кўрсаткичлари ҳамда ўсимликларнинг яшаш муҳитига бўлган талаблари ва таъсирлари гуруҳланди.

Замонавий геоахборот тизими технологияларига асосланган қишлоқ хўжалиги экинларини жойлаштириш-нинг оптималлашган тизими яратилди. Олинган барча маълумотлар асосида «Тупроқ хосса-хусусиятларига кўра экинларни жойлаштириш» дастурий таъминоти ишлаб чиқилди ва унинг ҳисоблаш алгоритмлари бўйича танланган ҳудудларнинг қишлоқ хўжалиги экинларини етиштиришга яроқлилиги баҳолаш имконияти яратилди.

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ANALYSIS OF SOIL TEXTURE USING ARTIFICIAL INTELLIGENCE MODELS AND REMOTE SENSING DATA

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Annotation. This article explores the use of artificial intelligence (AI) technologies for analyzing soil texture based on machine learning models and remote sensing data. Four datasets, combining archival and recent data with spectral indices, were used to evaluate model performance. The AdaBoost algorithm achieved the highest accuracy (68.2%) for soil texture prediction. The results demonstrate that AI models, especially those incorporating both historical and recent data, provide accurate and scalable solutions for soil texture analysis, contributing significantly to precision agriculture and sustainable land management.

Key words: soil texture, artificial intelligence models, remote sensing, soil analysis, modeling.

Аннотация. Ушбу мақолада машинавий ўрганиш моделлари ва масофадан зондлаш маълумотлари асосида тупроқ механик таркибини таҳлил қилиш учун сунъий интеллект (СИ) технологияларидан фойдаланиш ўрганилган. Модел ишлашини баҳолаш учун архив ва янги олинган маълумотларни спектрал индекслар билан бирлаштирилган тўртта маълумотлар тўплами ишлатилган. AdaBoost алгоритми тупроқ механик таркибини башорат қилишда энг юқори аниқликка (68,2%) эришди. Натижалар шуни кўрсатадики, СИ моделлари, айниқса тарихий ва сўнгги маълумотларни ўз ичига олган, тупроқ текстурасини таҳлил қилиш учун аниқ ва кенгайтириладиган ечимларни тақдим этади. Б у аниқ қишлоқ хўжалиги ва барқарор ер ресурсларини бошқарувига сезиларли ҳисса қўшади.

Калит сўзлар: тупроқ механик таркиби, сунъий интеллект моделлари, масофадан зондлаш, тупроқ таҳлили, моделлаштириш.

Аннотация. В этой статье рассматривается использование технологий искусственного

интеллекта (ИИ) для анализа текстуры почвы (механического состава) на основе моделей машинного обучения и данных дистанционного зондирования. Для оценки производительности модели использовались четыре набора данных, объединяющие архивные и недавние данные со спектральными индексами. Алгоритм AdaBoost достиг наивысшей точности (68,2%) для прогнозирования текстуры почвы. Результаты показывают, что модели ИИ, особенно те, которые включают как исторические, так и недавние данные, предоставляют точные и масштабируемые решения для анализа текстуры почвы, внося значительный вклад в точное земледелие и устойчивое управление земельными ресурсами.

Ключевые слова: механический состав почвы, модели искусственного интеллекта, дистанционное зондирование, анализ почвы, моделирование.

Introduction. Soil texture, determined by the proportions of sand, silt, and clay particles, is a critical property influencing soil fertility, water retention, aeration, and susceptibility to erosion. Understanding the mechanical composition of soils enables better land management decisions, optimizing crop productivity and sustainability. Traditional methods for determining soil texture are labor-intensive, time-consuming, and not scalable for large agricultural fields.

Advances in artificial intelligence (AI) and remote sensing technologies offer new approaches to soil texture analysis. AI models, integrating ground-based measurements with satellite imagery, allow for efficient and accurate prediction of soil properties across large areas. These technologies provide significant potential for precision agriculture by enabling real-time monitoring and data-driven management of soil resources [1-6].

This study investigates the application of AI technologies in analyzing soil texture in the Syrdarya region's key agricultural lands. By leveraging machine learning algorithms and integrating spectral indices derived from remote sensing data, the research aims to provide scalable solutions for characterizing soil mechanical composition.

The research object and methods.

1. Study area and data collection

The study was conducted on irrigated agricultural lands in the Syrdarya region. The soils in the key fields include light and medium loamy textures, with varying proportions of physical clay (<0.01 mm) and fine clay (<0.001 mm) fractions.

Soil samples were collected from multiple soil layers, ranging from 0–27 cm to 81–130 cm depth, across various locations. The physical clay content ranged from 14–45%, and fine clay fractions ranged from 0.7–14%.

Remote sensing data was obtained from Landsat 8 satellite imagery, focusing on bands relevant to soil and vegetation analysis, such as near-infrared (NIR), red, and shortwave infrared (SWIR) bands. Derived indices, including the Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI), were also used.

2. Data preprocessing

Standardization: Soil texture data and spectral indices were normalized to ensure uniform scaling across all features.

Data cleaning: Missing or outlier values were addressed using interpolation and outlier removal techniques.

Feature selection: Spectral bands and vegetation indices most correlated with soil texture properties were selected as inputs for the AI models. Key features included Band 5 (NIR), Band 7 (SWIR), NDVI, and SAVI.

3. Dataset description

Four datasets were developed to assess model performance:

All Data Full: Combines archival and recent data, including all spectral bands and vegetation indices.

All Data Bands: Combines archival and recent data but excludes vegetation

indices.

Last Data Full: Includes only recent data with spectral bands and vegetation indices.

Last Data Bands: Includes only recent data with spectral bands, excluding vegetation indices.

4. AI algorithms

Various machine learning algorithms were employed to predict soil texture properties. These included Ridge Classifier, Decision Tree, and AdaBoost models. The models were trained using a combination of spectral and ground-based data.

5. Model evaluation

Model performance was assessed using 5-fold cross-validation with an 80/20 train-test split. Accuracy was the primary metric for evaluating prediction effectiveness.

The research results.

1) Soil texture analysis

The study revealed significant variability in soil texture across the Syrdarya region's irrigated lands.

The table 1 highlights the soil texture classifications of key fields in the Syrdarya region, based on particle size distribution and physical clay content. The data reveals significant variability across different depths and locations. For instance, light loamy soils dominate the 0–80 cm depth in fields like Section 63, characterized by a physical clay content of approximately 21–33%. In contrast, sandy soils are prevalent in Section 105, with physical clay percentages as low as 8–10%, indicating minimal clay content and high sand proportions.

Medium loamy soils, which have higher physical clay content (30–46%), are observed in deeper layers or specific sections such as 165 and 274. These soils are indicative of better water retention and structural stability compared to sandy textures. Such variability underscores the importance of localized soil management strategies to optimize agricultural productivity and sustainability in the region.

Table 1.

Mechanical composition of soils of key areas of Syrdarya region

Key Field, Section No.	Layer depth (cm)	Particle size in mm., amount in %.							Physical clay (%)	Soil Texture
		Sand			Silt			Clay		
63	0-27	2,4	0,6	19,3	50,2	10,1	7,7	9,7	27,5	Light loamy
	27-51	0,4	0,1	24,1	46	10,5	11,3	7,6	29,7	Light loamy
	51-81	0,8	0,2	16,8	48,8	13,9	9,6	9,9	33,4	Medium loamy
	81-130	1,6	0,4	22	36,7	11,4	14,1	13,8	39,3	Medium loamy
75	0-22	1,6	0,4	19,1	55,7	6,5	9,8	6,9	23,2	Light loamy
	22-41	1,2	0,3	24,7	52	7,5	7,8	6,5	21,8	Light loamy
	41-80	1,6	0,4	35,8	40,9	6,6	7,4	7,3	21,3	Light loamy
	80-120	0,8	0,2	32,6	36,7	11	8,2	10,5	29,7	Light loamy
105	0-29	1,6	0,4	17,8	69,4	7,3	2,5	1	10,8	Sandy
	29-56	3,2	0,8	27,1	59,9	6,7	1,4	0,9	9	Sand
	56-89	2,4	0,6	29,9	57,9	4,4	3,7	1,1	9,2	Sand
	89-130	2,4	0,6	40,7	48,3	4,8	2,1	1,1	8	Sand
165	0-24	1,6	0,4	10,7	53,2	10,2	12,9	11	34,1	Medium loamy
	24-46	1,2	0,3	0,9	48,6	21,3	13	14,7	19	Sandy
	46-78	2	0,5	11,9	40,2	13,2	19	13,2	15,4	Sandy
	78-110	1,2	0,3	20,3	40,7	13,4	15	9,1	37,5	Medium loamy

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Key Field, Section No.	Layer depth (cm)	Particle size in mm., amount in %.							Physical clay (%)	Soil Texture
		Sand			Silt			Clay		
207	0-27	1,6	0,4	22,6	44,9	11,8	17,3	1,4	30,5	Medium loamy
	27-55	3,2	0,8	17,7	41,4	23,7	11,9	1,3	36,9	Medium loamy
	55-87	2	5	18,7	46,2	22,6	9,1	0,9	32,6	Medium loamy
	87-123	2	0,5	10,8	48,7	12,7	14,8	10,5	38	Medium loamy
225	0-17	8,4	2,1	26,7	43	14,4	4,7	0,7	19,8	Sandy
	17-41	4,8	1,2	35,2	40,3	13,3	4,4	0,8	18,5	Sandy
	41-76	2,8	0,7	41,5	33,3	15,6	5,3	0,8	21,7	Light loamy
	76-119	4	1	41,5	37,7	10,2	4,7	0,9	15,8	Sandy
254	0-18	3,6	0,9	17,2	45,8	22,5	9,1	0,9	32,5	Medium loamy
	18-40	8	2	14,2	40,3	26,7	8,1	0,7	35,5	Medium loamy
	40-80	7,6	1,9	17,9	42,6	19,7	9,6	0,7	30	Light loamy
	80-120	6,8	1,7	12,5	52,5	18,7	7,1	0,7	26,5	Light loamy
274	0-27	1,6	0,4	6,8	57	25	7,4	1,8	34,2	Medium loamy
	27-55	2,4	0,6	7	43,9	34,7	10,4	1	46,1	Heavy loamy
	55-82	1,2	0,3	18,4	45	28,1	5,8	1,2	35,1	Medium loamy
	82-120	2,8	0,7	11,5	57,5	22,1	4,3	1	27,4	Light loamy

2) Data Analysis

Soil texture prediction:

The AdaBoost algorithm achieved the highest accuracy (68.2%) when trained on the Last Data Bands dataset. Ridge Classifier performed best on the All Data Full dataset, with an accuracy of 57.0%. Decision Tree models provided moderate accuracy (56.4%) on Last Data Full datasets. Models trained on datasets with recent and localized data performed better for predicting soil texture properties, emphasizing the importance of up-to-date and region-specific data.

3) Model performance comparison

Table 2.

Comparison of different AI models based on datasets

Parameter	All Data Full	All Data Bands	Last Data Full	Last Data Bands
Accuracy (%)	57.0	67.2	56.4	68.2
Best Model	Ridge Classifier	AdaBoost	Decision Tree	AdaBoost

4) Validation and calibration

To ensure the reliability of the AI model predictions, the results were validated against ground-truth soil sample data. In areas where significant discrepancies were observed, further calibration was performed to improve the accuracy of the predictions. For humus content, the prediction closely matched the traditional laboratory results, confirming the model's validity. Similarly, phosphorus and potassium predictions showed strong correlations with the ground measurements, demonstrating the models' effectiveness in capturing nutrient variability across the study area.

5) Comparison with traditional methods

The AI-driven predictions were compared with results from traditional soil testing methods. In most cases,

the AI models provided comparable, if not better, accuracy in predicting soil humus and nutrient content. Traditional methods, while precise, require labor-intensive sampling and lab analysis. In contrast, AI technologies, when combined with remote sensing data, provide a more efficient and scalable solution for monitoring soil fertility over large areas.

Calibration with traditional methods helped fine-tune the AI models, particularly in regions with extreme nutrient levels, where initial predictions showed slight deviations from ground-truth data. The calibrated models showed improved prediction accuracy in those areas.

Conclusion. This research highlights the potential of AI technologies for analyzing soil texture and mechanical composition. By integrating machine learning algorithms with remote sensing data, we achieved efficient and scalable predictions of soil properties. Among the tested models, AdaBoost provided the highest accuracy for soil texture classification, particularly when using recent datasets and spectral indices.

The findings demonstrate the value of combining archival and recent data to enhance prediction accuracy. Future work should focus on incorporating additional variables, such as soil moisture and organic matter, to further refine the models. Expanding the study to other regions with diverse soil types and climatic conditions will also improve the generalizability of the results.

By adopting AI-driven approaches, precision agriculture can be advanced, enabling better soil management and sustainable agricultural practices.

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