КОЛЕКТИВНА МОНОГРАФІЯ

МІЖДИСЦИПЛІНАРНІ ВИМІРИ ІННОВАЦІЙ: ВІД ТЕОРІЇ ДО ПРАКТИКИ СОЦІАЛЬНО-ЕКОНОМІЧНОГО РОЗВИТКУ

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Міждисциплінарні виміри інновацій: від теорії до практики соціально-економічного розвитку: колективна монографія. Вип. 2 / за ред. М. Швардак, О. Попович, В. Іванової. Мукачево: Мукачівський державний університет – Спілка науковців України, 2026. 420 с.

У монографії розглянуто теоретичні та практичні аспекти інноваційних процесів у контексті сучасного розвитку освіти та соціально-економічної сфери. Акцентовано увагу на широкому спектрі системних інновацій в освітній галузі – від управління безпекою середовища й упровадження новітніх педагогічних технологій до цифровізації мовної підготовки та інклюзивних рішень, а також на проблемах цифрової трансформації бізнесу, інтеграції штучного інтелекту та стратегічного управління людським капіталом у кризових умовах. Відображено погляди вітчизняних дослідників на вирішення актуальних завдань у сферах педагогіки, економіки, менеджменту та соціокультурної діяльності в контексті побудови інноваційного суспільства.

Адресується фахівцям-практикам, науковим і науково-педагогічним працівникам, докторантам, аспірантам та студентам; усім, хто цікавиться актуальними проблемами інноваційного розвитку суспільства.

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1.3. Intelligent Data Processing Systems for Uav-Based Monitoring of Agroecosystems

1.3. Інтелектуальні системи обробки даних для моніторингу агроекосистем на основі безпілотних літальних апаратів

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Abstract. *The study is devoted to intelligent data processing systems that ensure effective monitoring of agroecosystems using unmanned aerial vehicles. The purpose of the study is to determine the features of data collection, processing, interpretation and visualization in UAV monitoring systems of agroecosystems, as well as to clarify their significance for increasing the efficiency of agricultural production management. During the scientific study, general scientific methods of cognition were used, in particular analysis, synthesis, comparison, generalization, systematization and predictive methods. The results of the study show that intelligent data processing systems for UAV monitoring form a holistic digital circuit of monitoring the agroecosystem, within which the emphasis is placed on a consistent combination of the stages of collection, processing, interpretation and visualization of information. It was investigated that modern data collection is no longer limited to aerial photography, but includes the selection of a platform, sensor equipment, flight planning, calibration, georeferencing, as well as the integration of aerial data with satellite and ground measurements. It is shown that the most promising is the transition from irregular to continuous monitoring, which involves continuous collection of field data. The stage of processing the collected information converts the data collected by sensors into understandable information that can be processed by agricultural specialists for further decision-making. The conclusion is made about the importance of methods for photo analysis, plant condition assessment, computer training to find patterns, the use of smart programs, digital maps and online processing of large amounts of data for assessing plant condition, detecting diseases, stress, decline, predicting yield and spatial zoning of fields. Today, the obtained data is not just shown on the map, but also combined with convenient screens with indicators, electronic maps and systems that help people make decisions.*

Keywords: *UAV, agriculture, agro-industry, monitoring, data processing.*

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Анотація. *Дослідження присвячене інтелектуальним системам обробки даних, що забезпечують ефективний моніторинг агроекосистем із використанням безпілотних літальних апаратів. Метою дослідження є визначення особливостей збору, обробки, інтерпретації та візуалізації даних у системах моніторингу агроекосистем на основі БПЛА, а також уточнення їхнього значення для підвищення ефективності управління сільськогосподарським виробництвом. У ході наукового дослідження застосовано загальнонаукові методи пізнання, зокрема аналіз, синтез, порівняння, узагальнення, систематизацію та прогностичні методи.*

Результати дослідження показують, що інтелектуальні системи обробки даних для моніторингу за допомогою БПЛА формують цілісний цифровий контур спостереження за агроекосистемою, у межах якого акцент зроблено на послідовному поєднанні етапів збору, обробки, інтерпретації та візуалізації інформації. Встановлено, що сучасний збір даних уже не обмежується лише аерофотозйомкою, а включає вибір платформи, сенсорного обладнання, планування польотів, калібрування, геоприв'язку, а також інтеграцію аероданих із супутниковими та наземними вимірюваннями. Показано, що найбільш перспективним є перехід від нерегулярного до безперервного моніторингу, що передбачає постійний збір польових даних. Етап обробки зібраної інформації перетворює дані, отримані сенсорами, на зрозумілу інформацію, яка може бути використана аграрними фахівцями для подальшого прийняття рішень. Обґрунтовано доцільність використання інтелектуальних програмних рішень, цифрових карт і технологій онлайн-обробки великих масивів даних для комплексної діагностики стану посівів, своєчасного виявлення захворювань, стресових станів та деградаційних процесів, а також для прогнозування врожайності та здійснення просторового зонування сільськогосподарських угідь.

Ключові слова: *БПЛА, сільське господарство, агропромисловість, моніторинг, обробка даних.*

Introduction. The agricultural drone market is showing one of the highest growth rates among all segments of unmanned aerial vehicles. According to Market.us (2025), in 2023 its volume was about $2.3 billion, and by 2033 it is predicted to grow to $16.9 billion with an average annual growth rate of 22.1%. However, behind these figures is not only technological progress – a deeper structural transformation of approaches to agroecosystem management is taking place. Traditional field survey methods have significant limitations: they are labor-intensive, often involve destructive sampling and often give subjective results. Unmanned aerial vehicles in agriculture have already gone beyond experiments and are gradually moving from innovations into the sphere of conventional technological equipment of modern agricultural production processes.

By the end of June 2024, agricultural drones were used on over 500 million hectares of arable land worldwide (IMARC Group, 2025). The regional distribution of the market is uneven. North America retains its leadership with a share of about 35% of the global market in 2025, while the Asia-Pacific region is the fastest growing with a projected CAGR of 23% by 2032, which is explained by government subsidies in India and China, as well as growing demand for food (Persistence Market Research, 2025). It is worth noting that in the Asia-Pacific region, China is the undisputed leader in drone adoption, where government subsidies covered over 150 million acres of land as early as 2021 (Radhakrishnan & Sharma, 2025).

Among the key trends in the UAV market in agriculture, it is worth highlighting:

1. In 2025, the largest (61.7%) market share will be occupied by drones with rotary propellers. This is due to the fact that they are increasingly used in precision agriculture. Such popularity is explained by the fact that multi-rotor drones can hover over the desired area of the field and spray very accurately (Raeva et al., 2019);

2. In 2025, the largest market share (68.8%) will be occupied by drone technical equipment. Its most important parts are modern sensors, cameras and navigation systems. Multispectral (allowing to assess the condition of plants using different light spectra), hyperspectral (providing a very detailed analysis of plants and soil) and thermal sensors (determine temperature and help detect overheating or lack of moisture) form the basis of modern agricultural drones (Coherent Market Insights, 2025; Wang, 2024).

3. Increasingly, farmers do not buy a drone themselves, but hire specialists to perform the necessary work with a drone. This is convenient for small farms, because they do not need to spend a lot of money on their own equipment (Grand View Research, 2025; Kale et al., 2026).

4. Machine and deep learning algorithms are increasingly used to analyze changes in source data. In agriculture, this can include: detecting plant and animal disease based on their appearance; overgrowing of fields with planting material and harmful plants; changes in crop conditions after weather changes: winds, downpours, hurricanes, thunderstorms, etc. (Oghaz et al., 2019). If such changes are not tracked automatically, or "by eye," then it is currently impossible to cover hectares of land, and using

automated analysis of large volumes of data, technologies can handle the analysis of 100% of the surface.

The long-term forecast is even more ambitious: according to Market Research Future, the agricultural drone market will grow from $7.9 billion to $10.9 billion. in 2025 to $70.6 billion by 2035 at a CAGR of 24.46% (Market Research Future, 2025). This forecast corresponds to the broader context of the growth of global demand for food. Raeva P. L. and co-authors emphasize that by 2050 the world population will reach 9 billion people, which will radically exacerbate the problem of food security and require the implementation of precision agriculture technologies on a much larger scale (Raeva et al., 2019). Already today, the use of drones allows you to reduce water use for irrigation by up to 90% and increase yields by 5–10% depending on the crop (Coherent Market Insights, 2025), which forms a sustainable economic incentive for further market growth.

Presentation of the main material. Intelligent data processing systems for UAV monitoring of agroecosystems should be considered as a set of software, analytical and algorithmic tools that transform primary aerial data into practically meaningful information for managing agricultural production. Their function is not limited to the accumulation of images. The main goal is to determine the state of the crops that the agricultural business deals with, their changes, and, against the background of the analysis, make decisions about further care (de Castro et al., 2021).

In a general sense, such systems cover the stages of data collection, processing, interpretation and visualization.

Stage 1. Data collection

The data collection stage in UAV monitoring intelligence systems is the initial, but at the same time, decisive link in the entire analytical cycle. It is at this stage that the array of primary information is formed, on which the accuracy of mapping, index construction, assessment of phenological phases, stress detection and the quality of predictive models depend. The attached document shows that data collection in modern agromonitoring is no longer limited to aerial photography. It combines flight planning, platform selection, sensor selection, calibration, georeferencing, and integration of aerial data with satellite and ground measurements.

As de Castro et al. (2021), the advantage of UAVs for agricultural monitoring is the ability to operate at low altitudes, obtain images with ultra-high spatial resolution, perform surveys at the desired phases of plant development, and use various sensors, including visible, infrared, and thermal ranges (de Castro et al., 2021). This means that data collection does not begin with the flight itself, but with the task. First, it is determined what state of the agroecosystem needs to be recorded: morphological characteristics of plants, spectral characteristics, temperature anomalies, spatial structure of crops, or environmental parameters. After that, the type of UAV is selected. Based on the study of L. Wang (2024), light multi-rotor platforms with a medium range of action are most suitable for precision agriculture, since they combine maneuverability, sufficient load capacity, and the ability to work with high-precision sensors.

The choice of sensor equipment capable of reading information is one of the basic stages of monitoring. Here, it is not so much the aircraft that is important as the sensor with which it is equipped. There are several options that are most common in the agricultural industry. The first is RGB cameras. They provide high image detail and have proven themselves well for building surface models of crops, visual assessment of plant condition and classification of objects. Cameras are especially relevant if the plants are of the same type, then there is no need to expand the spectrum of analysis (Wang,2024; Raeva et al., 2019)

Multispectral cameras allow reading a larger color spectrum. Such information allows calculating vegetation indices and detecting hidden changes in the condition of crops. In practice, such cameras determine the degree of maturity of fruits or crops.

Hyperspectral sensors provide even higher spectral resolution, but their practical application, as Wang (2024) notes, is limited by the significant cost, which may not be remunerative compared to the economic efficiency of a wider data set. At the same time, such spectra are used in the agricultural industry for disease diagnostics, determination of chlorophyll content and degree of maturity. Thermal imaging sensors are used to measure temperature. This is necessary for measuring the stress state of plants, again for other types of condition diagnostics.

A separate group consists of radar tools, such as LiDAR and millimeter systems, which allow obtaining spatial information about the structure of vegetation cover even in conditions where optical devices have significant limitations, for example due to poor visibility, obstacles, and humidity. In the example given, multispectral survey of winter wheat was carried out on several dates of the season, at an altitude of 50 m, with cross-routes and 90% overlap of flight lines (Moletto-Lobos et al., 2024). Such a scheme is required in order to obtain complete coverage of the area, minimize geometric gaps and create a correct orthomosaic. In the study by Jena et al. (2026) also show that in another scenario, flights can be carried out at an altitude of 120 m, with an 85% overlap and a fixed sampling rate, where the priority is to combine UAV data with Sentinel-2 satellite materials (Jena et al., 2026). Therefore, the flight parameters are not fixed. They depend on the crop, the scale of the plot, the type of sensor and the research objective.

The calibration and georeferencing stage occupies a special place in the overall data processing chain. Raw digital data from a multispectral camera cannot immediately serve as a reliable basis for analytics – before use, they undergo several successive stages of preparation.

Moletto-Lobos et al. (2024) highlight the following key steps:

- radiometric calibration – conversion of raw pixel values into emissivity and reflectance characteristics using a calibrated white panel, image metadata and standard transformation models;
- orthocorrection – spatial alignment of images using RTK GPS and ground control points, which ensures accurate georeferencing of data;
- pre-flight calibration using reference panels – minimization of atmospheric distortions even before data collection begins, which is also confirmed in the study by Jena et al. (2026).

Drone data is supplemented with field measurements and satellite imagery. Field data on plant health, yield, nutrient content and protein content are needed to verify the accuracy of aerial imagery. Satellites allow for long-term monitoring of large areas, while drones provide very detailed field-level data. Therefore, data collection combines drone, ground and space-based information. The main sources and types of data are presented in Table 1.5.

Table 1.5

Data collection sources and components in UAV monitoring of agroecosystems

Source	How data are collected	Significance for monitoring
UAV platform, including multirotor and fixed-wing systems	It is selected according to field size, maneuverability, payload capacity, and the flight scenario. In precision agriculture, lightweight multirotor platforms are used more often (Wang, 2024).	It determines flight stability, available altitude, mission duration, and compatibility with a specific sensor (Raeva et al., 2019).
RGB cameras	They collect data in the visible spectrum and provide high-detail imagery of the field surface and vegetation cover (Raeva et al., 2019).	They make it possible to capture plant morphology, visible symptoms of damage, and build crop surface models (Wang, 2024).
Multispectral sensors	Imaging in multiple spectral bands allows for more data collection but requires calibration (Jena et al., 2026; Moletto-Lobos et al., 2024).	Used to check fruit maturity and damage (Moletto-Lobos et al., 2024; Raeva et al., 2019).
Hyperspectral sensors	They record a large number of narrow spectral bands, which makes it possible to detect subtle differences in spectral response (Wang, 2024).	They increase sensitivity to hidden changes in plants, although their use is still limited by high cost and operational complexity (Wang, 2024).
Thermal sensors	They register thermal radiation from the surface of plants and soil. Weather factors must be taken into account, and careful initial calibration is required (Wang, 2024).	They make it possible to detect water stress, temperature anomalies, and indirect signs of physiological disorders (Raeva et al., 2019; Wang, 2024).
LiDAR and radar sensors	Data are collected through laser or electromagnetic scanning. Such systems can be used for 3D modeling and under conditions of limited visibility (Wang, 2024).	They provide spatial reconstruction of vegetation cover, partial penetration through plant biomass, and the generation of high-precision 3D maps (Semiriakov, 2025; Wang, 2024).

Flight parameters: altitude, overlap, timing, repeatability	The flight mission is planned taking into account flight altitude, weather, route corrections and possible image overlap of up to 80%. (Jena et al., 2026; Moletto-Lobos et al., 2024).	These parameters determine orthomosaic quality, spatial accuracy, coverage completeness, and the suitability of the data for further processing (Jena et al., 2026; Moletto-Lobos et al., 2024).
Ground measurements and ground truth	Field observations, canopy measurements, yield collection, protein and nitrogen determination, and other validation procedures are carried out (Moletto-Lobos et al., 2024). In addition, visual interpretation and field verification of classes are used (Jena et al., 2026).	They establish the benchmark for verifying the accuracy of remote assessments and training classification models (Jena et al., 2026; Moletto-Lobos et al., 2024).
Satellite data, including Sentinel-2 and PlanetScope	Multi-temporal image series are downloaded and undergo orthorectification, atmospheric correction, and geometric correction (Moletto-Lobos et al., 2024).	They ensure temporal continuity of observations, large-scale coverage, and strengthen UAV data in integrated monitoring systems (Jena et al., 2026; Moletto-Lobos et al., 2024).
IoT sensors and cloud-based systems for collecting field parameters	Soil moisture, temperature, and air humidity sensors, Wi-Fi modules, and cloud servers are used to transmit data from the field (Karar et al., 2021).	They are expanding data collection, studying not only images but also measuring the state of the environment (Karar et al., 2021).
RF energy-harvesting sensor tags and autonomous systems	Passive tags receive energy from radio frequencies and do not require significant power consumption (Kudyba & Sun, 2025).	Reduces electricity costs (Kudyba & Sun, 2025).

Note: compiled by the author based on sources (Jena et al., 2026; Karar et al., 2021; Kudyba&Sun, 2025; Moletto-Lobos et al., 2024; Raeva et al., 2019; Wang, 2024)

A review of available technologies has shown that there is still no single, agreed-upon approach among them. That is, there is no consistent set of methods and tools that would be used equally for different tasks. For example, a well-established approach is one in which a field is photographed several times with a multi-channel camera, the data is precisely tied to the terrain and checked using a special reference surface. At the same time, some types of equipment, in particular more complex sensors for detailed spectral, thermal and radar analysis, still need to be refined, as they are expensive, difficult to use and depend on external conditions. A combination of drones and satellite images is promising, as it allows you to simultaneously obtain very detailed data for a separate field and regularly observe changes over time. However, in this case, too, it is still necessary to improve the uniform rules for combining such data so that they coincide well with each other and are checked using field measurements (Jena et al., 2026).

In the near future, the use of several areas at the data collection stage is likely to increase:

- autonomous UAVs with software control (Wang, 2024),
- swarm data collection and mapping systems based on the information gain principle (Carbone et al., 2022),
- new generation LiDAR- and GIS-oriented platforms (Semiriakov, 2025; Wang, 2024),
- integration of UAVs with IoT field infrastructure (Karar et al., 2021),
- RF energy-harvesting sensor tags for continuous collection of environmental parameters with minimal energy consumption (Kudyba & Sun, 2025).

That is, if we consider all these devices together, we can talk about a transition from episodic aerial photography to multi-source, multi-purpose, multi-source photography with the possibility of autonomous data collection, which allows for the automation of crop cultivation.

Stage 2. Data Processing

The data processing stage in AI systems for UAV monitoring of agroecosystems performs a transformative function. At this level, the raw aerial images, spectral values, coordinate information and ground observations are transformed into a form suitable for analytical use. The accompanying document emphasizes that the significant amount of detailed data obtained from UAVs requires the use of powerful analysis procedures capable of extracting information about the structural and biochemical characteristics of plants (de Castro et al., 2021). This means that processing is not an auxiliary stage.

It actually forms the basis for further interpretation of crop conditions, stress assessment, mapping of field heterogeneity and supporting management decisions.

Data processing begins with radiometric calibration. At this stage, according to the results of the study by Moletto-Lobos et al. (2024), the original digital pixel values are converted into spectral radiance and surface reflectance characteristics. In parallel, orthocorrection, georeferencing, and orthomosaic construction are performed using RTK GPS, ground control points, and photogrammetric procedures. The Structure from Motion method deserves special attention. This allows obtaining digital surface models and three-dimensional vegetation cover based on a series of overlapping images, which significantly expands the analytical potential of aerial data.

This is followed by calculation of the vegetative state index (i.e., fruit maturity), temporal analysis (how plants change under the influence of time), statistical evaluation (quantitative measurement of yield), classification and modeling using machine learning and deep neural networks (Carbone et al., 2022; Kale et al., 2026; Moletto-Lobos et al., 2024; Oghaz et al., 2019; Raeva et al., 2019). Let us consider the main processing technologies in Table 1.6.

Table 1.6

Main technologies and methods of data processing in UAV monitoring of agroecosystems

Technology / processing method	Description and purpose
Structure from Motion (SfM) de Castro et al. (2021); Moletto-Lobos et al. (2024)	A photogrammetric technique used to create 3D surface models, digital elevation models, and orthomosaics by aligning a large number of overlapping images. It makes it possible to obtain a spatially consistent representation of crops and vegetation structure.
Object-based image analysis (OBIA) de Castro et al. (2021)	A processing method in which analysis is carried out not at the level of an individual pixel, but at the level of defined objects. This improves the accuracy of vegetation classification and better accounts for shape, context, and spatial relationships between elements of the agricultural landscape.
Convolutional neural networks (CNN) Kale et al. (2026); Oghaz et al. (2019); Carbone et al. (2022)	Deep learning methods used for disease detection, plant classification, assessment of the degree of damage, and automated weed counting. Such models make it possible to process large image datasets automatically and with high accuracy.

Calculation of vegetation indices (NDVI, GNDVI, etc.) Raeva et al. (2019); Moletto-Lobos et al. (2024)	Mathematical combinations of spectral bands used to assess plant condition, vegetation intensity, green cover fraction, moisture status, and yield forecasting. This approach is what translates multispectral data into indicators suitable for agronomic interpretation.
Savitzky–Golay filter Moletto-Lobos et al. (2024)	It is used to smooth time series of vegetation indices and reduce noise. This is especially important for identifying phenological stages, including the beginning, peak, and end of the season.
Machine learning (Random Forest, SVM, MLP) Kale et al. (2026); Jena et al. (2026); Oghaz et al. (2019)	Machine learning algorithms are used to predict agricultural performance targets. Their advantage lies in identifying nonlinear relationships between data collected in the field.
GIS technologies (GIS) Semiriakov (2025)	Tools for the systematization, integration, and spatial interpretation of processing results. They make it possible to generate multilayer electronic maps, support variable-rate resource application, and convert measurements into a format suitable for practical management.
Atmospheric and radiometric correction Moletto-Lobos et al. (2024)	A set of procedures through which digital values are converted into physically accurate surface reflectance indicators. The document mentions the use of 6SV2.1 and supporting atmospheric data to improve the reliability of spectral analysis.
Statistical analysis (ANOVA, Fisher's LSD test, Shapiro–Wilk test) Moletto-Lobos et al. (2024)	Methods for the mathematical testing of hypotheses regarding the effects of fertilizers, observation dates, and other factors on crop development. Such procedures ensure the scientific verification of the identified patterns.
Foundation spectral models, including SpectralGPT Kale et al. (2026)	AI models allow you to increase the resilience of modeling to various changes and predict development scenarios in crisis conditions.
Cloud computing and Big Data analytics	Scalable platforms for storing, transmitting and processing large data sets from drone sensors and satellite systems. Their use is associated with the automation of analytics, reducing the load on local systems and supporting real-time operation and monitoring

Note: compiled by the author

In the coming years, the processing of data obtained using drones for monitoring agroecosystems is likely to become more automated, capable of working with larger amounts of information, and more intelligent. That is, the system will be able to perform a significant part of the analysis itself, faster and more accurately than it is done now. According to Kale et al. (2026), universal computer models for analyzing spectral data, as well as complex learning models whose work can be better explained, will play an important role in the future. These are programs that can process very large amounts of data that are not usually processed manually. If data is collected simultaneously using multiple drones equipped with different types of equipment, the information will be even more accurate and suitable for accurate forecasting.

This means that a group of drones will be able to not only collect data, but also partially analyze it during the flight. This will allow you to more quickly identify problem areas in the field and immediately change the route or investigate individual places in more detail. Kudyba and Sun (2025) show that combining data from drones with a network of autonomous wireless tags placed directly in the field is promising. These devices are able to constantly collect information about the state of the environment, such as humidity, temperature, or other indicators. If you combine this data with information collected by a drone, you can almost continuously update analytical models directly in the field. This allows you to observe changes not from time to time, but almost constantly.

All data storage takes place in the cloud environment. First of all, this allows you to remotely manage processes and involve specialists from different industries, regions and even corners of the world in the business.

Combined with new laser scanning systems and electronic maps, which are discussed in Semiriakov (2025), this creates the basis for moving to a new level of analysis. It is no longer just about processing data after the observation is completed, but about creating a dynamic intelligent system that can support agricultural production in almost real time. That is, such a system will be able not only to record changes, but also to help make quick decisions during crop cultivation.

Stage 3. Data processing and visualization

The stage of data interpretation and visualization is the final one in the structure of intelligent information processing for UAV monitoring of agroecosystems. It is at this level that the results of preliminary calculations are translated into a form suitable for professional interpretation and practical use. To systematize these tools, we will consider Table 1.7.

Table 1.7

Data interpretation and visualization technologies in UAV monitoring of agroecosystems

Technology / method	Description and role in visualization and interpretation
Index maps Raeva et al. (2019)	A visual representation of quantitative vegetation or soil characteristic values in the form of map-based schemes. They are used to localize zones with different levels of “greenness,” moisture, or other indicators of agroecosystem condition.
Digital surface models (DSM) and 3D metrics de Castro et al. (2021); Moletto-Lobos et al. (2024); Wang (2024)	A three-dimensional visualization of vegetation structure that makes it possible to assess plant height, the spatial configuration of crops, and individual morphometric parameters.
GIS Semiriakov (2025)	A combination of several spatial layers within a single cartographic system for interpreting the agronomic situation, zoning the field, and supporting management decisions.
Visualization of time series and phenological metrics Moletto-Lobos et al. (2024)	A graphical representation of crop development through SOS, POS, EOS, and LOS indicators. It makes it possible to trace the seasonal dynamics of the crop and compare them with actual development stages.
Bounding box method Carbone et al. (2022)	Visually highlight detected objects, including crops and weeds, directly on the image. This approach makes it easier to verify the results of automated detection.
Confusion matrices and classification probability tables Carbone et al. (2022)	Tools for interpreting model accuracy that show the relationship between the actual and detected number of objects. They are used to assess the reliability of weed and crop recognition.
Pixel color coding and gradient schemes Moletto-Lobos et al. (2024)	A visualization of spatial overlap, the quality of pixel inclusion within plot boundaries, or the degree of correspondence between data sources. The study used a color gradient to show the share of a pixel within the experimental plot.
Orthomosaics as the basic visual foundation Moletto-Lobos et al. (2024)	A spatially seamless image created from a large number of individual frames. It serves as the basis for further mapping, plot comparison, and the alignment of analytical layers.
Comparative visualization of UAV and satellite data Jena et al. (2026); Moletto-Lobos et al. (2024)	It makes it possible to interpret highly detailed local UAV data together with broader satellite time series. This improves the multiscale analysis of field processes.
Intuitive interfaces and dashboards Karar et al. (2021); Kudyba & Sun (2025)	Mobile and cloud interfaces designed to display real-time environmental parameters, irrigation status, and sensor data streams. These tools transform complex data into a format suitable for continuous monitoring.

Decision support systems (DSS) de Castro et al. (2021); Semiriakov (2025)	Integrated analytical environments that transform maps, indices, and models into practical recommendations for fertilization, irrigation, or plant protection.
Future technologies: cloud-network visualization and multimodal platforms Kale et al. (2026); Karar et al. (2021); Kudyba & Sun (2025); Semiriakov (2025)	A promising direction that combines cloud services, IoT infrastructure, wireless tags, GIS, and artificial intelligence models for the continuous visualization of agroecosystem condition. Such systems are expected to provide more timely map updates and support a shift toward near-real-time operation.

Note: compiled by the author

Data visualization in UAV monitoring has gone beyond simple cartographic display. Today, full-fledged analytical foundations for decision-making are being formed based on dashboards that notify about problems, predict changes in real time, prepare for future costs or investments. At the same time, another direction is being formed in which visualization is integrated with mobile interfaces, sensor networks and cloud environments (Karar et al., 2021; Kudyba & Sun, 2025).

In the future, the development of the following tools is expected:

- interactive dashboards – for the operational display of spatial changes in the state of crops;
- multimodal geoinformation platforms – for the integration of heterogeneous data sources in a single environment;
- intelligent visual support systems – which will not only reflect spatial differences, but also automatically form the context of their agronomic interpretation (Kale et al., 2026; Semiriakov, 2025).

The complex combination of data collection, their intelligent processing, interpretation and visualization significantly changes the very logic of agricultural monitoring using UAVs. If the traditional observation model was dominated by selective field surveys, then in the modern approach a continuous digital loop of observation of the agroecosystem is formed.

Economic effect. In China, the introduction of UAVs in agricultural production has increased income by 434–488 USD per hectare and reduced labor costs by 14.4–

15.8 hours per hectare. Reduced labor and agrochemical costs are one of the main factors in the long-term economic feasibility of UAVs (Kale et al., 2026).

Environmental impact. UAVs can provide effective pest and disease control even with reduced pesticide doses, and in some cases, more than 20% reduction in pesticide use has been recorded compared to traditional approaches (Kale et al., 2026). More precisely, the use of remote sensing technologies in agriculture is associated with reduced agrochemical loads, reduced fuel and time costs, and the support of more sustainable agricultural landscapes (Kale et al., 2026; Librán-Embid et al., 2020).

Impact on production. The production of agricultural products is gradually becoming fully automated, involving a minimum number of unskilled resources, and with the use of drones, the need for skilled analysts has disappeared. The initial investment in technology is being repaid by reducing costs and improving the quality of not only products, but also after-sales service (de Castro et al., 2021; Moletto-Lobos et al., 2024).

Management effect. The integration of LiDAR and GIS allows for the creation of multi-layered electronic maps, support differentiated input, predict yield, and increase the consistency of technical and agronomic decisions. This means that UAV monitoring moves the farm to a model where management decisions are based not on average estimates, but on specific digital parameters of individual field sections (Semiriakov, 2025).

The global food dimension is of particular importance: by 2050, the world population may reach 9.8 billion people, and therefore agricultural production should increase by 70% compared to the current level. Under such conditions, UAV monitoring in combination with intelligent data processing acquires not only technological, but also strategic importance. Its role is to increase the sustainability of production in the face of climate change, resource constraints and the need for operational management of crop productivity (de Castro et al., 2021; Jena et al., 2026). That is why the expected effect of the implementation of these technologies should be associated not only with local optimization of the economy, but also with strengthening food security at a broader level.

Conclusions. Thus, the comprehensive implementation of aircraft and innovative data processing technologies changes the logic of agricultural production management: observations cease to be selective, they become comprehensive and continuous. The practical effect of such an approach is manifested in saving money, saving resources, including time, increasing yields and more efficient agriculture. Further investments in the development of autonomous UAVs, swarm systems, LiDAR and GIS platforms, cloud analytics, IoT infrastructure create an intelligent environment where the agricultural industry reaches an advanced innovative level of equipment.

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