ГЕОЛОГІЧНА ІНФОРМАТИКА

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UTILIZING GIS, GPS, REMOTE SENSING, AND AI IN THE STUDY OF SOIL CHARACTERISTICS

(*Представлено членом редакційної колегії д-ром геол. наук, ст. дослідником О.І. Меньшовим*)

Background. ***Modern agriculture faces numerous challenges associated with climate change, economic factors, and increasing demands for production efficiency. The implementation of advanced technologies, particularly Geographic Information Systems (GIS), Remote Sensing (RS), Global Navigation Satellite Systems (GNSS/GPS), and Artificial Intelligence (AI), allows for the optimization of agrotechnical processes and improved productivity in precision farming.***

Methods. ***This study examines the application methods of GIS, GPS, RS, and AI in precision agriculture. It employs the analysis of satellite and aerial imagery, spatial modelling techniques, geostatistics, and machine learning for yield prediction and optimization of management decisions. Additionally, the use of sensor systems for field data collection and their integration into digital agricultural platforms is analysed.***

Results. ***The study implemented a comprehensive model for assessing soil characteristics by combining GIS, GPS, remote sensing, and artificial intelligence methods. The results confirmed the effectiveness of using digital maps and satellite images for spatial interpolation of soil parameters (such as potassium, moisture, and humus content), yield mapping, and real-time crop monitoring. GPS navigation ensured high accuracy in machinery positioning and soil sampling, while machine learning algorithms (particularly LAI-based models and Random Forest) demonstrated yield prediction accuracy above 80 %. A crop rotation model built using Python libraries enabled the development of an optimal five-year rotation plan, considering soil types, climatic conditions, and potential yield. Variability maps and zoning results served as the basis for scenario-based field management at the enterprise level.***

Conclusions. ***The integration of GIS, GPS, RS, and AI into agricultural practices significantly enhances the accuracy of soil analysis and the efficiency of agroprocess management. The developed model enables the automation of decision-making processes based on large volumes of spatial and field data, contributing to cost reduction, increased productivity, and preservation of soil fertility. The implementation experience in the Kyiv region has demonstrated its practical applicability and potential for scaling within the framework of modern precision agriculture.***

Keywords: ***geographic information systems (GIS), remote sensing (RS), global navigation satellite systems (GNSS/GPS), artificial intelligence (AI), precision agriculture (PA), geoinformation technologies (GIT), APSIM (Agricultural Production Systems Simulator), DSSAT (Decision Support System for Agrotechnology Transfer).***

Background

In the current context of global climate change, soil degradation, and the growing need to intensify agricultural production while adhering to principles of sustainable development, the use of high-precision technologies in soil cover research is gaining relevance. One of the most effective approaches is the integration of Geographic Information Systems (GIS), GPS navigation, Remote Sensing (RS), and Artificial Intelligence (AI) into the comprehensive study of the spatial variability of soil characteristics.

Recent studies confirm that the integration of these technologies significantly improves the accuracy of agroecosystem monitoring and management. In particular, the use of high-resolution satellite imagery and deep learning has proven highly effective in modeling soil moisture under various climatic conditions (Hassan-Esfahani et al., 2021). The combination of GIS with GPS and RS data enables the creation of highly accurate maps of fertility, moisture levels, pH, and other soil indicators, which are critical for planning agrotechnical operations. The integration of satellite data and machine learning has achieved up to 92 % accuracy in predicting the spatial variability of soil organic matter (Ahmad, Khan, & Ali, 2022).

Additionally, AI algorithms-especially deep neural networks-allow the analysis of large volumes of agricultural data, revealing patterns and forecasting changes in soil conditions over time and space. Integrating AI into agricultural models is a key stage in the digital transformation of agriculture (Wang et al., 2023).

In the Ukrainian context, the urgency of applying such technologies is rising against the backdrop of declining soil fertility, increasing climate risks, and the need to optimize resource use. As highlighted in literature, the integration of digital technologies into agriculture forms the basis for making effective decisions in the management of soil and agricultural resources (Burliai, & Okhrymenko, 2021).

Moreover, modern GIS systems not only accumulate data on soil properties but also visualize them spatially, significantly simplifying the decision-making process at various levels. The use of interactive maps combined with predictive models enables the evaluation of the agricultural potential of land under different climate change scenarios (Shrestha, & Pradhanang, 2022).

For instance, as of 2024, the average cost of analyzing a single soil sample in Ukrainian agricultural laboratories ranged from 1500 to 2500 UAH. For fields larger than 300 hectares, it is typically necessary to analyze between 30 and 80 samples (depending on the sampling grid), amounting to between 45,000 and 200,000 UAH. Therefore, interpolation and geostatistical methods enable the estimation of spatial distribution parameters using fewer field measurements-i.e., with larger sampling grids-while maintaining high prediction accuracy. The application of such methods significantly improves resource management, reduces costs, and minimizes environmental impact.

GIS is the core tool for data processing, analysis, and management used in precision agriculture. It ensures the effective integration of spatial and digital data, assisting farmers in optimizing production processes and making well-grounded management decisions. However, GIS alone does not guarantee efficient agro-territorial management. It must be embedded into agronomic platforms that collect, store, and interpret information from diverse sources, model scenarios, and provide a solid basis for sound decision-making. The concept of active information-implying real-time data updates from multiple sources has already become standard practice in modern precision farming. This includes the use of high-resolution satellite images, data from unmanned aerial vehicles (drones), and information from IoT sensors placed in fields. Agricultural platforms are built on a modular architecture, where functions such as land bank management, field mapping, task planning, real-time work monitoring and analysis, weather tracking, document automation, logistics, and even product sales are all integrated into a single digital system. Currently, the most popular agro-platforms in Ukraine are Agrilab, Soft. Farm, Forland, and OneSoil (Fig. 3) (Precision Farming and Agro IT Solutions, n.d.). Recent research also emphasizes the role of precise soil modeling in adapting to climate change. For instance, the combination of remote sensing, deep learning, and big data analytics is the foundation of effective soil mapping in regions with high spatial variability (Morales, Zhang, & Wang, 2023).

Special attention should be given to machine learning tools that enable the creation of automated systems for real-time soil condition assessment. Classification algorithms can be used to identify soil types and predict their erosion susceptibility with an accuracy exceeding 90 % (Singh, Sharma, & Kumar, 2021).

It is worth noting that digital tools not only enhance agricultural productivity but also play a vital role in environmental protection. Reducing ecological pressure, optimizing the use of fertilizers and pesticides, and preserving biodiversity are all made possible through precision agricultural technologies. The use of GIS and AI enables the integration of soil research into a comprehensive sustainable land use strategy.

Modern precision agriculture actively integrates innovative technologies for crop and soil monitoring-form, ground-based sensors and drones to satellite systems. By employing LiDAR, fluorescence spectroscopy, thermal imaging, and AI, farmers gain accurate data for optimizing fertilization, irrigation, and yield prediction. This promotes increased agricultural efficiency, reduced costs, and minimized environmental impact.

A successful example of AI integration in agriculture is John Deere, whose farming equipment is equipped with AI systems that autonomously determine the appropriate quantity of seeds and fertilizers, as well as the techniques for their application in soil. Companies such as John Deere and CNH Industrial are developing tractors and combines harvesters with AI components, including autopilot systems and precision control for field operations. These technologies are successfully implemented in many countries, including the USA, Germany, and Australia. The world's first unmanned grain harvester (Fig. 1) and autonomous tractor developed for precision farming were introduced in China in 2021 by the Chinese company Country Garden (Fig. 2).

Fig. 1. Unmanned harvester by Country Garden (China presented the operation of…, n.d.)

Fig. 2. Autonomous tractor developed for the needs of precision agriculture in China (China presented the operation of…, n.d.)

The Stout Smart Cultivator uses machine vision and artificial intelligence to mechanically cultivate and weed fields with precision blades (Smart Cultivator Stout, n.d.). Blue River Technology has developed the See & Spray system, which leverages computer vision and AI to detect weeds and apply herbicides with pinpoint accuracy, significantly reducing chemical usage (Blue River Technology, n.d.). CropX offers a solution for real-time soil moisture monitoring using sensors and AI algorithms, allowing for optimized irrigation management (Agronomic Farm Management System, n.d.).

AI integration enables drones to autonomously plan flight paths while avoiding obstacles, enhancing both safety and operational efficiency. The application of swarm technology makes it possible for multiple spraying drones to work collaboratively in an automated manner. Additionally, AI enhances target identification, allowing drones to more accurately recognize and classify objects, thereby improving the precision of monitoring and resource application (Zhang, & Kovacs, 2020).

Artificial intelligence (AI) is rapidly being integrated into various sectors, and agriculture is no exception. In the context of precision farming, AI offers innovative solutions to increase efficiency, productivity, and sustainability in agricultural production. It is projected that the global AI in agriculture market will grow from USD 2.08 billion in 2024 to USD 5.76 billion by 2029, reflecting a compound annual growth rate (CAGR) of 22.55 % over the period 2024–2029 (Filippov, 2024).

Thus, studying the specific applications of GIS, GPS, RS, and AI in soil characteristic analysis holds significant theoretical and practical value for the development of precision agriculture, crop rotation forecasting, yield improvement, and environmental conservation. The integrated use of spatial analysis, digital mapping, satellite technologies, and machine learning models opens new frontiers for the efficient management of land resources.

Methods

One of the main objectives of precision agriculture addressed through GIS is the identification of zones with varying productivity potential within a single field. This enables the application of site-specific management strategies, allowing farmers to optimize resource use, minimize costs, and increase yields through a differentiated approach to fertilization, irrigation, soil treatment, and other agronomic practices (Brovarets, 2018).

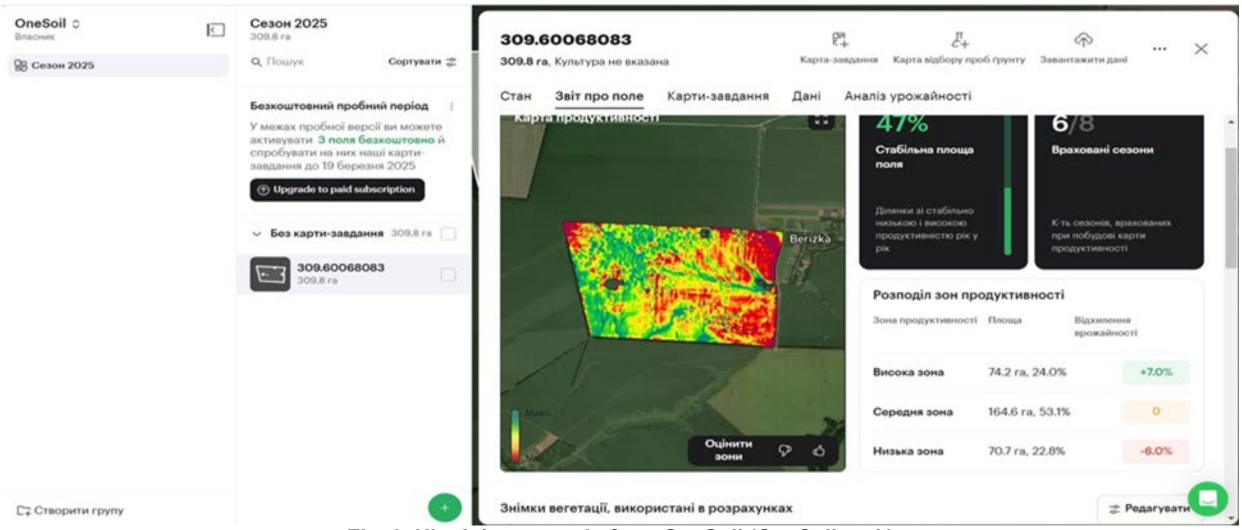
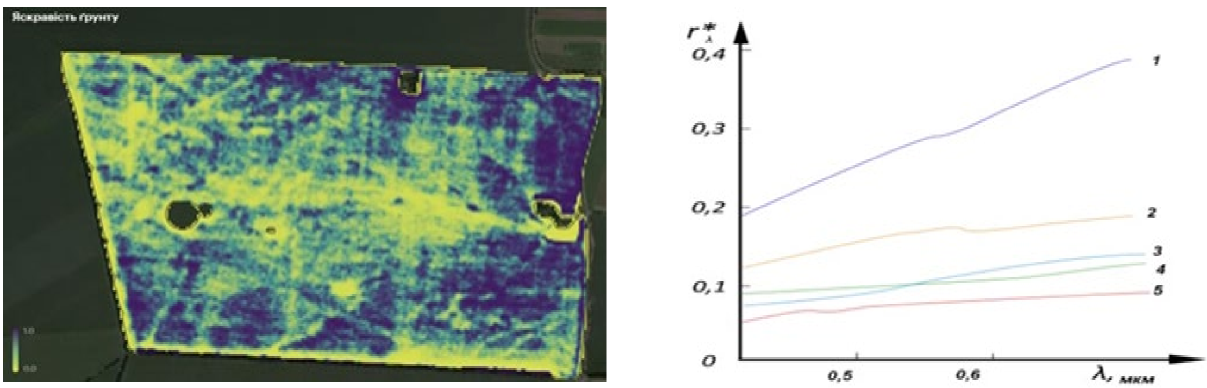


Fig. 3. Ukrainian agro-platform OneSoil (OneSoil, n.d.)

The Global Positioning System (GPS) is a U.S.-based radio navigation satellite system used to determine the location of stationary and mobile objects in three global coordinates: longitude, latitude, and altitude, with an accuracy of several tens of meters (Tsyhanenko, 2015). In addition to GPS, there exist other Global Navigation Satellite Systems (GNSS), such as Galileo (EU), BeiDou (China), and QZSS (Japan). GNSS receivers do not rely on electronic components that may change their parameters over time, which ensures consistently accurate positioning without the need for frequent calibration.

Remote Sensing (RS) plays a crucial role in the development of precision agriculture by providing timely spatiotemporal information on the condition of agricultural land. Thanks to modern satellite and aerial imagery, farmers gain access to detailed data on crops, soil characteristics, and climatic conditions, enhancing the efficiency of agricultural process management (Fig. 4).



a) b)

Fig. 4. Brightness of soils of typical low-humus and degraded light loamy chernozems (a) (author's own development); spectral brightness curves of main soil types:

1 – sierozem; 2 – sod-podzolic; 3 – dark chestnut; 4 – dark gray forest; 5 – chernozem (b) (Zatserkovnyi, 2018)

Unlike vegetation, bare soil reflects radiation based on its physical and chemical properties. The key factors determining the spectral characteristics of soil include the provided below (Zatserkovnyi, 2018).

In most agricultural fields, both bare soil and vegetation are present simultaneously. This creates mixed spectral signals, which can complicate the accurate interpretation of data, as the reflected light contains information from both the plants and the soil. To isolate the information specific to vegetation cover, specialized mathematical and algorithmic methods are used (Zatserkovnyi, 2018).

Modern remote sensing (RS) technologies have significantly expanded the range of parameters that can be analysed to improve the efficiency of precision agriculture. In addition to traditional indicators, such as biomass, plant stress (detecting signs of disease, pests, or nutrient deficiency), and growth rate modern RS methods allow for the assessment of:

- soil and air moisture (via microwave scanning – radio waves with wavelengths from 1 cm to 1 m);
- surface temperature (using thermal infrared and microwave radiation);
- ozone concentration in the atmosphere (which influences the photosynthetic activity of plants);
- chlorophyll levels (visa hyperspectral scanning).
- Soil electrical conductivity (sensor equipment evaluates soil structure and moisture content).

Application of AI in Precision Agriculture (Colback, 2025):

- crop monitoring: The use of high-resolution drones and satellite imagery enables real-time imaging of fields. Computer vision systems powered by artificial intelligence can detect early signs of disease, pests, or other stress factors in plants, allowing for prompt intervention and control.
- yield prediction: AI models can forecast crop yields based on historical data, weather conditions, and other influencing factors. This helps farmers plan harvest logistics and marketing strategies.
- resource optimization: AI analyses data on soil moisture, weather forecasts, and crop health to determine optimal timing and dosage for irrigation, fertilization, and pesticide application.
- autonomous machinery: The development of autonomous tractors and robotic systems controlled by AI allows for the automation of tasks such as sowing, spraying, and harvesting, reducing the need for manual labour and increasing operational accuracy (Colback, 2025).

A team of scientists and engineers at EOS Data Analytics (EOSDA) has developed effective methods for crop yield estimation using remote sensing and machine learning models, particularly LAI assimilation. The company conducted a yield prediction for a large Ukrainian agroholding, achieving over 80 % accuracy in the green-labelled areas (EOS Data Analytics, n.d.).

The same algorithm was applied in 2020 to estimate crop yields for a Canadian agricultural company, with the data presented in Tab. 1.

These specialists worked on implementing a hybrid approach that combines biophysical and statistical models to achieve high-precision yield forecasting.

Table 1

Crop yield estimates for a Canadian agricultural company in 2020 (EOS Data Analytics, n.d.)

Crop	Modelled yield, tons per field	Actual yield, tons per field
Canola	40.19	39.00
Corn	119.14	110.00
Oats	125.03	125.00
Winter rye	64.39	75.00
Confectionery sunflower	2063.60	1800.00
Annual sunflower	1834.19	1800.00
Wheat	61.73	65.00

Within the scope of the study, an integrated methodology was applied to develop an optimal crop rotation plan by combining machine learning capabilities with the principles of physiological modelling of crop growth. The foundation of this methodology was based on principles like those used in APSIM (Agricultural Production Systems Simulator) and DSSAT (Decision Support System for Agrotechnology Transfer)-agronomic simulators capable of modelling crop growth dynamics while accounting for climatic conditions, soil properties, and agricultural practices (Confalonieri et al., 2010).

The machine learning logic embedded in the algorithm follows key agronomic crop rotation rules:

- the possibility of growing the same crop on the same plot for two consecutive years is excluded to prevent soil exhaustion.
- crops with higher potential yield are prioritized in the initial years of planning – this reflects the adaptive strategies embedded in DSSAT-based models.
- local soil and climatic conditions, such as temperature regimes, precipitation levels, and soil characteristics are incorporated into the calculations.

Based on these principles, the model automatically generates a five-year crop rotation plan, selecting optimal crop combinations to ensure stable yields and maintain soil fertility. An important component of the model is the assimilation of the Leaf Area Index (LAI) – a biophysical indicator of crop condition, which can also be calculated from remote sensing data (e.g., Sentinel-2). LAI is integrated into the forecasting system to refine yield predictions. For this, data assimilation algorithms are applied, particularly the Ensemble Kalman Filter (EnKF). This algorithm continuously updates its system state estimates by combining model predictions with newly obtained observations, reducing the influence of noise. It fuses LAI observations with internal model variables, thereby improving model accuracy (Hassan-Esfahani et al., 2021).

This approach ensures flexibility and adaptability of the system to spatial and temporal changes in growing conditions, allowing agricultural producers to optimize the planning of agronomic operations, increase productivity, and simultaneously maintain ecological balance in soil systems.

The application of these methods to a large Ukrainian agroholding has demonstrated their effectiveness and practical value in the agribusiness sector.

Results

One of the key tools in precision agriculture is the use of GPS technology, whose core applications include:

- farm planning: Information gathered from various satellite sources and georeferenced via GPS can be integrated to develop field management strategies, including fertilizer application, soil treatment, and harvesting.

• field mapping.

• soil sampling: GPS enables the precise identification of soil sampling locations, ensuring more accurate analysis of soil fertility and condition (Fig. 5).

• navigation of agricultural machinery: GPS guidance allows tractors, harvesters, and other equipment to operate in the field with high precision, minimizing overlaps and skips during operations, thereby reducing fuel consumption.

• crop monitoring: With GPS, it is possible to track crop development in different areas of a field, enabling timely detection of problem zones and implementation of corrective measures.

• variable-rate application of fertilizers and pesticides: Integration of GPS with variable-rate technology allows precise dosing of fertilizers and pesticides based on the needs of specific field zones, reducing input costs and environmental impact.

• yield mapping: During harvest, GPS-enabled functions in combine harvesters allow for the creation of yield maps, visualizing the productivity of different field areas. This helps identify causes of yield variability and supports the development of strategies to improve future efficiency (Fig. 6).

• operation under low visibility: GPS navigation ensures accurate machinery operation even under challenging weather conditions or at night, expanding the window for fieldwork and increasing productivity.

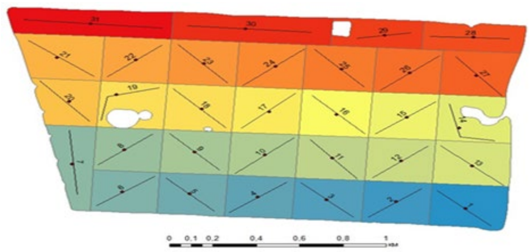


Fig. 5. Locations and routes of soil sampling with GPS referencing

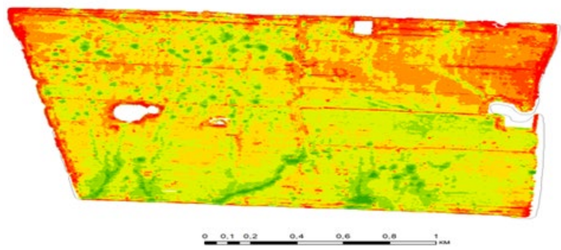


Fig. 6. Yield map (cartogram) of the field

The yield data were obtained from a combine harvester owned by the agricultural enterprise "Kernel", located near the village of Beryzka, within the Varva Territorial Community of Pryluky District, Chernihiv Region. The machinery was equipped with a yield monitoring system and GPS navigation, which allowed for recording the yield at each point of the field during harvesting. Based on these spatially referenced point values, a yield map was created using spatial interpolation methods in a GIS environment (Fig. 6). The map shows the spatial distribution of corn grain yield for a 309.6 hectare field in 2020.The highest yield values, reaching 11.3–14.4 tons per hectare (dark green areas), are observed locally in the central part of the field, likely near zones with better water availability due to terrain depressions or higher soil fertility. Most of the field is covered by areas with average yield (7.8–11.2 t/ha), indicating stable agri-production conditions without major constraints. Meanwhile, the lowest yields (2.89–6.14 t/ha), shown in red and dark orange, are mostly concentrated along the field's perimeter, particularly in the north and east. This may indicate the presence of adverse factors such as soil compaction, erosion, moisture or nutrient deficiency, or inconsistent machinery operation. Thanks to digital technologies and big data analysis, farmers can make well-informed decisions about optimizing tillage, fertilization, crop protection, and irrigation.

The visualization of data in map format greatly enhances the understanding of spatial patterns, particularly the relationships between natural factors and crop performance. In Figure 7, the left image shows the grid of soil sampling points with indicated levels of available potassium in each cell. The right image illustrates the spatial modelling result of potassium content, generated using the Inverse Distance Weighting (IDW) interpolation method, which creates a continuous surface from discrete measurements. The IDW interpolation method assumes that values at any unknown location depend on nearby known values, with closer points exerting a stronger influence than distant ones. In this method, the unknown value is calculated as a weighted average of neighbouring points, where weights are inversely proportional to the distance. This approach enables the construction of a continuous surface from a limited number of spatial samples, as shown in the map. An analysis of the available potassium distribution in the soil for 2020 reveals significant spatial heterogeneity. Most of the field area is characterized by elevated (81–120 mg/kg) and high (121–150 mg/kg) potassium content. Zones with very high levels (>181 mg/kg) are localized in the northeastern part of the field (marked in purple). In contrast, the lowest values (less than 100 mg/kg) are recorded in the southeastern sector and in some central areas, indicating the need for localized potassium fertilization adjustment. The obtained data can be used to create task maps for variable-rate potassium fertilizer application (Zatserkovnyi, & Vorokh, 2024).

However, graphical interpretation alone is not sufficient, as it does not allow determining whether the observed relationships are statistically significant or merely due to random factors or measurement errors. When using classical interpolation methods, such as Inverse Distance Weighting (IDW), it is assumed that the predicted value at an unknown point is determined solely by the values at known points, with distance being the primary influence factor. However, this approach may lack accuracy, as the spatial distribution of measured characteristics may depend not only on distance but also on other factors. For example, soil moisture content may vary not just with proximity but also due to terrain, soil type, or hydrological conditions. Furthermore, some parameters may exhibit a distinct spatial trend, such as a gradual increase or decrease in nutrient concentration (e.g., nitrogen) in a certain direction across the field.

Accounting for such patterns is only possible using geostatistical analysis methods, particularly kriging, which evaluates spatial autocorrelation and builds more accurate models of spatial variability.

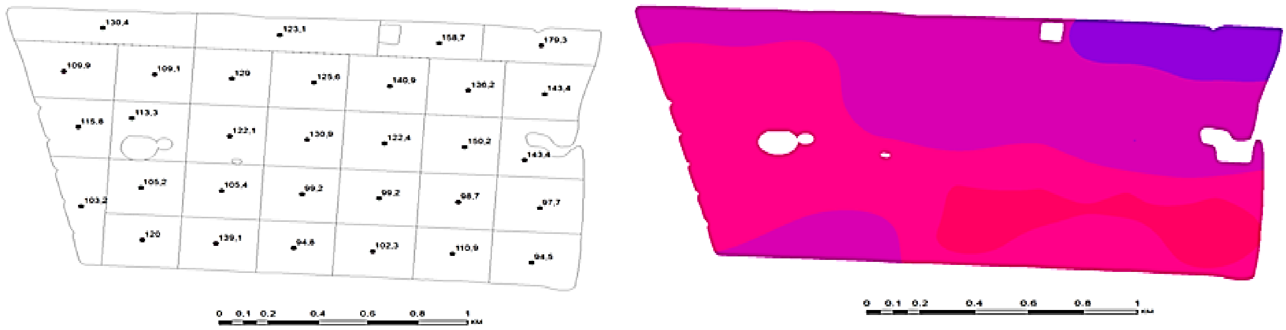


Fig. 7. Cartogram of available potassium distribution in soil, created using the IDW interpolation method

Thanks to accurate monitoring and management powered by AI, farmers will be able to achieve higher crop yields from their fields. AI-driven optimization of fertilizer, water, and pesticide use will help reduce costs and minimize negative environmental impact. Big data analysis performed by artificial intelligence will enable farmers to make informed decisions based on real-time indicators and AI-generated recommendations.

The subject of this study is LLC "FK LTD", an agricultural enterprise located in the urban-type settlement of Volodarka, Bilotserkivskyi District, Kyiv Region. The company's primary activities include the cultivation of grain crops, legumes, and oilseed crops. In addition, the enterprise grows corn, wheat, sunflower, and soybeans.

The land plots owned or operated by the company are located near Volodarka and in surrounding villages within the Volodarka Territorial Community (Fig. 8.). Some of the plots are leased, while others are owned directly by the enterprise.

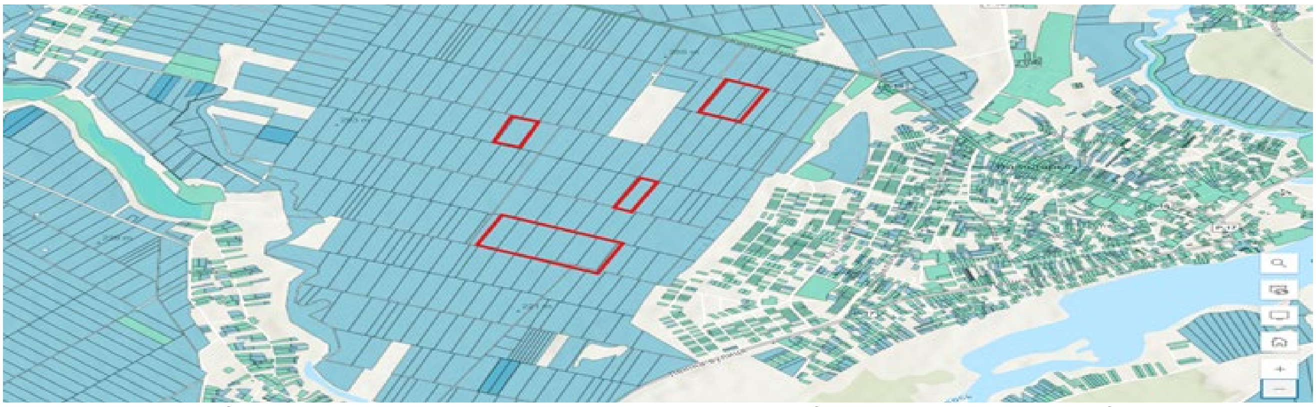


Fig. 8. Part of the land plots owned by the enterprise on the outskirts of the urban-type settlement of Volodarka

To adapt the digital model to the real operating conditions of LLC "FK LTD", a flexible solution was developed based on the Python programming language, utilizing specialized libraries for handling large volumes of numerical and tabular data. This approach enabled the personalization of the model, considering the specific features of the company's land bank, including soil types, agrochemical characteristics, meteorological conditions, and the range of cultivated crops. The input data included information on soil types, their agrochemical composition, average crop yields, and the climatic features of the region. All this information was systematized and presented in a tabular format for further analysis and integration into the model.

The next step involved developing an algorithm capable of automatically generating a crop rotation plan based on predefined constraints and criteria. For this purpose, Python was used along with the Pandas and NumPy libraries, enabling the processing of large datasets. The model incorporated key agronomic rotation rules, among which a central principle was the avoidance of growing the same crop on the same plot for two consecutive years. It also considered the need for alternating crops that have different impacts on soil fertility and prioritizing crops with higher yield potential at the initial stages of planning.

After configuring the algorithm, a series of simulations were conducted, during which the model generated several crop rotation options for a five-year period. Each proposed scenario was evaluated based on the balance of crop types, compliance with agrotechnical requirements, and forecasted yield indicators. The optimal variant was selected-combining grain, legume, and oilseed crops-ensuring the alternation of depleting and soil-enriching crops.

In the model, the first year was allocated to corn, a crop with high yield potential, laying the foundation for economic profitability but requiring careful planning for subsequent crops due to its significant impact on soil. The second-year proposed wheat, a less demanding crop that helps compensate for soil load. The third year included barley, providing additional balance to the rotation. The fourth year was designated for soybeans, enriching the soil with nitrogen and restoring its fertility. The fifth year concluded with sunflowers, completing the rotation cycle with different crop types.

The resulting crop rotation plan was analyzed and compared with average yield indicators across Ukraine, allowing the evaluation of the model's forecast accuracy. The discrepancies between the predicted and actual yields were minor, indicating high model accuracy. At the same time, alternative scenarios were tested, giving the enterprise multiple flexible options for final decision-making.

Thus, the developed crop rotation modeling scenario not only considered local soil and climatic conditions but also enabled the creation of an adaptive rotation strategy aimed at increasing yield and maintaining soil fertility in the long term.

The predominant soil types in the area are typical medium-humus and low-humus chernozems on loess deposits, occupying about 80 % of the territory. These soils contain 3–5 % humus, and the depth of the humus horizon exceeds 80 cm. They are most favorable for the cultivation of sugar beets, winter wheat, barley, forage, and vegetable crops. Generalized soil data are presented in Tab. 2.

Table 2

Information on the soil cover of the settlement

Code of the agro-production soil group	Name of the agro-production soil group
19e	Sod-podzolic and podzolic-sod soils with surface gleying, medium loamy
29d	Light gray and gray podzolized soils, medium loamy
52b	Typical low humus chernozems (sandy loam) and their complexes with solonetzic variants
54d	Typical medium humus chernozems, light loamy
54e	Typical medium humus chernozems, medium loamy

The average monthly temperatures in winter (January–February) are around –6 °C, and in summer (July) about +19.4 °C. In certain years and months, deviations from the average annual and monthly temperatures may occur. The absolute minimum recorded in the region was –35 °C, and the maximum was +37 °C.

The annual precipitation amounts to 525 mm, with about 150 days of precipitation per year. The highest precipitation occurs in summer, averaging 205 mm, while the lowest is in winter – 90 mm on average. The climograph is shown in Fig. 9.

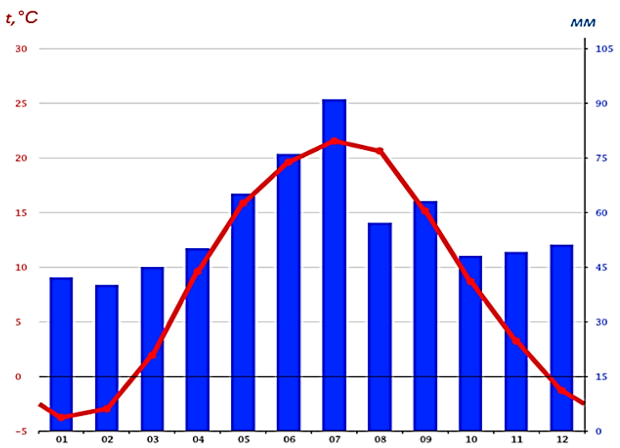


Fig. 9. Climograph of the Volodarka Territorial Community

The terrain is mostly flat, with minor elevation differences across the area. There are exposures of crystalline rocks, particularly granite. The surface slope trends from west to east. The company cultivates the following crops: wheat, barley, corn, sunflower, and soybeans.

The goal of crop rotation is to increase yields. Based on soil data, climate conditions, and the types of cultivated crops, it is possible to plan a five-year rotation to improve productivity and maintain soil fertility.

The model was developed in the Python environment using the Pandas and NumPy libraries, which are commonly used in AI model training. Pandas enable manipulation of tabular data-for example, the content of chemical components and humus in soils can be represented in table format. NumPy is used to process large data arrays.

We start by importing the libraries. As a first step, we define the list of crops and enter estimated yield values in conditional units, since real data was not available (Fig. 10).

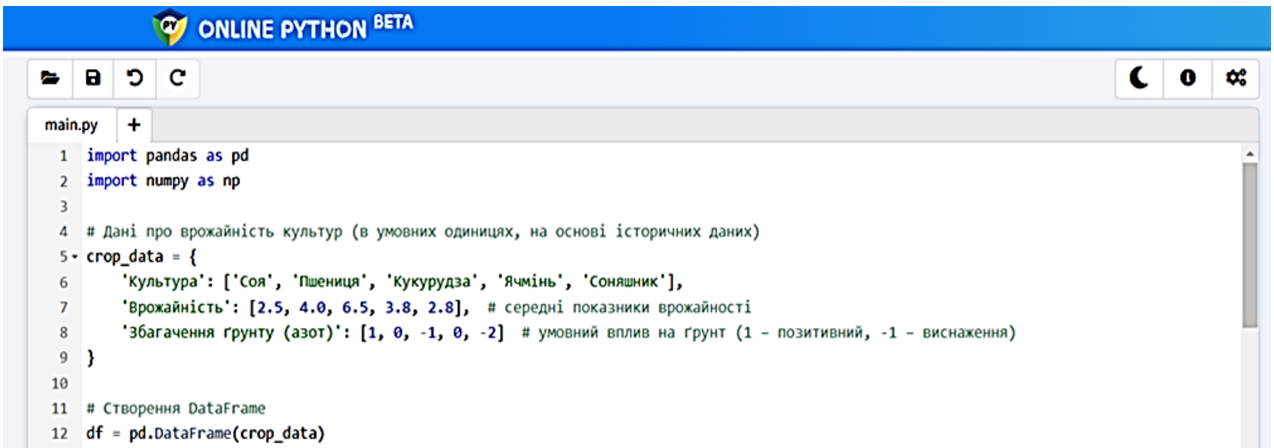
The "plan rotation" function allows the creation of a crop rotation plan, with the duration set to five years (Fig. 11). Additionally, several rules are introduced for training the model, for example, crops must not repeat for two consecutive years, and crops with the highest expected yield are given priority in the initial years.

At the end of the code, the return function is set to output the crop rotation plan. The results of the model are then analyzed. We run the model and receive the following crop rotation recommendation (Fig. 12.).

The expected yield results closely match the average yield indicators of these crops in Ukraine (Tab. 3). However, it should be noted that the accuracy and volume of input data can be improved, which would further enhance the precision of the model.

Overall, the model performed well, except for wheat in year 4. It would have been better to include soybean instead. To avoid this, the rule prioritizing high-yield crops could be improved. Returning the model can generate alternative crop rotations (Fig. 13).

Analysis of crop rotations based on commonly accepted crop rotation rules Tab. 4.




```python
import pandas as pd
import numpy as np

# Дані про врожайність культур (в умовних одиницях, на основі історичних даних)
crop_data = {
    'Культура': ['Соя', 'Пшениця', 'Кукурудза', 'Ячмінь', 'Соняшник'],
    'Врожайність': [2.5, 4.0, 6.5, 3.8, 2.8],  # середні показники врожайності
    'Збагачення грунту (азот)': [1, 0, -1, 0, -2]  # умовний вплив на грунт (1 - позитивний, -1 - виснаження)
}

# Створення DataFrame
df = pd.DataFrame(crop_data)
```

Fig. 10. Code snippet with input data

```
# Функція для моделювання сівозміни на кілька років
def plan_rotation(years=5):
    rotation_plan = []
    last_crop_index = -1  # Індикатор попередньої культури

    for year in range(years):
        # Умовний вибір культури для максимізації врожайності і дотримання ротації
        if last_crop_index == -1:
            chosen_crop = df.iloc[np.argmax(df['Врожайність'])]  # вибір початкової культури з найвищою врожайністю
        else:
            # Зміна культури, щоб уникнути однакової культури поспіль
            potential_crops = df[df.index != last_crop_index]
            chosen_crop = potential_crops.sample(1).iloc[0]  # випадковий вибір, щоб забезпечити ротацію
```

Fig. 11. Code snippet with rules for training the dataset

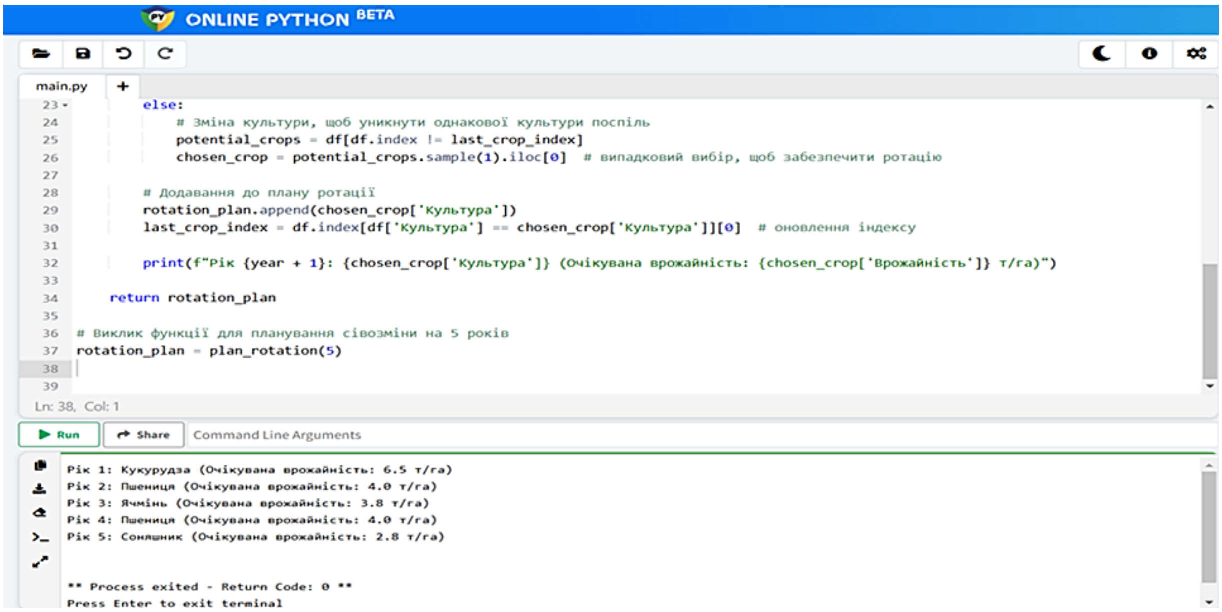


Fig. 12. Model testing and validation

Table 3

Comparison of yield indicators

Crop	Expected yield at LLC "FK LTD", t/ha	Average yield in Ukraine, t/ha
Corn	6.5	7.0
Wheat	4.0	4.0
Barley	3.8	3.5
Sunflower	2.8	2.3
Soybean	2.5	2.2

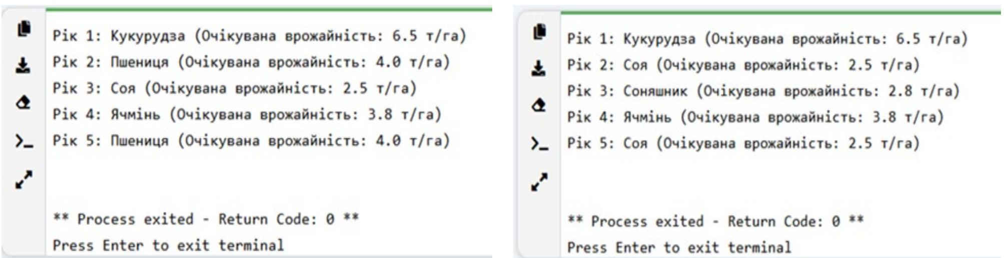


Fig. 13. Alternative crop rotation plans

Table 4

Commonly accepted crop rotation rules (crop rotation)

Crop characteristics in rotation	Year of rotation / crop
A high-yield crop that depletes the soil. The selection is based on the model rule of prioritizing high-yield crops in the initial years	Year 1: Corn
Does not deplete the soil and is a good choice to follow corn	Year 2: Wheat
A satisfactory option after wheat, if nitrogen levels remain adequate	Year 3 Barley
Growing cereals for several consecutive years may lead to soil depletion	Year 4: Wheat
Loosens the soil and creates a break in the cereal crop cycle	Year 5: Sunflower

Thus, the proposed crop rotation forecasting model has demonstrated strong results and can be used by the enterprise to optimize costs, increase yields, and preserve nutrients in the soil.

Despite its clear advantages, the implementation of AI in agriculture faces several challenges:

• high implementation costs: AI technologies and related equipment can be expensive, making them inaccessible for small farms.

• lack of technical training: Farmers often lack the knowledge and skills needed to operate new technologies.

• infrastructure issues: In remote areas, there may be no access to high-speed internet, which is essential for processing large datasets.

• incomplete or inaccurate data: AI systems require high-quality data to function effectively; poor or incomplete data may lead to incorrect results.

• integration complexity: Implementing AI often requires adaptation or replacement of existing equipment and software systems.

In the future, further integration of AI with other technologies, such as the Internet of Things (IoT), blockchain, and quantum computing is expected to create fully automated farms. Key directions for development include:

• expansion of IoT-based farm management systems: Integrating AI into soil sensors, weather stations, and automated irrigation and fertilization systems will not only provide a continuous flow of data but also allow for real-time adaptation of agronomic decisions.

• use of blockchain technologies will ensure transparent documentation, which is especially important for quality control and supply chain traceability of agricultural products.

• Intelligent software platforms will be capable of making independent decisions on fieldwork, optimizing processes, and even autonomously operating agricultural machinery.

Discussion and conclusions

The research conducted confirmed that the synergistic application of GIS, GPS, remote sensing (RS), and artificial intelligence (AI) provides a new level of precision in analyzing soil characteristics and making agrotechnical decisions within precision agriculture systems. The implemented model enabled not only the integration of large volumes of spatial and field data, but also the automation of agricultural management processes.

One of the key outcomes was the high effectiveness of using satellite imagery and digital maps for spatial analysis of soil parameters-particularly potassium, moisture, and humus content, which lays the foundation for an adaptive approach to agribusiness management. GPS navigation significantly improved the accuracy of equipment positioning and soil sampling locations, minimizing resource losses and ensuring stability in agri-production processes.

The integration of machine learning, particularly Random Forest models and LAI assimilation, made it possible to achieve yield prediction accuracy above 80 %, representing a major step toward scientifically grounded production strategy planning. The crop rotation model, developed using Python and the Pandas and NumPy libraries, was successfully adapted to the local soil and climatic conditions of the agricultural enterprise, demonstrating its flexibility and practical value.

The results confirmed that implementing such digital solutions contributes to cost reduction, increased productivity, and preservation of soil fertility, which are essential for the sustainable development of the agricultural sector. The experience of testing the model under conditions in the Kyiv region demonstrated the scalability potential of the proposed model for other regions and agricultural systems.

In conclusion, the comprehensive implementation of GIS, GPS, RS, and AI creates a foundation for the development of automated decision support systems that ensure not only high efficiency of agricultural processes but also promote the ecological stability of agro-landscapes.

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ОСОБЛИВОСТІ ЗАСТОСУВАННЯ ГІС, GPS, ДЗЗ ТА ШІ В ДОСЛІДЖЕННІ ҐРУНТОВИХ ХАРАКТЕРИСТИК

В с т у п . ***Сучасне сільське господарство наражається на численні виклики, пов'язані з кліматичними змінами, економічними факторами та зростаючими вимогами до ефективності виробництва. Впровадження передових технологій, зокрема геоінформаційних систем (ГІС), дистанційного зондування землі (ДЗЗ), глобальних навігаційних супутникових систем (GPS) та штучного інтелекту (ШІ), дає змогу оптимізувати агротехнічні процеси та підвищити продуктивність у прецизійному землеробстві.***

М е т о д и . ***У роботі розглянуто методи застосування ГІС, GPS, ДЗЗ та ШІ у точному землеробстві. Використано аналіз супутникових та аерофотознімків, методи просторового моделювання, геостатистику, машинне навчання для прогнозування врожайності та оптимізації управлінських рішень. Також досліджено використання сенсорних систем для збору польових даних та їх інтеграції у цифрові платформи агровиробництва.***

Р е з у л ь т а т и . ***У ході дослідження реалізовано комплексну модель оцінки ґрунтових характеристик на основі поєднання ГІС, GPS, дистанційного зондування та методів штучного інтелекту. Результати підтвердили ефективність використання цифрових карт і супутникових знімків для просторової інтерполяції параметрів ґрунту (вміст калію, вологи, гумусу), побудови карт врожайності та моніторингу посівів у реальному часі. Використання GPS-навігації забезпечило високу точність позиціонування техніки й польового відбору проб, а алгоритми машинного навчання (зокрема, моделі на основі LAI та Random Forest) показали точність прогнозу врожайності понад 80 %. Побудована модель сівозміни із залученням бібліотек Python дала змогу сформувати оптимальний п'ятирічний план ротації культур з урахуванням типів ґрунтів, кліматичних умов і потенційної врожайності. Карти варіабельності та результати зонування стали основою для сценарного управління полем на рівні аграрного підприємства.***

В и с н о в к и . ***Інтеграція ГІС, GPS, ДЗЗ та штучного інтелекту в аграрну практику суттєво підвищує точність аналізу ґрунтових характеристик і ефективність управління агропроцесами. Побудована модель дає змогу автоматизувати процеси прийняття рішень на основі великого обсягу просторових і польових даних, сприяє зниженню витрат, підвищенню врожайності та збереженню родючості ґрунтів. Досвід впровадження моделі в умовах Київської області засвідчує її практичну придатність і потенціал до масштабування в рамках сучасного точного землеробства.***

К л ю ч о в і с л о в а : ***геоінформаційні системи (ГІС), дистанційне зондування Землі (ДЗЗ), глобальні навігаційні супутникові системи (GPS) та штучний інтелект (ШІ), прецизійне землеробство (ПЗ), геоінформаційні технології (ГІТ), APSIM (Agricultural Production Systems Simulator), DSSAT (Decision Support System for Agrotechnology Transfer).***

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