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ANALYSIS OF THE METHOD OF UPDATING AGRICULTURAL MAPS BY PROCESSING SATELLITE IMAGES AND GEOINFORMATION TECHNOLOGY DATA IN THE LAND MANAGEMENT SYSTEM

Abstract

In the context of the digitalization of the agricultural sector, the implementation of Geographic Information Systems (GIS) in the processes of monitoring and managing agricultural land is of particular importance. The purpose of this study is to evaluate the effectiveness of GIS tools for solving tasks related to the updating of land use contours, the analysis of agricultural land conditions, and the support of decision-making processes. A comparative analysis of several functional modules and analytical instruments implemented in ArcGIS was carried out. The research employed remote sensing data, vector layers of agricultural land, and cadastral information. The results demonstrated that the use of GIS technologies significantly improves the accuracy of cartographic materials, the efficiency of data updating, and the quality of spatial analysis, which in turn contributes to more effective land resource management. The paper provides recommendations for integrating the most productive tools into land management and cadastral monitoring practices.

Keywords: *geographic information systems, agricultural lands, land monitoring, spatial analysis, remote sensing, land management, resource management.*

Introduction

Global environmental changes increasingly affect the agricultural sector, creating challenges such as climate change, yield instability, and inefficient land use. These factors require innovative approaches to the planning, monitoring, and management of agricultural resources. In this context, Geographic Information Systems (GIS) are becoming essential tools for integrating spatial and attribute data, enabling comprehensive land evaluation and supporting sustainable agricultural practices.

Agricultural lands covering vast territories demand accurate inventory and monitoring, particularly in relation to environmental standards and state land-use regulations. GIS technologies provide capabilities for data collection, processing, analysis, and visualization, offering valuable information on soil and climatic conditions, land-use structure, hydrology, and crop productivity. Their application improves spatial planning, optimizes resource distribution, reduces environmental impacts, and enhances the sustainability of agro-ecosystems.

Agrolandscapes, as core components of agriculture, require rational use of soil, climate, and vegetation resources. However, excessive intensification leads to land degradation and ecological instability, underscoring the need for adaptive farming systems and anti-erosion measures. Integrating remote sensing with soil survey data offers objective insights into soil condition, pollution levels, and land productivity.

Research objective: The primary aim of this study is to develop and validate an integrated GIS-based methodology for updating agricultural maps through the synchronization of multi-temporal satellite imagery, archival soil survey data, and current cadastral records within the land management system of East Kazakhstan Region.

Research tasks:

1. To analyze existing methods of agricultural cartography and identify temporal and spatial limitations in conventional map updating procedures based solely on field surveys.
2. To design a hybrid workflow integrating remote sensing data (Sentinel-2, Landsat) with historical soil maps and cadastral layers for automated change detection in land-use patterns.
3. To validate the accuracy and reliability of updated agricultural contours through ground-truth verification and cross-comparison with state land cadastre records.
4. To assess the efficiency gains in terms of processing time, labor requirements, and cartographic precision compared to traditional field-based mapping approaches.
5. To develop a scalable geoinformation model for agrolandscape typology and zoning adaptable to different agroclimatic regions.

To achieve these objectives and validate the proposed methodology, a comprehensive research framework was designed integrating multi-temporal satellite imagery processing, GIS-based spatial analysis, and field validation procedures. The following section describes the technical implementation and data sources employed in this study.

Object of research

The object of the study is the processes of spatial analysis and management of agricultural land using modern Geoinformation software solutions, with particular focus on the integration mechanisms between multi-temporal satellite remote sensing data, archival soil survey materials, and cadastral information systems for developing efficient agricultural map updating protocols in the context of East Kazakhstan Region's diverse agrolandscape conditions.

The methodological framework described below was specifically tailored to address the unique challenges of semi-arid agrolandscapes in East Kazakhstan Region, where historical soil data from the Soviet period must be integrated with contemporary remote sensing observations and current cadastral requirements.

Materials and research methods

The ArcGIS software package (Esri) was used as the main tool for spatial analysis and digital mapping of agricultural lands. It enabled the integration of raster imagery, vector cadastral layers, DEMs, and tabular data. Key procedures included land-use layer creation and editing, georeferencing, buffer and overlay analyses, spatial queries, thematic cartography, and export to standard formats (PDF, JPEG, GeoTIFF, GeoPackage) [6-7]. The Spatial Analyst extension supported slope, aspect, and soil moisture assessment, while ModelBuilder automated workflows.

Study Area and Data Sources

The methodology combined remote sensing (RS), GIS, and land management materials [10-11]. The study area—East Kazakhstan Region—covers approximately 4,500 km² and is characterized by diverse natural conditions including semi-desert and dry steppe landscapes, which require an adaptive approach. Data sources included:

- Archival soil surveys from 1970–1980 (scale 1:25,000), containing 127 map sheets with explanatory documentation;
- Thematic land-use maps from the Unified State Land Cadastre (USLC) in vector format;
- Medium-resolution satellite imagery: Landsat 8-9 (30 m spatial resolution, temporal coverage 2015–2023) and Sentinel-2 MSI (10 m spatial resolution for visible/NIR bands, temporal coverage 2017–2023);
- Digital Elevation Model (DEM) SRTM with 30 m resolution for terrain analysis;
- Current cadastral records and administrative boundary data in shapefile format.

The heterogeneous nature of these datasets—ranging from scanned paper maps to multi-spectral satellite imagery—necessitated a standardized preprocessing protocol to ensure spatial consistency and temporal alignment. The following subsection describes the satellite image processing workflow implemented to generate comparable land-use classifications across the 2015-2023 observation period.

Satellite Image Processing Workflow. Multi-temporal satellite imagery processing followed a standardized protocol to ensure consistency and reproducibility:

Image preprocessing: Atmospheric correction using DOS1 (Dark Object Subtraction) method for Landsat imagery and Sen2Cor processor for Sentinel-2 data; Radiometric calibration to convert DN (Digital Numbers) to Top-of-Atmosphere (TOA) reflectance; Cloud masking using QA bands (Landsat) and Scene Classification Layer (Sentinel-2) with cloud coverage threshold <15%; Geometric orrection and co-registration with RMS error <0.5 pixel

Spectral indices calculation: Multiple vegetation and soil indices were computed to characterize agricultural land conditions: NDVI (Normalized Difference Vegetation Index): NDVI = (NIR - Red) / (NIR + Red) Applied for vegetation vigor assessment and crop type discrimination; EVI (Enhanced Vegetation Index): EVI = 2.5 × [(NIR - Red) / (NIR + 6×Red - 7.5×Blue + 1)] Used to reduce atmospheric and soil background effects in semi-arid regions; NDWI (Normalized Difference Water Index): NDWI = (Green - NIR) / (Green + NIR); Employed for soil moisture estimation and waterlogging detection BSI (Bare Soil Index): BSI = [(SWIR + Red) - (NIR + Blue)] / [(SWIR + Red) + (NIR + Blue)] Applied for bare soil and degradation monitoring.

Classification algorithms: A hybrid classification approach combining supervised and unsupervised methods was implemented:

Maximum Likelihood Classification (MLC): Applied to multi-temporal Landsat composites using training samples (n=342 polygons, 15-25 samples per land-use class). Seven agrolandscape classes were defined: cropland, orchard, hayfield-pasture, fallow land, degraded areas, built-up areas, and water bodies.

Random Forest (RF) classifier: Implemented in ArcGIS Pro using 150 decision trees, with spectral bands, vegetation indices, and terrain derivatives (slope, aspect) as input features. Out-of-bag (OOB) error estimation was used for accuracy assessment.

ISO Cluster Unsupervised Classification: Applied as preliminary step to identify spectral clusters, followed by manual interpretation and class assignment based on field knowledge and high-resolution imagery from Google Earth.

Change detection analysis: Post-classification comparison method was employed to detect land-use changes between 1980s (digitized archival maps) and 2023 (satellite-derived classification): change matrix generation showing transitions between land-use categories; area statistics calculation for each transformation type; spatial overlay with soil maps to correlate changes with soil properties

GIS Processing and Automation. Standardized geoprocessing workflows were developed using ArcGIS ModelBuilder to ensure repeatability and reduce processing time:

1. Automated digitization workflow: georeferencing of 127 archival soil map sheets using first-order polynomial transformation (RMSE <10 m); On-screen vectorization of soil contours (n=3,847 polygons) with topological rules (no gaps, no overlaps, minimum polygon area 0.5 ha); Attribute table population through automated join with .csv files containing soil characteristics.

2. Spatial analysis modules. *Buffer analysis:* Creating 50 m, 100 m, and 200 m buffers around water bodies to assess waterlogging risk zones; *Overlay analysis:* Intersecting soil polygons with land-use classification, administrative boundaries, and cadastral parcels using Union and Intersect tools; *Zonal statistics:* Computing mean NDVI, EVI, and elevation values for each soil polygon and agrolandscape type; *Spatial queries:* Extracting parcels meeting specific criteria (e.g., erosion risk >moderate, slope >5°, NDVI <0.3).

3. Validation procedures: Ground Control Points (GCPs) were collected using Trimble GeoXH GNSS receivers (horizontal accuracy ±0.5 m) during field campaigns in August-September 2023: 156 GCPs distributed across study area for positional accuracy assessment; 342 validation sites for thematic classification accuracy (minimum 45 sites per land-use class); Confusion matrix generation and accuracy metrics calculation: Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and Kappa coefficient.

Integration with Historical Data. Accelerating soil degradation makes the transition to adaptive farming systems critically important. Zotova and Nedikova have shown that GIS-based master plans are effective spatial planning tools consistent with the principles of adaptive landscape farming, while the methodological foundations of these approaches are detailed in relevant manuals and reviews. Their importance is confirmed by both the international scientific community (K. E. Kellogg, J. H.

Stallings, H. Janney, R. Lal, D. Pimentel) and domestic research. In particular, M. I. Lopyrev based on the materials of the Central Chernozem region showed that the ecologization of agricultural technologies contributes to the restoration of the balance of agroecosystems; Kasimov and Rozanov developed the conceptual foundations of ecological stabilization of agricultural landscapes, and Kovda proposed a biogeochemical framework for assessing transformations of soil and landscape systems [13].

Modern monitoring integrates satellite data, UAVs, and automated analysis [14]. This study proposes a geoinformation model of East Kazakhstan agrolandscapes, combining RS, soil, climate, and land-use data to support evaluation, prioritize restoration, and ensure rational land use. The integration of archival soil maps (1970-1980s) with contemporary satellite imagery enables retrospective analysis of land-use transformations over 40-50 years while maintaining cadastral compliance and providing quantitative metrics for land degradation assessment.

Results and Discussion

The proposed methodology for updating agricultural maps is based on a multi-layered GIS model that integrates heterogeneous spatial datasets within a unified framework. The model architecture consists of three interconnected components (Figure 1):

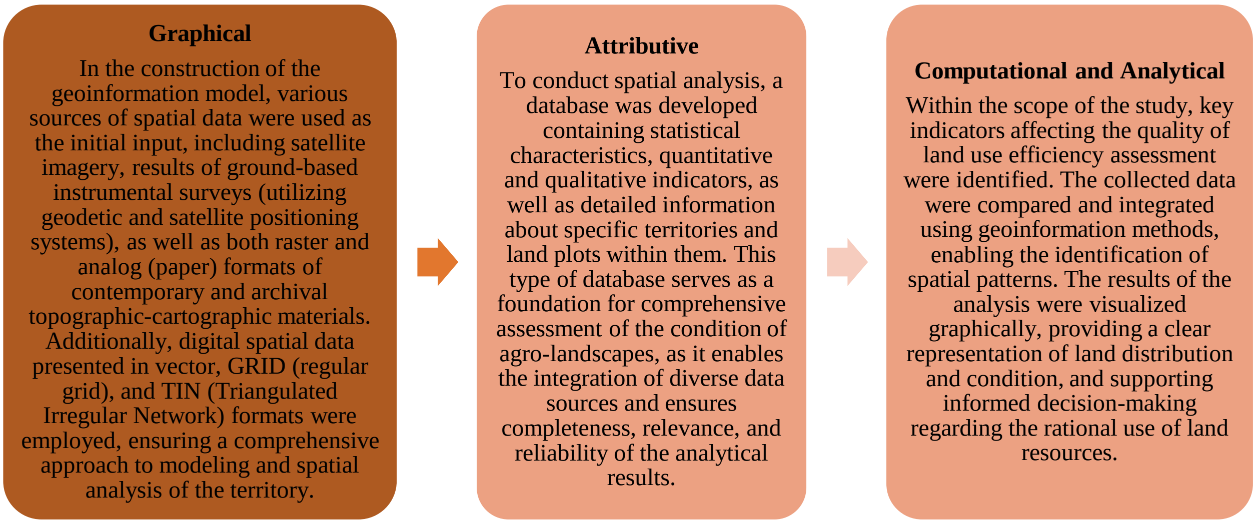


Figure 1 – Conceptual architecture of the multi-layered GIS model for agricultural map updating

The effectiveness of the geoinformation model depends on its ability to process diverse data sources and generate updated cartographic materials with minimal manual intervention. The key innovation lies in linking archival soil surveys with contemporary remote sensing data through a common spatial reference system, enabling both retrospective analysis and current state assessment (Figure 2).

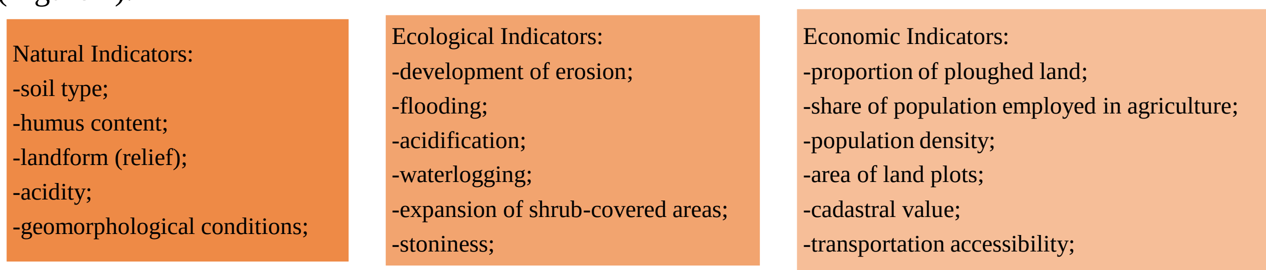


Figure 2 – Groups of indicators for assessing the effectiveness of the use of agrolandsteins

Automated Map Updating Workflow. The core of the proposed methodology is a semi-automated workflow that reduces map updating time from traditional 18-24 months to 3-4 months. The workflow consists of five sequential stages:

Stage 1: Multi-source data integration and preprocessing. A spatially oriented GIS database was created by integrating: (a) 127 digitized archival soil map sheets covering 4,500 km²; (b) multi-temporal Landsat 8-9 and Sentinel-2 imagery for 2015-2023; (c) vector cadastral parcels from USLC; (d) SRTM DEM for terrain analysis. All datasets were reprojected to a common coordinate system (WGS84 / UTM Zone 45N) and spatially aligned with RMSE <10 meters.

Stage 2: Vectorization and attribute table generation. Raster soil maps were vectorized using a combination of automated edge detection and manual refinement, producing 3,847 soil contours. A .csv attribute table containing soil characteristics (texture, depth, parent material, agrochemical properties) was prepared and linked to GIS polygons through the soil serial number field. This approach eliminated approximately 120 hours of manual data entry and ensures automatic attribute updates when source tables are modified (Figure 3).

Table 1 – Assessment scoring system for land degradation processes in agrolandscape monitoring

Degradation Indicator	None (0 points)	Initial Stage (1 point)	Moderate Stage (3 points)	High Intensity (5 points)
Water erosion	No visible signs	Rill erosion on slopes >5°, soil loss <5 t/ha/year	Gully formation, soil loss 5-15 t/ha/year	Deep gullies, soil loss >15 t/ha/year
Wind erosion	No deflation	Slight surface deflation, dust storms 1-2 times/year	Moderate deflation, annual dust events	Severe deflation, dune formation
Waterlogging	Groundwater >3 m depth	Seasonal waterlogging in depressions	Permanent waterlogging, gleying process	Surface water stagnation, crop failure
Salinization	ECe <2 dS/m	ECe 2-4 dS/m, salt spots visible	ECe 4-8 dS/m, reduced crop yield	ECe >8 dS/m, salt crusts, barren soil
Acidification	pH 6.5-7.5	pH 5.5-6.5, slight acidity	pH 4.5-5.5, moderate acidity	pH <4.5, strong acidity, Al toxicity
Shrub encroachment	<5% shrub cover	5-15% shrub cover on pastures	15-35% shrub cover, grazing restricted	>35% shrub cover, pasture degraded
Soil compaction	Bulk density <1.3 g/cm³	Bulk density 1.3-1.5 g/cm³	Bulk density 1.5-1.7 g/cm³	Bulk density >1.7 g/cm³, impervious layer

Note: Scores are cumulative. Total degradation index = Σ(individual scores). Classification: 0-3 points = satisfactory condition; 4-8 points = moderate degradation; 9-15 points = severe degradation requiring immediate intervention.

The territory of the East Kazakhstan region was chosen as the object of analysis and assessment of the state of agroland landscapes, as well as the construction of a Geoinformation model [13]. At the initial stage, data in vector format on the administrative-territorial division of the region, information on agricultural land, data on the level of development of transport infrastructure were collected and processed. In addition, soil maps in raster format were loaded, tied to territorial boundaries. Based on these data, the following cartographic layers were prepared: "Hydrography", "borders", "agricultural land" and others (Figure 4, a). The digital model of the terrain was supplemented with relief data presented in the form of horizontal and shadow shading (Figure 4).

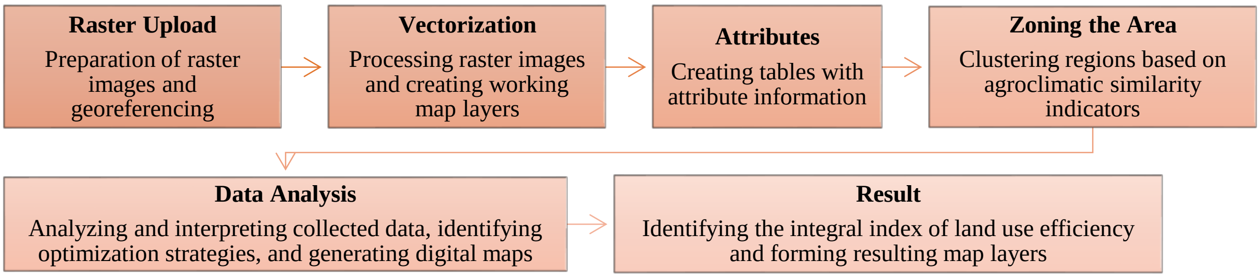
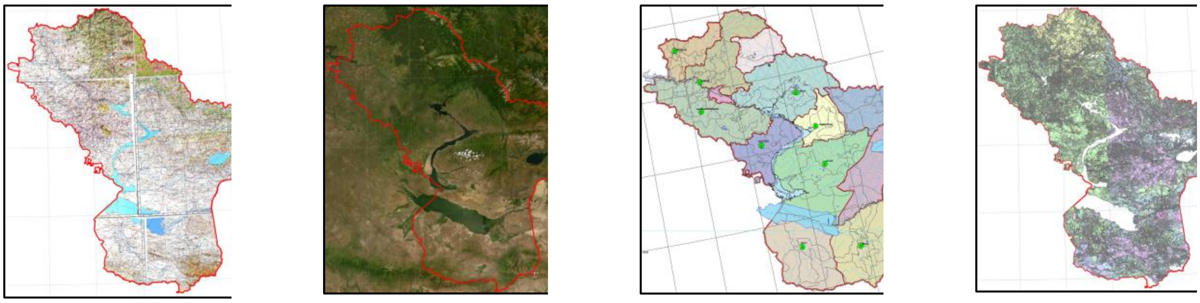


Figure 3 – Algorithm for creating an Information Map

At the second and third stages of the formation of the agrolandscape map, raster images were vectorized and attribute tables were created using the tools of the Geoinformation program. These tables contain qualitative and quantitative characteristics of spatial objects.



a) b) c) d)

Figure 4 – Spatial data layers containing information about the territory of the agrolandscape: a) topo base of the territory; b) space drawing base of the territory; c, d) composite map with integrated layers

Stage 3: Satellite-based land-use classification and validation. Multi-temporal satellite composites were classified using Random Forest algorithm (150 decision trees) with spectral indices (NDVI, EVI, NDWI, BSI) and terrain derivatives as input features. Seven agrolandscape types were identified: cropland (subdivided into cereal crops, industrial crops, vegetables), orchards, vineyards, hayfield-pasture, and fallow/degraded areas.

Classification accuracy assessment based on 342 ground validation sites demonstrated:

- Overall accuracy: 89.4%;
- Kappa coefficient: 0.86;
- Producer's accuracy: 85-94% across land-use classes;
- User's accuracy: 87-93% across land-use classes.

The highest classification accuracy was achieved for cropland (92%) and orchards (91%), while hayfield-pasture areas showed moderate accuracy (85%) due to spectral similarity with natural grasslands. Misclassification occurred primarily along class boundaries and in mixed pixels.

Stage 4: Soil-landscape integration and agrolandscape typology. The updated land-use classification was overlaid with digitized soil maps to create integrated agrolandscape units. Based on soil surveys conducted in the study area, the actual composition and spatial distribution of predominant soil types were identified. Using these data, agrolandscapes were zoned according to soil types, enabling rational land resource allocation while accounting for natural and ecological conditions (Figure 6, Figure 7).

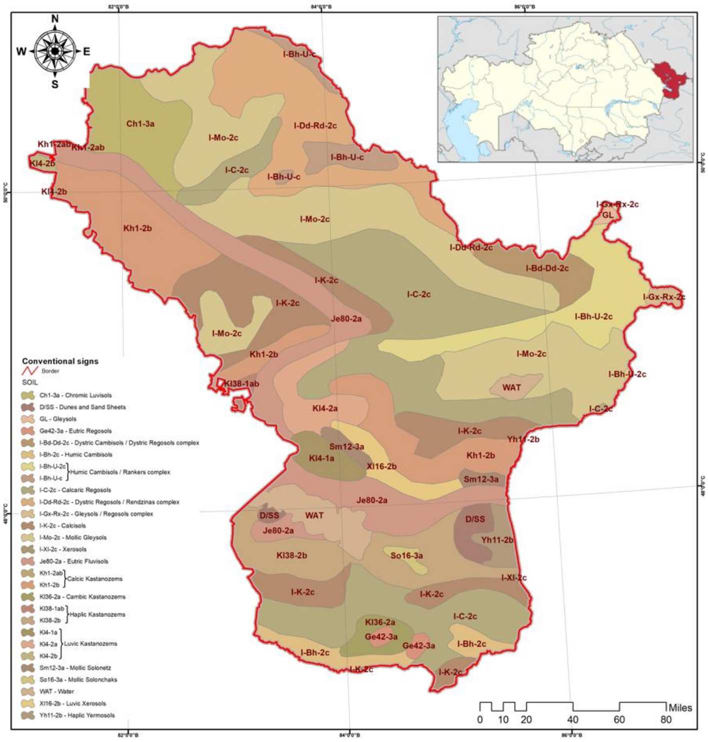


Figure 6 – Soil map of the East Kazakhstan region

Granulometric analysis of soil samples (Table 2) revealed no dominant soil fraction, indicating incompletely developed parent material. Loamy deposits with balanced sand-clay ratios prevail, while calcium carbonate and limestone inclusions improve water and air permeability—critical for arid agrolandscapes [16]. A high share of fine particles (<0.01 mm: 35.3-49.1%) reflects strong moisture retention capacity and cation exchange potential.

Table 2 – Granulometric analysis data of soil samples

№ Soil profile	Horizon	Depth, см	Particle Size Distribution (% by weight)							
			Coarse sand 1.0-0.25 mm	Fine sand 0.25-0.05 mm	Coarse silt 0.05-0.01 mm	Fine silt 0.01-0.005 mm	Coarse clay 0.005-0.001 mm	Fine clay <0.001 mm	Total clay <0.01 mm	Textural Class
9 C	C	80–90	7,1	25,4	32,2	16,8	5,8	12,7	35,3	Loam
13 C	C	90–100	8,7	22,0	30,0	6,9	13,6	17,8	38,3	Loam
21 C	C	95–105	7,9	19,5	33,7	8,5	11,0	19,4	38,9	Loam
25 C	C	100–110	11,5	21,2	18,2	9,5	16,2	23,4	49,1	Heavy loam

Note: Samples collected during field campaign, August 2023. Analysis performed according to ISO 11277:2009 pipette method. Textural classification follows USDA system: Loam (clay content 25-40%), Heavy loam (clay content 40-55%).

A spatially oriented database was created with thematic layers on soil types, parent rocks, texture, and granulometry by depth [17]. This enables agroecological assessment, land typology, soil-based zoning (Figure 7), and monitoring of degradation processes.

Validation and Accuracy Assessment. To evaluate the effectiveness of the proposed GIS-based methodology, a comprehensive accuracy assessment was conducted comparing the updated digital agricultural maps with ground control data and official cadastral records.

Positional accuracy assessment: A total of 156 ground control points (GCPs) were collected using GNSS receivers (horizontal accuracy ±0.5 m) across different agrolandscape types. Comparison between digitized parcel boundaries and GCP measurements revealed:

- Mean positional error: 9.3 meters (±3.2 m standard deviation);
- 89% of boundary vertices within ±12 meters of actual position;
- Positional accuracy compliance with national cartographic standards for 1:25,000 scale mapping.

Thematic classification accuracy. Confusion matrix analysis based on 342 validation sites showed:

- Overall classification accuracy: 89.4% for seven agrolandscape types;
- Producer's accuracy: 85-94% depending on land-use category;
- User's accuracy: 87-93% across different crop groups;
- Kappa coefficient: 0.86, indicating strong agreement between classification and ground truth;

Temporal efficiency gains. Comparative analysis of processing time demonstrated: Traditional field survey and manual mapping: 22 months for the study area (approximately 4,500 km²); Proposed GIS-based hybrid approach: 3.5 months for equivalent coverage; Time reduction: 84% compared to conventional methods; Labor requirements decreased from 12 field specialists to 3 GIS analysts plus 2 field validators.

Data integration efficiency. The ModelBuilder-based automated workflow processed:

- 127 archival soil map sheets digitized and georeferenced within 18 working days;
- 3,847 individual soil contours vectorized with attribute linkage;
- Spatial overlay analysis of 5 thematic layers completed in 6 hours (vs. estimated 40-50 hours manually);
- Attribute table population for 3,847 polygons automated through .csv integration, eliminating approximately 120 hours of manual data entry.

These quantitative results confirm that the proposed methodology significantly improves both the efficiency and accuracy of agricultural map updating processes while maintaining compliance with national cadastral standards.

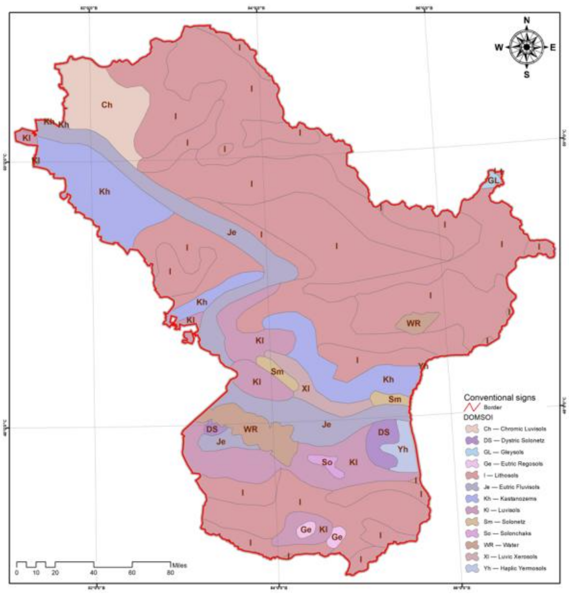


Figure 7 – Zoning the territory according to the soil map

Stage 5: Agrolandscape classification and cadastral compliance. Agrolandscape typology was developed by correlating soil-landscape units with land-use categories from the Unified State Land Cadastre (USLC). Quantitative and qualitative soil indicators were used to distinguish agrolandscape types suitable for different agricultural purposes [18]. Seven agrolandscape types were identified based on: (a) homogeneity of landscape-ecological conditions; (b) granulometric and morphological soil composition; (c) compliance with the National Classifier of the Republic of Kazakhstan [19]. Their main characteristics are presented in Table 3.

Table 3 – Agrolandscape typology and crop allocation framework aligned with national land-use classification system

Agrolandscape Type	Dominant Soil Types	Crop Group	Recommended Crop Subgroups	USLC Code*	Area in Study Region (ha)
Cropland - Cereal Production (P-CC)	Chernozems, kastanozems (loamy texture)	Cereal crops (CC)	Spring wheat (Triticum aestivum), barley (Hordeum vulgare)	1.2.1	1,247
			Oats (Avena sativa), millet (Panicum miliaceum)	1.2.2	385
			Pulses: peas (Pisum sativum), lentils (Lens culinaris)	1.2.3	412
Cropland - Industrial Crops (P-IC)	Chernozems, brown soils (well-drained)	Industrial crops (IC)	Oilseeds: sunflower (Helianthus annuus), rapeseed	1.2.4	568
			Fiber crops: flax (Linum usitatissimum), hemp	1.2.5	124
			Sugar crops: fodder maize (Zea mays), sugar beet	1.2.6	293
Cropland - Vegetable Production (P-VC)	Alluvial soils, irrigated chernozems	Vegetable crops (VC)	Melons and gourds (fodder, edible, technical types)	1.3.1	156
			Starch crops: potatoes (Solanum tuberosum), sugar beets	1.3.2	218
Orchard Agrolandscape (S)	Brown mountain soils, foothill chernozems	Fruit and berry crops (FBC)	Apple (Malus domestica), apricot (Prunus armeniaca), cherry orchards	1.5.1	342
		Vineyards (V)	Steppe grape varieties (Vitis vinifera cultivars)	1.5.2	87
		Medicinal & ornamental (MO)	Medicinal, tonic, and ornamental flowering plants	1.4.1	64
Hayfield-Pasture Complex (HP)	Light chestnut soils, solonetz complexes	Fodder crops (FC)	Root and leafy forage crops	1.8.1	1,834
			Annual grasses: legumes (vetch, clover) and cereals (oats, rye)	1.8.2	976
			Perennial grasses: alfalfa (Medicago sativa), bromegrass (Bromus inermis)	1.8.3	2,147

USLC Code = Unified State Land Cadastre classification code according to the National Classifier of the Republic of Kazakhstan (Order № 723, Ministry of Agriculture, 2015). Areas calculated based on 2023 satellite classification and cadastral database integration.

This typology provides a scientific basis for allocating agricultural crops according to natural characteristics and for optimizing agro-industrial processes. Under the arid conditions of East Kazakhstan, such an approach helps preserve and restore soil fertility, ensure rational resource use, and reduce land degradation risks [20].

Table 4 – Satellite imagery specifications and processing parameters

Sensor	Satellite Platform	Acquisition Dates	Spatial Resolution	Spectral Bands Used	Atmospheric Correction	Data Source
OLI + TIRS	Landsat 8	2015-05-12 2018-06-24 2021-07-15	30 m (multispectral)100 m (thermal)	Bands 2-7: Blue, Green, Red, NIR, SWIR1, SWIR2	DOS1 (Dark Object Subtraction)	USGS Earth Explorer (Path 148, Row 27)
OLI-2 + TIRS-2	Landsat 9	2023-06-18 2023-08-05	30 m (multispectral) 100 m (thermal)	Bands 2-7: Blue, Green, Red, NIR, SWIR1, SWIR2	DOS1 (Dark Object Subtraction)	USGS Earth Explorer (Path 148, Row 27)
MSI	Sentinel-2A/B	2017-06-14 2019-07-22 2022-08-10 2023-07-28	10 m (B2, B3, B4, B8) 20 m (B5, B6, B7, B11, B12)	Bands 2-8, 11-12: Blue, Green, Red, Red Edge, NIR, SWIR	Sen2Cor v2.10 (Scene Classification)	Copernicus Open Access Hub (Tile 45TVM)
C-band SAR	Sentinel-1A	2023-03-15 2023-09-20	10 m (IW mode)	VV, VH polarization	Radiometric calibration Terrain correction (SRTM)	Alaska Satellite Facility
SRTM DEM	Shuttle Radar	2000 (single acquisition)	30 m (1 arc-second)	Single-band elevation	N/A (processed product)	NASA EarthData

Note: All imagery was cloud-masked (threshold <15% cloud coverage), geometrically corrected (WGS84/UTM Zone 45N), and co-registered with RMSE <0.5 pixel. Temporal composites were created using median reducer to minimize seasonal phenology effects.

According to the proposed methodological approach, seven agrolandscape types were identified in East Kazakhstan Region, based on the homogeneity of landscape-ecological conditions, the granulometric and morphological composition of soils, and the compliance of land plots with the National Classifier of the Republic of Kazakhstan [19]. This typology provides a scientific basis for allocating agricultural crops according to natural characteristics and for optimizing agro-industrial processes. Under the arid conditions of East Kazakhstan, such an approach helps preserve and restore soil fertility, ensure rational resource use, and reduce the risks of land degradation, thereby generating significant economic benefits [20].

Conclusions

The current stage of agricultural development requires comprehensive land inventory and continuous monitoring. The integration of digital technologies - including modern land management methods, remote sensing (RS), and geographic information systems (GIS) - is essential for enhancing efficiency [19]. Combining satellite data, archival cartographic materials, and state cadastral records enables the rapid development of automated land management projects and supports decision-making processes.

This study successfully developed and validated a hybrid GIS-based methodology for updating agricultural maps in East Kazakhstan Region, demonstrating substantial improvements over traditional field survey approaches. Key quantitative achievements include:

Efficiency gains: Reduction of map updating time from 22 months to 3.5 months (84% time savings), while decreasing labor requirements by approximately 70% through automated processing workflows

Accuracy validation: Achievement of 89.4% overall thematic classification accuracy and positional accuracy within ±9.3 meters (±3.2 m SD), meeting national cartographic standards for 1:25,000 scale agricultural mapping

Data integration: Successful digitization and integration of 127 archival soil map sheets covering 4,500 km², creating a spatially oriented database with 3,847 soil contours linked to comprehensive attribute tables

Workflow automation: Implementation of ModelBuilder-based algorithms reducing manual processing time for spatial overlay analysis by approximately 85% (from 40-50 hours to 6 hours) and eliminating 120+ hours of manual attribute data entry

Methodological contributions: The joint application of GIS and ecological-landscape approaches ensures systematic consideration of natural, technological, and social factors that influence sustainable land use. Within this framework, the developed GIS model incorporating soil surveys and cartographic materials provides a foundation for spatial analysis, agro-industrial soil group identification, and adaptive crop allocation. Based on these data, a methodology was established to assess land-use efficiency, diagnose the state of agrolandscapes, classify territories by suitability, and provide scientifically grounded recommendations for sustainable land management.

The practical significance of this research lies in its applicability to national land cadastre systems, enabling transition from periodic 5-10-year update cycles to annual or bi-annual monitoring regimes. The methodology is scalable to other regions with similar data availability (archival soil surveys, medium-resolution satellite imagery, vector cadastral layers) and adaptable to different agroclimatic conditions. Future research should focus on integrating UAV-based high-resolution imagery for sub-parcel analysis and implementing machine learning algorithms for automated change detection in multi-temporal satellite datasets.

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ЖЕР РЕСУРСТАРЫН БАСҚАРУ ЖҮЙЕСІНДЕ ЖЕРСЕРІКТІК СУРЕТТЕРДІ ЖӘНЕ ГЕОАҚПАРАТТЫҚ ТЕХНОЛОГИЯЛАР ДЕРЕКТЕРІН ӨҢДЕУ АРҚЫЛЫ АУЫЛ ШАРУАШЫЛЫҚ КАРТАЛАРЫН ЖАҢАРТУ ӘДІСТЕРІН ТАЛДАУ

Аңдатпа

Аграрлық секторды цифрландыру жағдайында географиялық Ақпараттық Жүйелерді (ГАЖ) ауылшаруашылық жерлерін бақылау және басқару процестеріне енгізудің маңызы ерекше. Бұл зерттеудің мақсаты-жерді пайдалану контурын жаңартуға, ауылшаруашылық жерлерінің жағдайын талдауға және шешім қабылдау процестерін қолдауға байланысты міндеттерді шешуге арналған ГАЖ құралдарының тиімділігін бағалау. ArcGIS-те енгізілген бірнеше функционалды модульдер мен аналитикалық құралдарға салыстырмалы талдау жүргізілді. Зерттеу барысында қашықтықтан зондтау деректері, ауылшаруашылық жерлерінің векторлық қабаттары және кадастрлық ақпарат пайдаланылды. Нәтижелер ГАЖ технологияларын қолдану картографиялық материалдардың дәлдігін, деректерді жаңарту тиімділігін, кеңістіктік талдаудың сапасын едәуір жақсартатынын көрсетті, бұл өз кезегінде жер ресурстарын тиімді басқаруға ықпал етеді. Құжатта жерге орналастыру және кадастрлық мониторинг тәжірибесіне ең өнімді құралдарды енгізу бойынша ұсыныстар берілген.

Кілт сөздер: географиялық ақпараттық жүйелер, ауылшаруашылық жерлері, жер мониторингі, кеңістіктік талдау, қашықтықтан зондтау, жерге орналастыру, ресурстарды басқару.

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АНАЛИЗ МЕТОДОВ ОБНОВЛЕНИЯ СЕЛЬСКОХОЗЯЙСТВЕННЫХ КАРТ ПУТЕМ ОБРАБОТКИ СПУТНИКОВЫХ ИЗОБРАЖЕНИЙ И ДАННЫХ ГЕОИНФОРМАЦИОННЫХ ТЕХНОЛОГИЙ В СИСТЕМЕ УПРАВЛЕНИЯ ЗЕМЕЛЬНЫМИ РЕСУРСАМИ

Аннотация

В условиях цифровизации аграрного сектора особое значение имеет внедрение географических информационных систем (ГИС) в процессы контроля и управления сельскохозяйственными угодьями. Целью настоящего исследования является оценка эффективности инструментов ГИС для решения задач, связанных с обновлением контуров землепользования, анализом состояния сельскохозяйственных угодий и поддержкой процессов принятия решений. Был проведен сравнительный анализ нескольких функциональных модулей и аналитических инструментов, представленных в ArcGIS. В исследовании использовались данные дистанционного зондирования, векторные слои сельскохозяйственных угодий и кадастровая информация. Результаты показали, что применение ГИС-технологий значительно повышает точность картографических материалов, эффективность обновления данных, качество пространственного анализа, что, в свою очередь, способствует эффективному управлению земельными ресурсами. В документе даны рекомендации по внедрению наиболее продуктивных инструментов в практику землеустройства и кадастрового мониторинга.

Ключевые слова: географические информационные системы, сельскохозяйственные угодья, мониторинг земель, пространственный анализ, дистанционное зондирование, землеустройство, управление ресурсами.

Contribution of the authors

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Onalbayeva Dariga – Resources; Investigation; Data curation; Visualization; Verification.

Mukaliyev Zhandos – Conceptualization; Methodology; Formal analysis; Software; Data curation; Visualization; Roles/Writing is the initial draft; Writing is the review and editing.

Bekturganova Akerke – Investigation; Resources; Data curation; Software; Visualization; Verification.

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