which is inherent here, since non-field background pixels vastly outnumber field pixels in some tiles.

IoU and F1 were not disaggregated by field size or landscape zone, making it impossible to identify where the model struggles. Field-level verification relied on expert visual inspection within the same imagery used for training.

No comparison against cadastral records or GPS-surveyed field boundaries was made. This leaves key error types – missed fields, merged adjacent plots, boundary displacement – unmeasured in absolute terms. Inter-field boundaries narrower than the 2 m processing cell size were not always resolved, which caused some adjacent fields to merge into larger contiguous polygons, particularly in the western part of the district. Finally, the resulting dataset is a snapshot. Field configurations in Zhetysai shift with irrigation allocations, tenancy changes, and seasonal cropping decisions. Without a protocol for periodic model updating, the delineated boundaries will gradually diverge from ground reality.

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Data Availability Statement: The manually annotated training dataset (705 field polygons) and the field boundary delineation results presented in this study are available on request from the corresponding author. The satellite imagery used in this study was derived from the publicly available Esri World Imagery basemap (https://www.arcgis.com/home/item.html?id=10df2279f9684e4a9f6a7f08febac2a9).

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Use of Generative AI: During the preparation of this manuscript, the authors used Claude (Opus 5.5, Anthropic) for translation and language editing of the text. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Abbreviations: The following abbreviations are used in this manuscript: AI – Artificial Intelligence; CUDA – Compute Unified Device Architecture; GIS – Geographic Information Systems; GPS – Global Positioning System; GPU – Graphics Processing Unit; IoU – Intersection over Union; LoRA – Low-Rank Adaptation; ML – Machine Learning;

NDVI – Normalized Difference Vegetation Index; OBIA – Object-Based Image Analysis; R2U-Net – Recurrent Residual U-Net; ResNet – Residual Network; RS – Remote Sensing; SA-1B – Segment Anything 1-Billion mask dataset; SAM – Segment Anything Model; SEANet – Semantic Edge-Aware Network; SLIC – Simple Linear Iterative Clustering; WV03 – WorldView-3.

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