






## Automated Agricultural Land Mapping Using Landsat-8, ArcGIS, and NDVI: A Case Study from North Kazakhstan



Marzhan Nurpeissova<sup>1</sup>, Dinara Kirgizbayeva<sup>1</sup>, Aizhan Zhildikbayeva<sup>2</sup>, Almat Utesbayev<sup>1</sup>, Eldar Azizov<sup>3\*</sup>

<sup>1</sup> Mining and Metallurgical Institute named after O.A. Baikonurov, Department of Surveying and Geodesy, Kazakh National Research Technical University named after K.I. Satpayev, Almaty 050013, Kazakhstan

<sup>2</sup> Department of Land Resources and Cadastre, Kazakh National Agrarian Research University, Almaty 050000, Kazakhstan

<sup>3</sup> Department of Geography, Land Management and Cadastre, Faculty of Geography and Environmental Sciences, Al-Farabi Kazakh National University, Almaty 050040, Kazakhstan

Corresponding Author Email: Eldar\_14\_03@mail.ru

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### ABSTRACT

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*space images, geographic information systems, artificial intelligence, ArcGIS, automation, Normalized Difference Vegetation Index, agricultural maps*

The paper discusses approaches to improving the technology of creating digital agricultural maps based on geographic information systems (GIS) and remote sensing (RS) data. The aim of the study was to improve the methodology for agricultural digital mapping using GIS tools and Landsat-8 satellite imagery for the Timiryazevsky Rural District of the North Kazakhstan Region. The research methodology was based on cartographic, photogrammetric, and statistical methods, as well as field survey, GPS-based georeferencing, orthophoto interpretation, and Normalized Difference Vegetation Index (NDVI) calculation in the ArcGIS environment. Based on the obtained data, a technological flowchart of the study was developed, reflecting the main stages of digital map creation. The results of the study include the delineation of agricultural land contours, the identification of areas with low NDVI values, and the creation of thematic maps characterizing vegetation condition, relief features, agrometeorological conditions, and soil resources of the study area. The scientific novelty of the work lies in the integrated use of GIS tools, RS data, and thematic analysis for agricultural land mapping in the conditions of the North Kazakhstan Region. Considering the practical implications, the developed approach offers valuable insights for land use planning, enabling the estimation of current land productivity through NDVI maps and aiding in strategic decisions such as choosing areas for windbreaks. Ultimately, the developed method aims to support sustainable economic development and improve agricultural production efficiency by providing up-to-date and reliable cartographic information.

## 1. INTRODUCTION

Modern agriculture increasingly relies on digital technologies to improve the efficiency of land use. Digital maps, created using geographic information systems (GIS) and remote sensing (RS) data, are fundamental for analyzing land conditions, forecasting yields, and optimizing agricultural activities. However, while traditional cartographic methods provide foundational insights, they often face significant limitations in terms of efficiency, scalability, and the accuracy required for dynamic agricultural landscape management [1]. These conventional approaches frequently involve labor-intensive fieldwork and subjective assessments, leading to limited spatial coverage, a lack of real-time monitoring capabilities, and susceptibility to human biases [1]. Furthermore, existing crop classification and mapping products are often released with significant delays and struggle with the complexity of diverse agricultural systems, making it difficult to achieve the precision required for current-season production management [2].

The effective and rational use of agricultural land, ensuring

the population has access to local agricultural products, is one of the priority tasks for the sustainable development of any country. This requires establishing efficient land use and management systems, along with the creation of robust information databases containing up-to-date, reliable data on land characteristics, legal and environmental status, and economic efficiency. However, given the deterioration of land resources in Kazakhstan and the lowering efficiency of their use, it is crucial to develop improved methodological provisions for rational land use utilizing modern information technologies. The North Kazakhstan Region, being one of the key agricultural regions of Kazakhstan, particularly requires accurate cartographic data for sustainable economic development. The Government of the Republic of Kazakhstan has included the Agro-Industrial Complex (AIC) in the list of industries subject to digitalization, which makes it possible to improve labor productivity in agriculture and obtain data on the condition of agricultural land. In this context, GIS are of great importance [3], as they are used to monitor land, model, plan, and predict the rational use of land, conduct qualitative land assessment, and fulfill other tasks.

Agriculture is a complex and multifaceted economic system that benefits from a systems approach, which includes analytical and integrative mapping techniques. Agricultural maps, demonstrating the territorial differentiation of agricultural production and its economic and natural conditions, are essential for assessing resources. The most common thematic maps display sown areas, livestock density, crop yields, and productivity, providing the basis for assessing the economic efficiency and spatial organization of agricultural production. With the globalization of economic mechanisms in agriculture, food programs aimed at ensuring food security and providing raw materials to related industries are becoming increasingly important. Consequently, one of the main objectives of national agricultural policy is to increase productivity, quality, and sustainability of production through modern technologies [4]. The successful resolution of these tasks requires advanced cartographic support for agricultural management, capable of visualizing the state, structure, and results of agricultural inventories.

A significant technical bottleneck in current agricultural mapping stems from the inefficiency and lack of accuracy inherent in manual and semi-automated processes. Traditional methods are prone to “same material, different spectra” and “different material, same spectra” phenomena, leading to mixed classification results and uncertain accuracy [2]. The vast amounts of data generated by modern RS platforms necessitate more efficient and automated analysis techniques, as manual processing is almost impossible for large datasets [5, 6]. This highlights a clear scientific problem: how to develop an agricultural mapping technology that dramatically improves both the efficiency and accuracy of land analysis, moving beyond the limitations of traditional, often slow, repetitive, and error-prone data acquisition [7].

Recent advancements in Artificial Intelligence (AI), particularly deep learning, offer transformative solutions to these challenges [8, 9]. Deep learning models excel at recognizing complex patterns in large datasets, such as high-resolution images from drones and satellites, more effectively than traditional machine learning algorithms [9]. For instance, the U-Net architecture, initially developed for biomedical image segmentation, has been successfully adapted for agricultural applications to delineate field boundaries, classify crop types, and perform vegetation analysis [7, 10-12]. Studies from 2020 to 2025 demonstrate the effectiveness of U-Net and similar deep learning models in crop segmentation, achieving high accuracy rates—up to 90% overall accuracy in land cover classification [13] and Dice coefficients of 0.8324 for crop segmentation [14]. These methods significantly enhance the ability to capture semantic information in RS images compared to conventional machine learning techniques [6].

The global trend towards digital mapping—exemplified by modern GIS and UAV use in the USA, China, and Japan—and the increasing sophistication of internet technologies for interactive cartography further underscore the potential of AI to revolutionize agricultural analysis and management. New technologies provide opportunities to diversify methods of map visualization, modify design styles, apply computer design effects, and utilize animation and multimedia tools. Today, Kazakhstan and other countries alike are developing digital maps and atlases of an operational nature, relying on statistical materials and interactive GIS systems accessible online. One example of such cartographic products is digital maps of agricultural land, which represent a spatially integrated assessment of land fertility and suitability for

various agricultural purposes in a geoinformation environment [15, 16].

Geoinformation mapping methods based on RS data have been extensively studied [17, 18]. The research covers obtaining, processing, and interpreting satellite images of various spatial resolutions, as well as algorithms for their automated decoding and land cover classification. Particular attention is paid to raster data vectorization, spectral index calculation (including the Normalized Difference Vegetation Index), digital relief model construction, and thematic map creation for agricultural purposes. Modern studies emphasize an integrated approach combining satellite data with ground observations, geodetic measurements, and meteorological indicators to ensure higher reliability and the ability to solve a wide range of tasks—from land resource monitoring to yield forecasting.

However, the widespread operational adoption of deep learning in agricultural monitoring still faces challenges, including the scarcity of annotated datasets, limited model generalization across diverse environments, and complexities in fusing multi-source data [9]. Despite these hurdles, continuous improvement in satellite technologies and the success of deep learning in computer vision present a critical opportunity to revolutionize agricultural analysis [19].

Therefore, this research aims to address these scientific and technical challenges by developing an improved methodology for creating digital agricultural maps. The proposed approach integrates GIS and RS data (specifically from Landsat-8) with AI-based methods, focusing on deep learning for automatic vectorization within the ArcGIS environment. By leveraging U-Net for the precise identification of features such as field borders, roads, water bodies, and settlements, and combining this with spectral indices like NDVI, this study seeks to enhance the accuracy and speed of agricultural landscape monitoring. The proposed methodology is demonstrated using the example of the Timiryazevsky Rural District of the North Kazakhstan Region, providing a practical illustration of how an AI-driven approach can deliver up-to-date and reliable cartographic information for land use planning, vegetation monitoring, and improving agricultural production efficiency.

This study aimed to improve digital agricultural land mapping using GIS, RS, NDVI, and AI-assisted vectorization in ArcGIS, based on the case of the Timiryazevsky Rural District in the North Kazakhstan Region.

## 2. METHODS

The study was conducted in the North Kazakhstan region, one of the leading agricultural regions of the country. The analysis was conducted based on Landsat-8 Collection 2 Level-2 Surface Reflectance images for August 2024 obtained from the USGS EarthExplorer service.

For NDVI calculation, atmospherically corrected surface reflectance data were used, which improves the comparability of vegetation index values derived from satellite imagery.

The methodological framework included informational, cartographic, photogrammetric, and statistical methods for landscape analysis, as well as modern geoinformation modeling technologies.

The study focused on the Timiryazevsky Rural District of the North Kazakhstan Region.

North Kazakhstan is one of Kazakhstan's leading regions for agricultural crop production. The territory of the region spans

97,993 km<sup>2</sup>, accounting for 3.6% of the country's territory. Coordinates of the northernmost point of the region are 55°26' N, 68°59' E, the southernmost point — 52°13' N, 67° E, the westernmost point — 54° N, 65°57' E, and the easternmost point — 52°50' N, 74°02' E. The region is located within the forest-steppe and steppe zones. In the forest-steppe, the southern forest-steppe, and the kolok forest-steppe are distinguished. The southern forest-steppe occupies the north of the region and is represented by a combination of birch and aspen-birch forests on gray forest soils and solod soils with forb-grass meadow steppes on leached chernozems and meadow-chernozem soils; sedge swamps are found occasionally, sometimes with willow thickets.

The territory of the region is crossed almost in the meridional direction by the valley of the Ishim River, the width of which varies from several kilometers in the south to 20-22 km in the north of the region. By the area of the water table, the largest lakes are Silytyeniz (777 km<sup>2</sup>), Teke (265 km<sup>2</sup>), Shagalalyteniz (240 km<sup>2</sup>), and Kishi-Karoy (102 km<sup>2</sup>). In addition, Sergeyevsky Reservoir on the Ishim River is also located within the region's borders, occupying about 117 km<sup>2</sup>.

The research methodology relied on information, cartographic, photogrammetric, and statistical methods for analyzing the state of landscapes, and computer decoding and analysis of recent high- and ultra-high spatial resolution images. In this study, we used Landsat-8 images for August 2024.

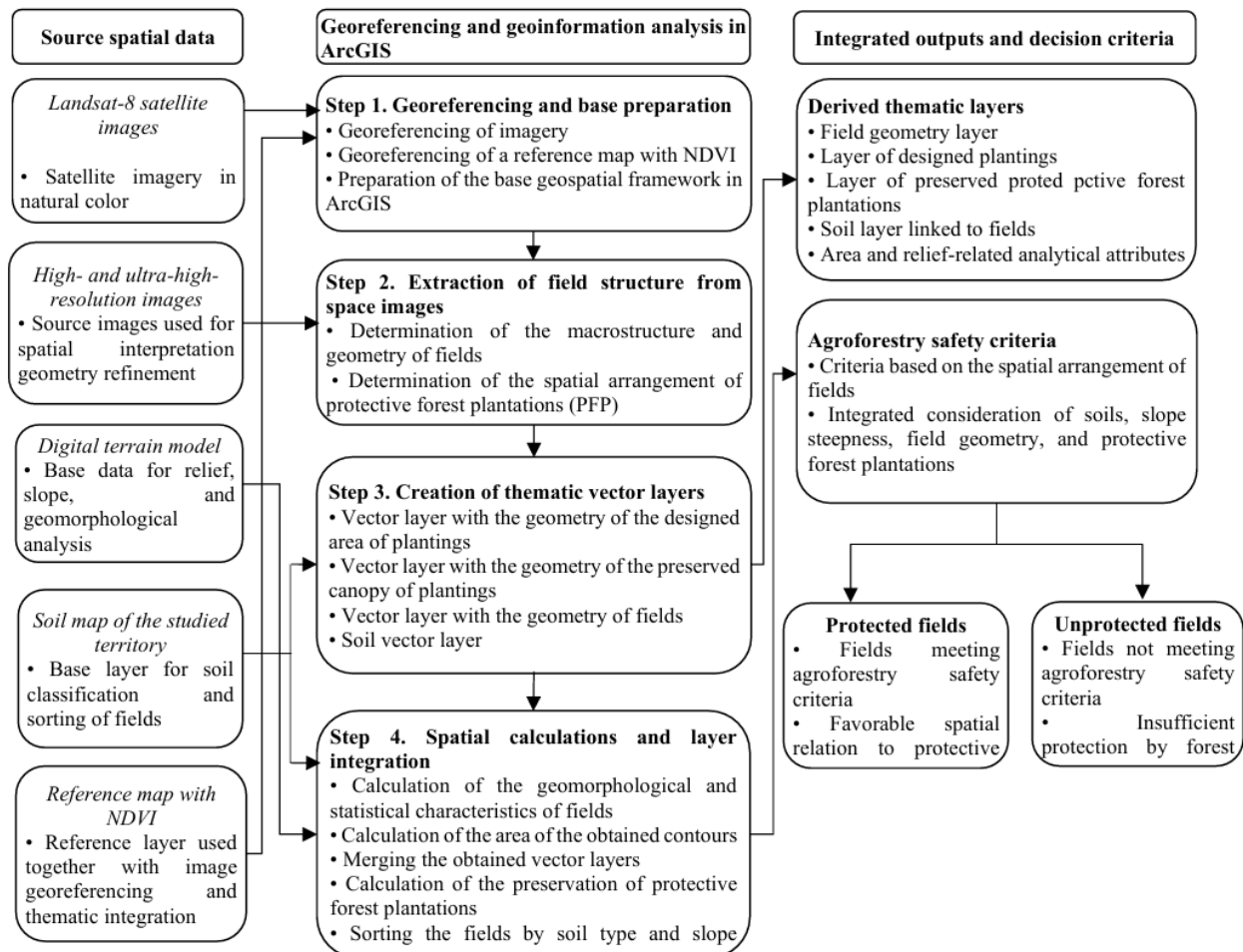
Satellite mapping is widely used in studying the condition of landscapes and crops [20, 21].

The methods used for data processing in ArcGIS included

the georeferencing of source spatial data, the creation of thematic vector layers, NDVI calculation, and the integration of raster and vector information for thematic mapping. Agricultural fields, protective forest plantations (PFP), soil units, and related spatial objects were delineated in the GIS environment on the basis of satellite imagery and reference cartographic materials. NDVI was calculated from Landsat-8 Collection 2 Level-2 Surface Reflectance data to assess vegetation condition within the study area. The resulting NDVI layer was subsequently integrated with vector layers in order to analyze the spatial distribution of vegetation characteristics and to create thematic maps.

The main tools used in this process were ArcGIS Pro for georeferencing, spatial analysis, vector layer creation, NDVI calculation, and map production, as well as the USGS EarthExplorer platform for downloading Landsat-8 Collection 2 Level-2 satellite data.

The macrostructure and geometry of the fields and the spatial arrangement of PFP were determined according to satellite images. The area and size of the fields were established, and the statistical characteristics of the relief of the fields located on the studied territory were determined [22]. The macrostructure and geometry of the fields, as well as the spatial arrangement of PFP, were determined from satellite imagery. The area and size of the fields were established, and the geomorphological and statistical characteristics of the fields within the study area were calculated. The geoinformation workflow used for these procedures is presented in Figure 1.



**Figure 1.** Workflow for geoinformation analysis of fields, protective forest plantations (PFP), and agroforestry safety

The thematic maps presented in Figures 2-5 were generated within the geoinformation workflow shown in Figure 1, but on the basis of different source datasets and processing operations. The geomorphological maps of elevation, slope, and exposure (Figure 2(a-c)) were derived from the digital terrain model in ArcGIS. The agrometeorological maps (Figure 3(a-c)) were produced from temperature, precipitation, and Selyaninov's HTC data for the growing season and then visualized in ArcGIS. The vegetation maps (Figure 4(a, b)) were generated from NDVI data, including the August 2024 NDVI calculated from Landsat-8 Collection 2 Level-2 Surface Reflectance imagery and the multi-year NDVI series used for interannual comparison. The soil map (Figure 5) was created from the georeferenced soil map and the corresponding soil vector layer. Thus, the proposed methodology combined georeferencing, vector layer creation, raster-vector integration, and thematic map generation within a single geoinformation environment.

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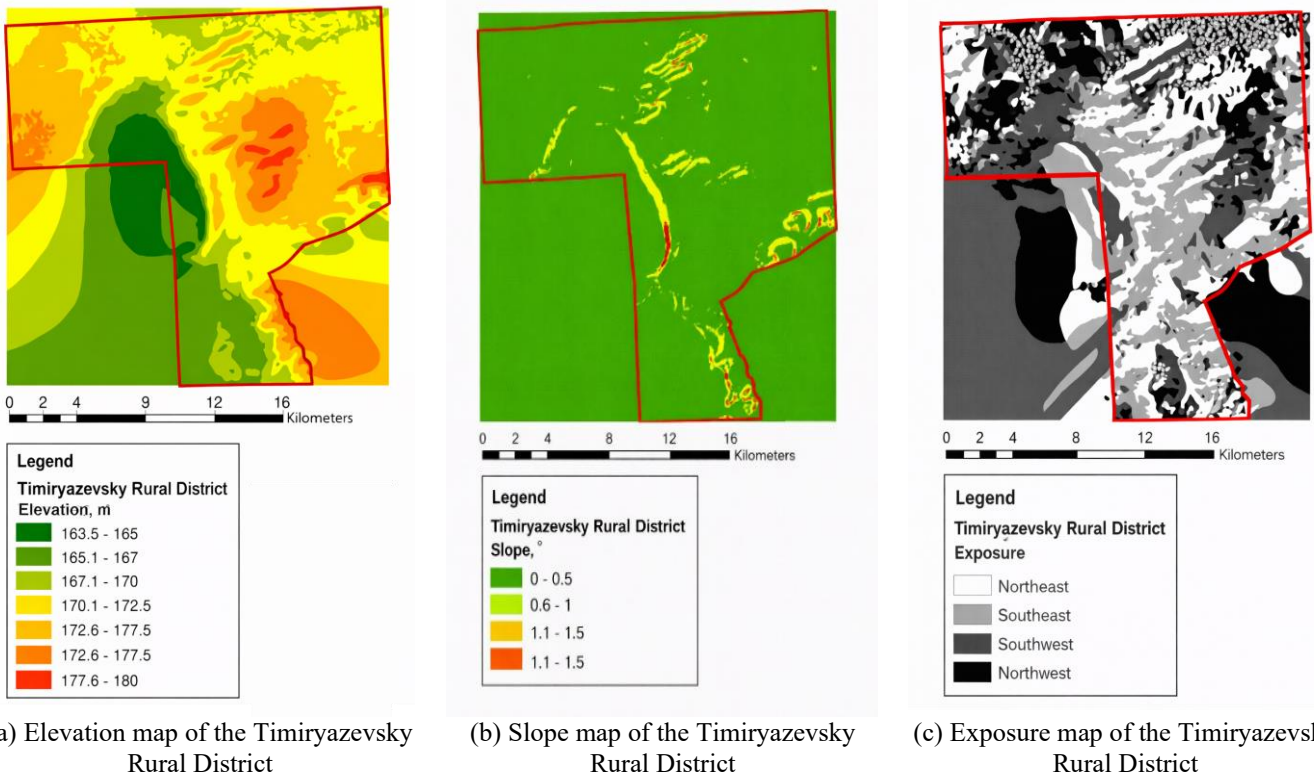


Figure 2. Geomorphological characteristics

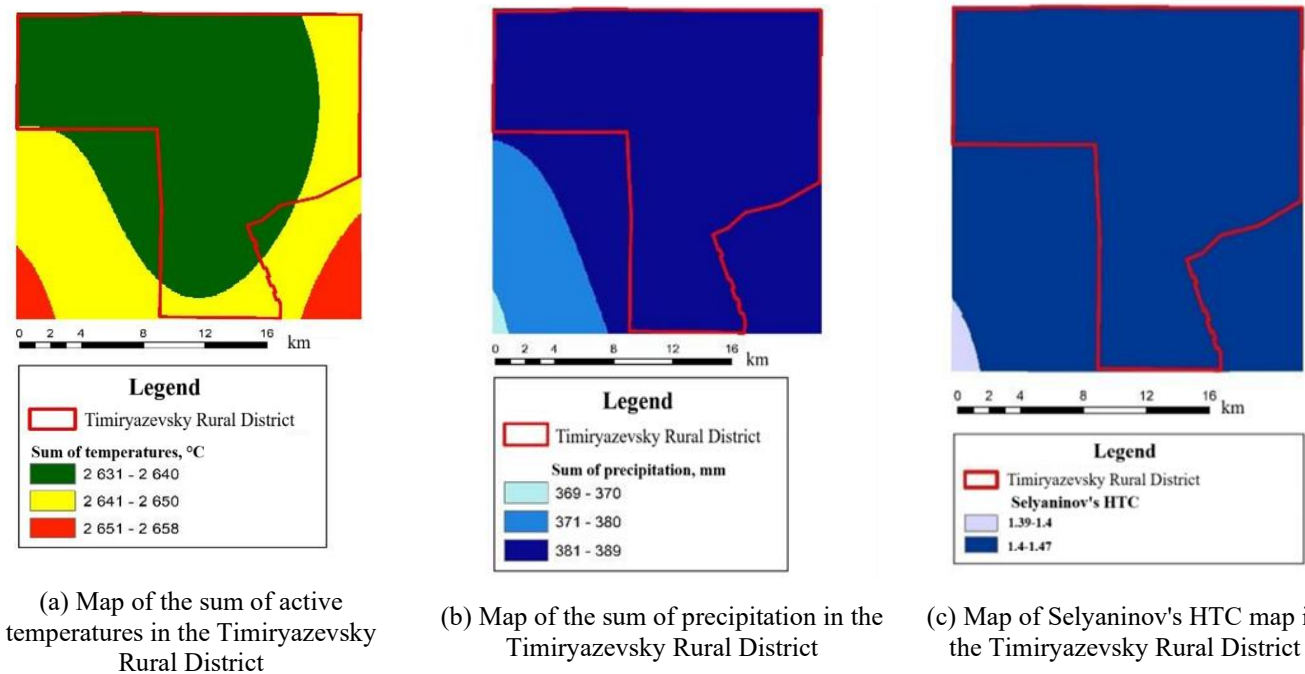
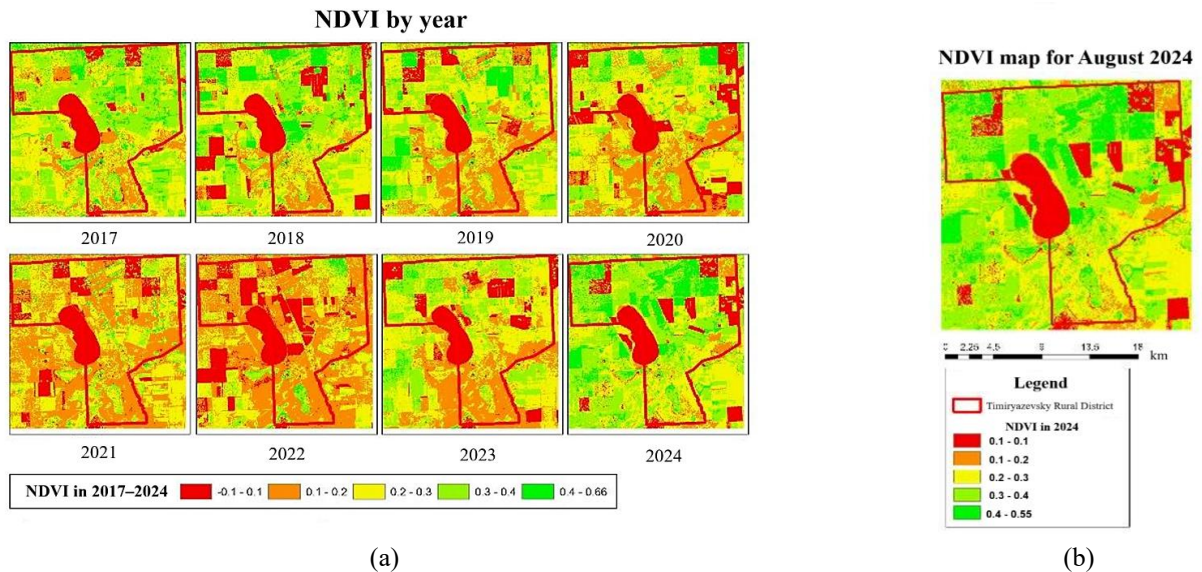
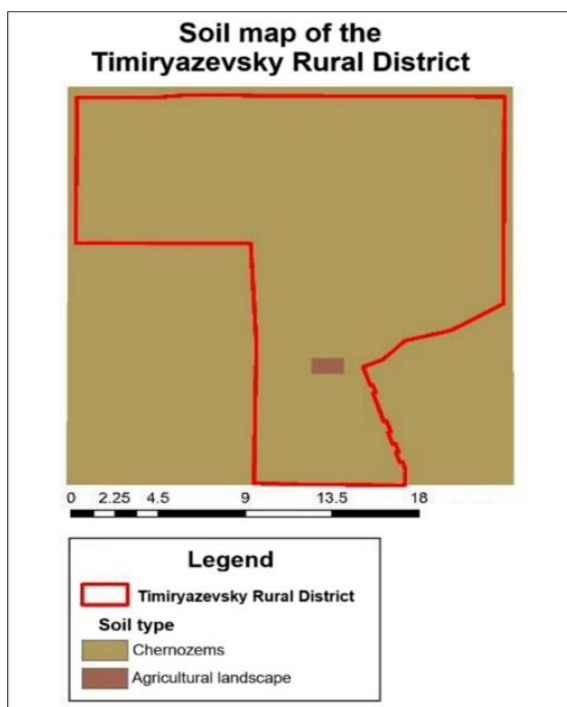


Figure 3. Agrometeorological conditions



**Figure 4.** The condition of vegetation



**Figure 5.** Soil map of Timiryazevsky Rural District

The studies were carried out on the territory of the Timiryazevsky District, North Kazakhstan. The district has an advantageous economic and geographical position, having a railway and a highway of republican significance passing through its territory. The area of the Timiryazevsky District is 4,510 km<sup>2</sup>, accounting for 4.6% of the region's total area. To the west, it borders Kostanay Region; to the north, Zhambyl District; and to the south, Gabit Musirepov District.

Most of the territory of the Timiryazevsky District belongs to the Kazakh Uplands and has a flat relief. The main natural resources of the region are chernozems, whose content in arable land reaches 80%. The territory of the district is characterized by a steppe landscape with carbonate chernozems. Intrazonal soils are very common. These are predominant solonchets and a variety of hydromorphic soils.

The surface waters of the Timiryazevsky District include about 50 lakes with a total area of 101.63 km<sup>2</sup>. Most of these

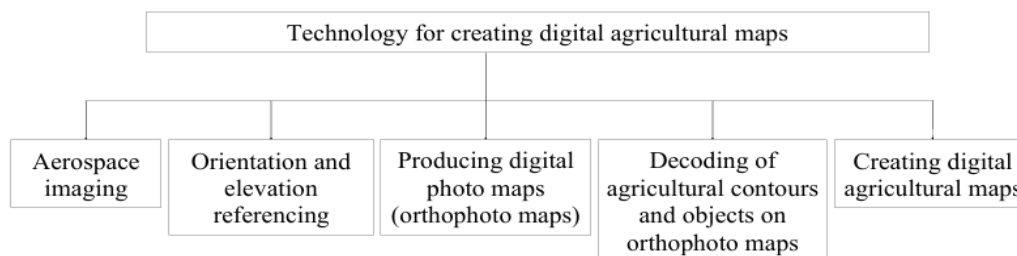
lakes are small and are prone to drying up and becoming swamps in summer (Figure 6). The Timiryazevsky District is located in a zone with insufficient moisture. In addition, this territory is marked by a general trend of declining atmospheric humidity, which, along with anthropogenic factors, leads to a decrease in water resources. The main sources of water pollution include agricultural and domestic effluents and floodwaters.



**Figure 6.** Map of the Timiryazevsky Rural District

The sown area in 2022 amounted to 258.9 thousand ha, including 205.0 thousand ha under cereals and legumes, 43.3 thousand ha under oilseeds, 9.1 thousand ha under fodder crops, 1.1 thousand ha under potatoes, and 0.4 thousand ha under vegetables.

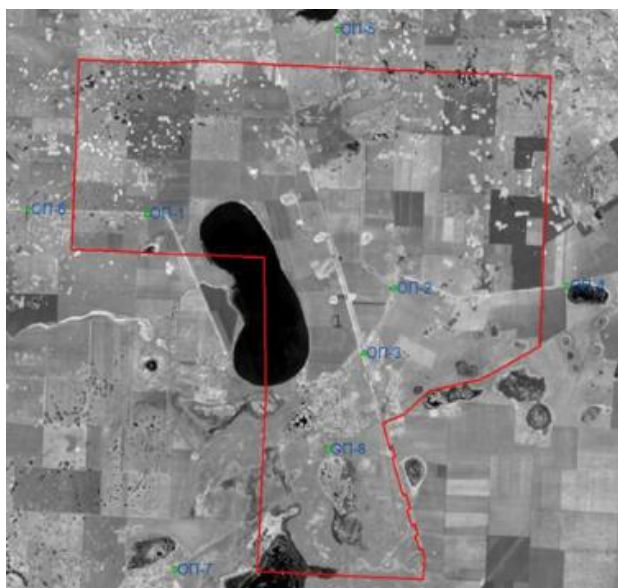
The creation of a digital map is a complex process consisting of different stages. Based on the results of the studies, we can distinguish five such stages (Figure 7).



**Figure 7.** Stages of creating a digital map

1. The first stage involved fieldwork. The territory was photographed from a certain distance away from the Earth's surface using a survey apparatus to obtain and provide objective spatial data on the surveyed areas. After aerial photography, a group of decoders conducted field surveys, i.e., visual inspections, to determine the borders of fields, protective forest strips, and water bodies, thus providing ground data.

2. Georeferencing based on GPS. A specialist used high-precision GPS equipment to record the coordinates of key objects, ensuring compliance with satellite images. Figure 8 shows the result of horizontal and vertical referencing.



**Figure 8.** Results of orientation and elevation referencing

3. Producing digital photo maps. To make digital orthophotography maps, the team marks the borders of fields and forest belts, which are then used to verify the results of automated vectorization. An orthophotomap is a photographic map of terrain based on precise geodetic data, which are obtained through aerial photography or space imaging, followed by converting the images from the central projection to the orthogonal using the orthogonal transformation method.

4. Field decoding to identify, recognize, and determine the characteristics of objects depicted on orthophoto maps, the borders of fields and forest belts were marked and used to verify the results of automated vectorization. Validation was performed using an independent dataset consisting of 120 field contours, which were verified directly on-site during field surveys conducted in 2024.

The comparison between the automated vector layers and the field data was carried out through layer overlay and the calculation of spatial agreement metrics. The quantitative

evaluation demonstrated an average Intersection over Union (IoU) of 0.86 and a boundary matching accuracy of 91%.

The validation dataset included objects of varying complexity (large and small fields, linear features, and water bodies) and was randomly selected from different parts of the Timiryazevsky Rural District. The obtained results confirmed the high reliability of the U-Net model and enabled refinement of its segmentation performance.

5. Creating digital maps using geoinformation programs based on orthophotography maps and decoding data (Figure 9).

Modern geoinformation technologies play a key role in agriculture, allowing to optimize the use of land resources, increasing productivity, and reducing costs. One promising area is the use of AI to automate data processing and create digital maps [23, 24].



**Figure 9.** Digital agricultural map

### 3. RESULTS

As a result of the study, geoinformational cartographic layers of agricultural land and field contours were created for the study area.

#### 3.1 Automatic vectorization

Data preparation:

First, Landsat-8 satellite imagery for August 2024 was uploaded to ArcGIS Pro and prepared for further geospatial analysis. Auxiliary reference materials, including interpreted contours of fields, roads, water bodies, and settlements, were used to support the extraction of vector objects. The model was trained on 650 training samples (patches of  $512 \times 512$  pixels) extracted from Landsat-8 imagery acquired during 2023–2024 for the Timiryazevsky Rural District and adjacent territories.

The data source comprised the USGS EarthExplorer archives, supplemented with results from field surveys. Object

labeling (annotation) was performed manually by qualified interpreters in ArcGIS Pro using the *Create Training Samples* tool, followed by verification based on field observations.

Choosing the AI model:

Given the objectives of automated object delineation from satellite imagery, deep learning approaches such as U-Net or Mask R-CNN were considered suitable for image segmentation tasks. In the ArcGIS Pro environment, this stage can be supported by built-in deep learning tools for object detection and feature extraction.

Model training:

The model was implemented using the Train Deep Learning Model tool in ArcGIS Pro and the ArcGIS API for Python. A U-Net architecture was employed, consisting of four encoder–decoder blocks with a ResNet-34 backbone pre-trained on the ImageNet dataset.

The key training parameters were as follows: learning rate = 0.0001, batch size = 16, number of epochs = 40, Adam optimizer, and a combined loss function (Dice + Binary Cross-Entropy). The pre-trained model was further fine-tuned on our dataset to adapt it to the spectral characteristics of Landsat-8 imagery in the steppe zone of North Kazakhstan.

Model performance was evaluated on an independent validation set (20% of the total samples) using standard metrics, including IoU, F1-score, Precision, and Recall.

Using the U-Net model, the following objects were successfully vectorized:

- Field borders.
- Roads and water bodies.
- Settlements.

The overall vectorization accuracy reached 87% based on the mean IoU metric (fields – 0.89; roads – 0.82; water bodies – 0.85), with an F1-score of 0.92.

### 3.2 Calculation of NDVI

Goal: to calculate the NDVI for vegetation analysis based on satellite data.

NDVI visualization:

The NDVI was calculated from Landsat-8 imagery to assess the condition of vegetation cover within the study area. A color scale was used to visualize the NDVI values, where lower values indicate sparse or stressed vegetation and higher values correspond to denser and healthier vegetation. The NDVI results were then overlaid on the vector layers obtained at the previous stage.

### 3.3 Integration of vectorization and the NDVI

The vector layers derived from automatic extraction were integrated with the NDVI raster in order to analyze vegetation condition within agricultural fields and related landscape elements. This made it possible to connect the spatial boundaries of fields with the condition of vegetation cover and to identify differences between individual land-use units.

### 3.4 Thematic maps

Thematic maps were created to reflect:

- The distribution of NDVI across agricultural fields.
- Areas with relatively low NDVI values require additional attention.
- The relationship between field contours and vegetation condition within the study area.

As a result, a set of geoinformational cartographic layers was created for the studied territory, reflecting the spatial structure of agricultural land and the boundaries of field contours.

### Geomorphological characteristics

The elevation map of the Timiryazevsky Rural District (Figure 2(a)) shows flat terrain with elevations between 150 and 200 m above sea level, which is typical of the steppe zone. The slope map (Figure 2(b)) reveals a prevalence of gentle slopes (0–1°) comprising more than 90% of the area, with rare areas of 1–2°. The exposure map (Figure 2(c)) demonstrates a uniform distribution of slopes by direction, which minimizes erosion risks and is favorable for mechanization [25, 26].

### Agrometeorological conditions

The map of the sum of active temperatures (Figure 3(a)) shows values ranging from 2,631 to 2,658 °C for the growing season, which are sufficient for grain crops. The precipitation map (Figure 3(b)) shows variation from 369 to 389 mm, with higher values in the central and eastern parts of the district. The map of Selyaninov's HTC (Figure 3(c)) demonstrates values ranging from 1.39 to 1.47, indicating generally sufficient moisture supply during the analyzed growing season, although irrigation may still be required in anomalously dry years.

### Condition of vegetation

NDVI data by year (Figure 4(a)) show the dynamics of vegetation cover from 2017 to 2024. According to the legend, NDVI values ranged approximately from –0.1 to 0.66, with higher vegetation activity observed in 2017 and 2020. The NDVI map for August 2024 (Figure 4(b)) shows values ranging up to 0.55, with areas of relatively high vegetation biomass mainly corresponding to the 0.3–0.55 classes in the southern part of the district. This indicates comparatively higher vegetation productivity in these areas.

The soil map of the Timiryazevsky Rural District (Figure 5) emphasizes the homogeneity of the soil cover, which makes it easier to plan agrotechnical measures. Chernozems have high natural fertility but require erosion control in areas with slopes greater than 1°, which can be found on the slope map (Figure 2(b)).

The exposure map of the Timiryazevsky Rural District (Figure 2(c)) complements the relief analysis by showing the orientation of the slopes. Northeast and southwest directions prevail, which affects the distribution of solar radiation and moisture. This factor is important for choosing crops: areas with southern exposure (warmer) are suitable for early planting, whereas northern slopes retain moisture better.

## 4. DISCUSSION

The integration of various cartographic layers—geomorphological characteristics, agrometeorological conditions, and vegetation health—provides a comprehensive understanding of the Timiryazevsky Rural District's agricultural landscape. The elevation map (Figure 3), with its flat terrain and gentle slopes (150–200m above sea level, over 90% with 1–2° inclination), confirms a low erosion potential, which, coupled with the prevalence of chernozems (up to 80% in arable land), establishes fundamentally favorable conditions for agriculture. Agrometeorological maps (Figure 4), showing

active temperatures sufficient for grain crops (2,631–2,658 °C) and varying precipitation (369–389 mm), indicate a stable climate, although Selyaninov's HTC below 0.7 suggests periodic dry conditions and the potential need for irrigation. The NDVI data (Figure 5), reflecting vegetation dynamics from 2016 to 2023, further highlights the dependence of vegetation health on these climatic factors, underscoring the importance of long-term monitoring for climate change adaptation.

However, the true significance of these thematic maps is profoundly enhanced when generated and analyzed through the proposed automated and AI-driven methodology. The manual and semi-automated approaches traditionally used for delineating agricultural land parcels are often labor-intensive, time-consuming, and require frequent updates due to the dynamic nature of agricultural practices [27, 28]. Digital services often resort to asking users to manually draw fields, which is inefficient and creates disincentives [29]. In contrast, the application of deep learning models, particularly the U-Net architecture, for automatic vectorization allows for the precise and efficient delineation of farmland management units, such as field borders, roads, water bodies, and settlements. This automation is crucial for reducing costs and time, and for increasing efficiency in agricultural management activities [30]. By automatically extracting accurate field boundary data from satellite imagery, our method directly supports improved accuracy in crop type classification and provides essential input for farm management software and government monitoring programs [7]. Deep learning models automatically learn multi-scale and multi-level feature representations, thereby enhancing their ability to effectively capture semantic information in RS images compared to conventional machine learning techniques [6]. Some studies report deep learning achieving over 20% performance gain in specific agricultural tasks compared to traditional machine learning methods [31].

Despite the evident advantages of automated mapping, it is important to acknowledge and analyze the method's uncertainties. The widespread operational adoption of deep learning in agricultural monitoring still faces challenges. These include the scarcity of consistently annotated datasets and difficulties in achieving robust model generalization across diverse environments, varying agricultural practices, climatic conditions, and soil properties [32]. Computational resources required for training and deploying advanced models can be substantial [32]. Errors in upstream preprocessing steps, such as cloud masking or data alignment, can propagate and affect the final predictions [33]. Furthermore, spectral variability of crop types due to local climate, farming practices, and phenological stages, as well as the presence of mixed pixels and transitional regions, can introduce uncertainty in classification and delineation [34, 35]. Future work must address these uncertainties through rigorous validation, development of more robust models adaptable to diverse conditions, and careful attention to data quality and annotation. Quantifying these uncertainties, for example, by integrating uncertainty metrics into the deep learning models, can characterize the confidence of field detection and delineation processes, providing more reliable information for decision-making [36].

The current study demonstrates the effectiveness of integrating AI in ArcGIS for automating data processing and creating digital agricultural maps. The enhanced accuracy and speed of analysis achieved through AI-driven vectorization and NDVI calculation, as shown in the Timiryazevsky Rural

District, are particularly significant for modern agricultural enterprises. This automated approach facilitates more dynamic and precise monitoring of agricultural landscapes, enabling timely identification of problem areas with low NDVI, and supporting the creation of comprehensive thematic maps crucial for optimizing land use and increasing agricultural production efficiency.

Based on the results obtained, the following measures are proposed to improve the creation and use of digital maps:

**Improved data resolution:** The transition from Landsat 8 to Sentinel-2 will increase the detail of NDVI and soil maps, especially for small areas within the Timiryazevsky Rural District, further enhancing the precision of AI-driven vectorization [37].

**Integration of additional data:** Incorporating data from local weather stations (e.g., Kazhydromet data) and detailed soil analysis will improve the accuracy of precipitation, temperature, and soil cover maps, providing a richer context for the AI models and reducing prediction uncertainties.

**Process automation:** Automating the calculation of NDVI and Selyaninov's HTC using Python scripts in ArcGIS will further reduce data processing time, extending the efficiency benefits of the AI-driven approach.

**Practical implementation:** The AI-generated slope (Figure 3(b)) and exposure maps (Figure 2(c)) can help in strategically choosing areas for windbreaks, while the refined NDVI map for August 2024 (Figure 2(b)), derived from accurate vectorization, can be used for more precise estimation of current land productivity and resource allocation.

**Expanding monitoring and validation:** It is recommended to add 2025 data for NDVI analysis to evaluate the temporal stability of the AI models and to supplement maps with information on nutrient content in soils based on more extensive field studies, which can also serve as crucial ground truth for model refinement and uncertainty assessment.

## 5. CONCLUSION

The created digital maps present a valuable tool for managing the agricultural resources of the Timiryazevsky Rural District. Their comprehensive application allows not only to assess current conditions but also to predict changes in land productivity. The implementation of the proposed recommendations will ensure further improvement of mapping technologies and increase the efficiency of agriculture in the region.

The integration of automatic vectorization with the NDVI provides a powerful tool for analyzing agricultural data. This combination not only speeds up the process of creating digital maps but also offers valuable information on the state of vegetation, which can be used to improve the performance of agriculture.

The study demonstrates the effectiveness of using AI in ArcGIS to automate data processing and create agricultural digital maps. The example of the Timiryazevsky Rural District shows that the accuracy and speed of analysis can be increased using AI, which is especially significant for modern agricultural enterprises.

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