UDC 528.854:681.5.015.42(045)
DOI:10.18372/1990-5548.83.19866

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PROBLEMS OF MULTISPECTRAL IMAGE PROCESSING IN AGRICULTURE

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***Abstract*—*This study provides a comprehensive comparative analysis of satellite-based and drone-based imaging platforms for agricultural monitoring, with particular emphasis on multispectral imaging capabilities. Our analysis reveals that while satellite systems offer broad coverage and cost-effectiveness for large-scale monitoring, drone-based platforms provide superior spatial resolution (up to 2.5 cm/pixel) and greater flexibility for targeted data acquisition, making them ideal for medium-sized agricultural plots. The research examines key imaging technologies and platforms, including the Sentinel-2 satellite system and drone-mounted sensors such as the MicaSense RedEdge-MX, evaluating their performance across critical agricultural applications. The paper further explores the implementation of convolutional neural networks for processing multispectral data, demonstrating their exceptional capability in performing crucial agricultural tasks including crop classification, disease detection, and stress assessment. By incorporating spectral indices, thermal indices and biophysical parameters (LAI, chlorophyll content) into neural network training, we develop a robust framework for agricultural monitoring and yield prediction. This research contributes both to the theoretical understanding of remote sensing in agriculture and provides practical guidance for implementing precision agriculture solutions that enhance productivity and sustainability in modern farming systems.*

Keywords—Multispectral imaging; precision agriculture; crop yield prediction; satellite-based monitoring; drone-based monitoring; spectral indices; convolutional neural network.

I. INTRODUCTION

Agriculture has long been the backbone of human civilization, yet it faces numerous challenges that threaten productivity and sustainability. Traditional farming methods struggle to meet the increasing demand for food due to climate change, soil degradation, pest outbreaks, and inefficient resource management.

To properly configure processing systems and select appropriate analysis methods, it is essential to clearly define the key tasks for computer vision systems in the agricultural sector. Let's review the main ones:

- *Determining the Morphological Similarity of Plants*: identification of plant varieties and hybrids, assessment of crop uniformity, detection of atypical plants in the fields, monitoring of phenological development stages [17].
- *Disease Diagnosis*: early detection of disease symptoms, classification of disease types, assessment of damage severity, disease progression prediction, mapping of infection hotspots.
- *Pest Monitoring*: detection of pest presence, determination of pest developmental stages, prediction of potential outbreaks, mapping of risk zones.

To effectively address these tasks, it is crucial to select the appropriate data collection tools and processing methods [1], [10].

Among these technologies, remote sensing, particularly multispectral imaging, has gained significant attention for its ability to provide detailed spectral information about crops, enabling the detection of subtle variations in plant health, nutrient status, and water stress [2]. Coupled with thermal imaging, which captures temperature variations indicative of crop stress, these technologies offer a powerful toolset for predicting yields and identifying issues before they escalate [3].

The consideration of metrics for evaluating the effectiveness of the chosen image processing methods is an important aspect of this research. Classification accuracy, the in formativeness of the data used, and the cost of technologies – all these parameters must be balanced to achieve the maximum result with minimal costs. It is important to note that overly high accuracy requirements can lead to increased costs for equipment and data processing, as well as longer processing times. To achieve optimal results, we consider the use of multispectral cameras and, when necessary, thermal cameras to detect various plant characteristics.

Multispectral imaging provides more information about the condition of plants compared to conventional cameras, as this imaging in multiple spectral bands can detect defects and diseases that are not visible to the naked eye.

Despite these advancements, predicting crop yields and diagnosing agricultural issues remain complex tasks. Challenges such as spatial and temporal variability in crop conditions, the influence of environmental factors, and the need for high-resolution data complicate the development of accurate predictive models [4]. Traditional methods of yield prediction, which rely on manual field surveys and historical data, are often labor-intensive, time-consuming, and insufficient for real-time decision-making [5]. Furthermore, the integration of multispectral and thermal data into predictive models requires sophisticated analytical approaches, such as artificial intelligence (AI), to process and interpret the vast amounts of data generated [6].

II. Key Challenges in Agriculture

One of the most pressing challenges is climate change, which affects crop yields and farming practices. Rising temperatures, unpredictable rainfall patterns, and extreme weather events contribute to reduced agricultural productivity [13]. AI-driven models can help predict climate patterns and optimize crop selection and irrigation schedules to mitigate risks [21].

Intensive farming practices have led to soil degradation and nutrient depletion, making it harder to sustain high yields. Traditional soil analysis methods are time-consuming and costly. AI-powered multispectral imaging and remote sensing technologies can assess soil health in real-time, allowing farmers to implement precision agriculture techniques.

Pests and plant diseases cause significant economic losses globally. Conventional pest control methods rely on excessive pesticide use, which can harm ecosystems and human health. AI models trained on convolutional neural networks (CNNs) can analyze multispectral imagery and detect early signs of diseases or pest infestations, enabling targeted interventions [9].

Water scarcity is an increasing concern in agriculture, particularly in arid and semi-arid regions [12]. Inefficient irrigation practices contribute to water waste and soil salinization. Remote sensing with multispectral imaging enables precise monitoring of crop water requirements, improving irrigation scheduling and water conservation efforts [20]. This technology allows for the differentiation between healthy and water-stressed plants, ensuring that irrigation resources are used optimally.

Accurate yield prediction is crucial for food security and market stability. Traditional yield estimation methods rely on manual sampling, which can be time-consuming and inaccurate. Multispectral imaging provides a non-invasive means of assessing crop biomass, chlorophyll content, and growth stages, leading to more reliable yield forecasts [11]. This information helps farmers and policymakers plan for storage, distribution, and trade more effectively.

The agricultural sector faces increasing labor shortages, particularly in regions reliant on manual labor. Automation and remote sensing technologies, including drones equipped with multispectral cameras, can help mitigate these shortages by providing comprehensive field assessments with minimal human intervention. This reduces labor costs and improves decision-making efficiency.

Farmers must comply with evolving regulations regarding pesticide use, environmental impact, and land management [16]. Multispectral imaging supports compliance efforts by providing objective, data-driven insights into field conditions. This technology can be used to generate reports that meet regulatory requirements and optimize farming practices in accordance with sustainability standards.

The integration of multispectral imaging into modern agriculture presents a transformative opportunity to address many of the sector's most pressing challenges. From climate adaptation and resource optimization to pest control and regulatory compliance, this technology enhances decision-making and promotes sustainable practices. As advancements in remote sensing and artificial intelligence continue, the potential for precision agriculture to revolutionize food production will only grow, ensuring greater efficiency, resilience, and profitability for farmers worldwide.

III. Background and Literature Review

A. *Multispectral Imaging*

Multispectral cameras are specialized imaging devices that capture data from multiple wavelengths across the electromagnetic spectrum, typically beyond the visible range. Unlike traditional RGB cameras, these cameras can detect near-infrared (NIR), shortwave infrared (SWIR), and other spectral bands that provide critical insights into plant health, soil composition, and water content [17] (Figs 1 and 2).

Multispectral imaging (MSI) captures data in a smaller number of discrete spectral bands, typically ranging from 3 to 15 bands, covering key regions of the electromagnetic spectrum such as visible, red-edge, and NIR. Multispectral imaging offers lower spectral resolution, it provides sufficient information for many agricultural applications, such as vegetation index calculation (e.g., NDVI, EVI) and broad-scale crop health assessment [5].

Fig. 1. Multispectral image, infrared color

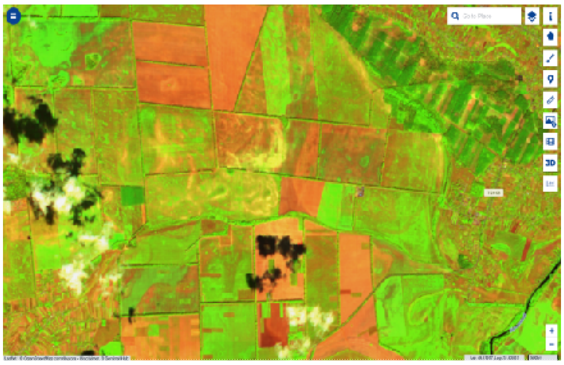

Fig. 2. Multispectral image, agriculture composite

Multispectral imaging works by detecting variations in how plants reflect and absorb light across different wavelengths. Healthy vegetation, for example, reflects more NIR light due to chlorophyll presence, while stressed or diseased plants exhibit different reflectance patterns. This capability allows researchers and farmers to assess crop stress levels, identify nutrient deficiencies, and predict yield more accurately [4].

B. Applications of Multispectral Cameras in Agriculture

Crop Health Monitoring: Multispectral imaging enables early detection of diseases, pests, and nutrient deficiencies by identifying subtle changes in leaf reflectance before they become visible to the naked eye [15].

Soil Analysis: Multispectral imaging can be used to analyze soil moisture content, organic matter, and nutrient levels, improving precision in fertilization and irrigation practices.

Yield Prediction: By analyzing plant vigor and chlorophyll content, multispectral data can help forecast crop yields and optimize harvest planning [14].

Irrigation Management: Water stress in plants can be detected using specific spectral indices, such as the Normalized Difference Water Index (NDWI), allowing for optimized irrigation strategies.

Weed and Pest Identification: Differentiating between crops and weeds using spectral data helps reduce herbicide usage by enabling targeted application. Despite their advantages, multispectral cameras have certain limitations:

High Cost: Advanced multispectral sensors can be expensive, limiting their accessibility for small-scale farmers [22].

Data Processing Complexity: Large amounts of spectral data require sophisticated algorithms and computational power for meaningful interpretation [23].

Weather Dependency: Cloud cover and lighting conditions can affect data quality, requiring frequent calibration and corrections [4].

Limited Penetration: Unlike radar or LiDAR, multispectral imaging cannot penetrate dense canopies or soil, restricting its applicability in certain conditions.

C. Imaging Platforms

Satellite-based imaging systems, such as Sentinel-2, Landsat, and MODIS, are widely used for large-scale agricultural monitoring. These platforms provide regular and consistent data acquisition over vast areas, making them ideal for monitoring crop growth and environmental conditions at regional or global scales [7]. Sentinel-2, for example, offers multispectral data with a spatial resolution of up to 10 meters and a revisit time of 5 days, enabling detailed monitoring of crop phenology and health [19]. Hyperspectral satellites, such as Hyperion and PRISMA, provide higher spectral resolution but are often limited by lower spatial resolution and longer revisit times [6].

Drone-Based Imaging. The integration of unmanned aerial vehicles (UAVs) with multispectral imaging systems has emerged as a transformative development in precision agriculture (Fig. 3), offering unprecedented capabilities for high-resolution temporal and spatial data acquisition [7]. Research conducted by [24] demonstrates that UAV-based multispectral imaging systems can achieve spatial resolutions of up to 2.5 cm/pixel when operating at optimal altitudes, significantly surpassing traditional satellite-based remote sensing solutions, while maintaining the capability to cover substantial agricultural areas of up to 100 hectares per flight session.

Contemporary research has established several methodological frameworks for implementing UAV-based multispectral imaging systems in agricultural contexts. According to comprehensive studies the optimization of flight parameters, including altitude, speed, and overlap percentage, plays a crucial role in data quality and processing efficiency. The research demonstrates that maintaining a consistent flight altitude between 80–120 m, coupled with an image overlap of 75% front and 65% side, produces optimal results for most agricultural applications, while facilitating efficient post-processing workflows.

Fig. 3. UAV used for fields scanning

Recent developments in flight planning methodologies, as documented [18] have led to the emergence of adaptive multi-altitude protocols that significantly enhance data quality while optimizing resource utilization. Their research indicates that implementing a dual-altitude approach, combining high-altitude overview flights (120 m) with targeted low-altitude (40 m) data collection over regions of interest, can reduce total flight time by up to 35% while maintaining or improving data quality compared to traditional single-altitude methodologies. Headwall Nano-Hyperspec – a compact drone-mounted hyperspectral camera operating in the 400–1000 nm range, ideal for precise vegetation analysis.

The selection of appropriate multispectral imaging systems represents a critical decision point in UAV-based agricultural monitoring programs. Extensive research [25] evaluating various commercial multispectral cameras has identified several key performance metrics that significantly impact data quality and reliability.

The MicaSense RedEdge-MX [37] series has demonstrated superior performance in capturing narrow-band spectral signatures (Fig. 4), particularly in the red-edge region (approximately 717 nm), which has proven crucial for early stress detection in various crop species. Their research indicates that the combination of 1.6 MP global shutter sensors with precisely defined spectral bands results in more reliable normalized difference vegetation index (NDVI) calculations compared to systems utilizing rolling shutters or broader spectral ranges.

The integration of UAV-based multispectral imaging systems in agriculture represents a rapidly evolving field with significant potential for further development. Recent research [19] suggests that emerging technologies, including advanced machine learning algorithms and improved sensor technologies, will continue to enhance the capabilities of these systems. Successful implementation requires careful consideration of both technical capabilities and operational constraints, with particular attention to data quality assurance and resource optimization protocols.

Fig. 4. MicaSense RedEdge-MX

IV. COMPARATIVE ANALYSIS OF IMAGING SYSTEMS

A. Satellite-Based Imaging

Satellite-based imaging systems are indispensable for large-scale agricultural monitoring due to their ability to provide consistent and comprehensive coverage over vast areas. Recent advancements in satellite technology have significantly improved their capabilities for precision agriculture.

Advantages

● *Large-Scale Coverage*: Satellites like Sentinel-2, Landsat 9, and PlanetScope can capture data over entire regions or countries in a single pass, making them ideal for monitoring large agricultural areas [7], [20], [21].

● *Regular and Consistent Data Acquisition*: Many modern satellites, such as Sentinel-2, offer frequent revisit times (e.g., 5 days), enabling consistent monitoring of crop growth and environmental conditions [19].

● *Cost-Effectiveness*: Satellite data is often freely available or relatively inexpensive, making it a cost-effective solution for long-term monitoring [6].

Challenges:

● Lower Spatial Resolution: Compared to drone-based systems, satellites generally offer lower spatial resolution (e.g., 10–30 m), which may limit their ability to detect small-scale variations in crop conditions [5].

● *Weather Dependency*: Cloud cover and atmospheric interference can significantly reduce the quality and availability of satellite imagery, particularly in regions with frequent cloud cover [6].

● *Limited Revisit Frequency*: While some satellites, like Sentinel-2, offer frequent revisits, others, such as Landsat 9, have longer revisit times (16 days), which may not be sufficient for monitoring rapidly changing crop conditions [20].

Examples of Current Satellites:

Sentinel-2: Part of the European Space Agency's Copernicus program, Sentinel-2 provides multispectral data with up to 10-meter spatial resolution and a 5-day revisit time, making it a popular choice for agricultural monitoring [19].

Landsat 9: The latest in the Landsat series, Landsat 9 offers multispectral data with 30-meter resolution and a 16-day revisit time, widely used for long-term agricultural studies [20].

PlanetScope: Operated by Planet Labs, PlanetScope satellites provide daily global coverage with 3–5 meter resolution, enabling high-frequency monitoring of agricultural fields [21].

The databases and tools that can be used to explore data and provides an ability to work with visualisations and measurements:

Google Earth Engine: A cloud-based platform for analyzing satellite imagery, including data from Sentinel-2, Landsat, and MODIS [32].

EO Browser: A web-based tool for visualizing and analyzing satellite data from Sentinel-2, Landsat, and other missions [31],[33].

NASA's Harmonized Landsat and Sentinel-2 (HLS) Dataset: A harmonized dataset combining Landsat 8/9 and Sentinel-2 data for improved temporal and spatial coverage [30], [34]

B. Drone-based Imaging

Unmanned aerial vehicles, or drones, have emerged as a powerful tool for precision agriculture, offering high-resolution data and flexibility in data acquisition.

Advantages:

● *High Spatial Resolution*: Drones can capture imagery with centimeter-level resolution, enabling the detection of small-scale variations in crop health, such as early signs of disease or nutrient deficiencies [8].

● *Flexibility in Data Acquisition*: Drones can be deployed on demand and programmed to fly at specific altitudes and times, allowing for targeted data collection [15].

● *Ability to Capture Data Under Cloud Cover:* Unlike satellites, drones can operate below cloud cover, ensuring consistent data acquisition even in adverse weather conditions [6].

Challenges:

● *Limited Coverage Area:* Drones are typically limited to small areas (e.g., individual fields), making them less suitable for large-scale agricultural monitoring [5].

● *Higher Operational Costs*: The cost of drones, sensors, and operational logistics can be prohibitive, particularly for frequent or large-scale deployments [8].

● *Regulatory Restrictions:* Drone operations are subject to strict regulations, including flight altitude limits, no-fly zones, and licensing requirements, which can complicate their use in certain regions [15].

Examples of Current Drone Systems:

DJI Phantom 4 Multispectral: A popular drone equipped with a multispectral camera, widely used for precision agriculture applications [35].

Parrot Sequoia: A lightweight multispectral sensor designed for drones, capable of capturing high-resolution imagery for crop monitoring [36].

MicaSense Altum: A multispectral camera with thermal imaging capabilities, used for advanced crop analysis [25], [40].

The databases and tools that can be used to explore data and provides an ability to work with visualisations and measurements:

Pix4D: A software platform for processing drone imagery and generating orthomosaics, 3D models, and vegetation indices [38].

DroneDeploy: A cloud-based platform for drone data processing and analysis, offering tools for agricultural mapping and monitoring [39].

In this work, we justify the use of drones for monitoring medium-sized agricultural plots due to their high spatial resolution, which allows for more detailed insights into crop health, such as detecting early signs of disease or nutrient deficiencies. In comparison to satellite systems, which excel in covering large areas, drones offer significantly better image accuracy at the centimeter level, which is crucial for making precise agronomic decisions. While drones have limitations in coverage area and higher operational costs, their ability to operate under cloud cover and the precision of the data make them ideal for addressing fundamental issues in modern agriculture, where detailed data is needed even for medium-sized plots.

V. AI ALGORITHMS, NEURAL NETWORKS, AND DATA PROCESSING

The application of Convolutional Neural Networks (CNNs) in agricultural remote sensing requires a well-defined problem statement to guide the research and ensure practical impact. The primary objective of this study is to leverage CNNs for analyzing remote sensing imagery in agriculture. This encompasses three key tasks: feature extraction, classification, and segmentation. Each of these tasks plays a crucial role in enhancing precision agriculture by providing detailed insights into plant health, growth patterns, and environmental stress factors.

Feature extraction involves identifying and isolating essential attributes from remote sensing images that contribute to accurate classification and segmentation. In agricultural applications, relevant features include:

1) *Spectral signatures*: Different wavelengths reflect differently from healthy and unhealthy plants, making multispectral and thermal imaging essential for analysis [21].

2) *Texture patterns*: Surface irregularities and variations in texture may indicate diseases, pest infestations, or nutrient deficiencies.

3) *Morphological characteristics*: Plant shape, leaf size, and growth patterns provide key indicators of plant health and developmental stages.

By automating feature extraction using CNNs, we eliminate the need for manual feature engineering, allowing the network to identify and learn patterns from raw data effectively. This significantly enhances the accuracy and efficiency of plant health assessment and stress detection.

Classification is a fundamental task in remote sensing analysis, where CNNs assign labels to images or specific regions based on extracted features. The following classification tasks are crucial in precision agriculture:

1) *Plant disease identification:* CNNs can be trained to distinguish between healthy plants and those affected by diseases such as blight, rust, or fungal infections [26].

2) *Crop and weed differentiation:* The ability to distinguish between crops and weeds supports automated weed management, reducing the reliance on herbicides and improving yield [28].

3) *Growth stage classification:* Identifying plant growth stages ensures optimal application of fertilizers, pesticides, and irrigation, enhancing overall crop management [27].

Effective classification enables farmers and agronomists to make data-driven decisions, improving agricultural productivity and sustainability.

Segmentation is the process of dividing an image into meaningful regions to analyze specific components, such as plant parts or affected areas. In agricultural applications, segmentation serves the following purposes:

1) *Plant part identification*: Segmenting images into leaves, stems, and roots allows for targeted analysis of specific plant structures.

2) *Pest and disease localization*: Highlighting affected areas within an image aids in early disease detection and intervention [29].

3) *Soil and vegetation separation*: Differentiating between soil and crops is essential for precision irrigation and soil health monitoring.

Semantic segmentation, where each pixel is assigned to a category, is particularly useful for delineating plant boundaries and detecting stressed regions. This facilitates precise treatment applications and improves resource allocation in farming.

Convolutional neural networks (CNNs) are particularly well-suited for analyzing agricultural remote sensing imagery due to their ability to automatically learn and extract hierarchical features from complex image data. The key reasons for selecting CNNs in this study include.

1) *Automatic Feature Learning:* unlike traditional machine learning methods, CNNs do not require manual feature engineering. Instead, they learn relevant spatial and spectral features directly from the raw image data, making them highly adaptable to various agricultural scenarios.

2) *Robustness to Variability:* agricultural images often contain variability due to changes in lighting conditions, plant growth stages, and environmental factors. CNNs are capable of handling such variability by learning invariant features through multiple convolutional layers [27].

3) *Efficient Spatial Feature Extraction:* the convolutional layers in CNNs efficiently capture spatial dependencies, making them ideal for detecting plant structures, segmenting fields, and identifying diseases based on leaf textures and color variations [26].

4) *Scalability for Large Datasets:* given the high volume of remote sensing data in agriculture, CNNs can process large datasets efficiently using parallel computing on GPUs, making them scalable for real-world applications.

5) *High Accuracy in Image Classification and Segmentation:* CNNs have demonstrated superior performance compared to traditional machine learning models such as Support Vector Machines (SVMs) and Random Forests in tasks like plant disease detection, weed classification, and yield estimation [28].

6) Integration with Multispectral and Hyperspectral Data: CNNs can process multispectral and hyperspectral images, allowing for the extraction of spectral signatures critical for plant health assessment, nutrient analysis, and precision farming applications.

The integration of CNN-based feature extraction, classification, and segmentation provides a comprehensive solution for agricultural remote sensing. By automating these processes, we can improve early detection of diseases and nutrient deficiencies. Enhance precision farming by optimizing the use of resources such as water, fertilizers, and pesticides. Reduce manual effort and dependency on expert knowledge for plant health assessment. Increase overall agricultural efficiency and sustainability.

VI. CONCLUSIONS

The integration of multispectral and thermal imaging with advanced AI algorithms has the potential to revolutionize agricultural monitoring and yield prediction. This paper provides a comprehensive comparative analysis of satellite-based and drone-based imaging systems, emphasizing their advantages and challenges for agricultural applications. While satellite-based imaging offers large-scale coverage and cost-effectiveness, its lower spatial resolution and weather dependency limit its effectiveness for precision tasks. Drone-based systems, on the other hand, stand out as the preferred option for small- to medium-scale, high-precision agricultural applications due to their superior spatial resolution, flexibility, and ability to capture detailed imagery even under challenging weather conditions. Their capacity to cover targeted areas with high accuracy makes them a better fit for addressing the specific needs of modern agriculture, where detailed monitoring of crop health and early detection of issues are essential for maximizing yield and minimizing resource use.

The application of convolutional neural networks (CNNs) to multispectral and thermal data has shown remarkable promise in overcoming the challenges of crop monitoring and yield prediction. CNNs excel at extracting spatial and spectral features from complex imagery, enabling accurate tasks such as crop classification, disease detection, and stress assessment. By incorporating critical plant criteria—such as spectral indices (e.g., NDVI, EVI), thermal indices (e.g., CWSI), and biophysical parameters (e.g., LAI, chlorophyll content)—into neural network training, we can develop robust models capable of providing precise predictions of crop yields and early detection of problems.

In conclusion, drone-based imaging systems, when combined with multispectral and thermal imaging and AI-driven approaches, provide a powerful framework for advancing precision agriculture. By addressing the limitations of satellite-based systems and leveraging the strengths of CNNs, drones unlock new possibilities for sustainable and efficient agricultural practices. This research not only contributes to the scientific understanding of remote sensing and AI in agriculture but also offers practical solutions for farmers, policymakers, and researchers working to ensure global food security.

REFERENCES

[1] A. F. H. Goetz, G. Vane, J. E. Solomon, & B. N. Rock, "Imaging spectrometry for Earth remote sensing," *Science*, 228(4704), 1147–1153, 1985. https://doi.org/10.1126/science.228.4704.1147

[2] R. D. Jackson, S. B. Idso, R. J. Reginato, & P. J. Pinter, "Canopy temperature as a crop water stress indicator," *Water Resources Research*, 17(4), 1133–1138, 1981. https://doi.org/10.1029/WR017i004p01133

[3] D. B. Lobell, D. Thau, C. Seifert, E. Engle, & B. Little, "A scalable satellite-based crop yield mapper," *Remote Sensing of Environment*, 164, 324–333, 2015. https://doi.org/10.1016/j.rse.2015.02.016

[4] D. J. Mulla, "Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps," *Biosystems Engineering*, 114(4), 358–371, 2013. https://doi.org/10.1016/j.biosystemseng.2012.08.009

[5] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, & B. A. Johnson, "Deep learning in remote sensing applications: A meta-analysis and review," *ISPRS Journal of Photogrammetry and Remote Sensing*, 152, 166–177, 2019. https://doi.org/10.1016/j.isprsjprs.2019.04.015

[6] M. Drusch, U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, ... & P. Bargellini, "Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services," *Remote Sensing of Environment*, 120, 25–36, 2012. https://doi.org/10.1016/j.rse.2011.11.026

[7] C. Zhang, & J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: a review," *Precision Agriculture*, 13(6), 693–712, 2012. https://doi.org/10.1007/s11119-012-9274-5

[8] A. Matese, P. Toscano, S. F. Di Gennaro, L. Genesio, F. P. Vaccari, J. Primicerio, ... & M. Mancini, "Intercomparison of UAV, aircraft, and satellite remote sensing platforms for precision viticulture," *Remote Sensing*, 7(3), 2971–2990, 2015. https://doi.org/10.3390/rs70302971

[9] J. Boulent, P. Foucher, J. Théau, & S. St-Charles, “Convolutional neural networks for the automatic identification of plant diseases. Computers and Electronics in Agriculture,” 2019. https://doi.org/10.3389/fpls.2019.00941

[10] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, & R. Moore, “Google Earth Engine: Planetary-scale geospatial analysis for everyone” *Remote Sensing of Environment*, 202, 18–27, 2017. https://doi.org/10.1016/j.rse.2017.06.031

[11] J. G. P. W. Clevers, & L. Kooistra, “Using hyperspectral remote sensing data for retrieving canopy chlorophyll and nitrogen content,” *IEEE Transactions on Geoscience and Remote Sensing*, 2012. https://doi.org/10.1109/JSTARS.2011.2176468

[12] J. A. Foley, N. Ramankutty, K. A. Brauman, E. S. Cassidy, J. S. Gerber, M. Johnston,, … & D. P. Zaks, Moscow, *Solutions for a cultivated planet. Nature*, 478, 2011, pp. 337–342. https://doi.org/10.1038/nature10452

[13] D. B. Lobell, W. Schlenker, & J. Costa-Roberts, Climate trends and global crop production since *Science*, 333(6042), 616–620, 1980. https://doi.org/10.1126/science.1204531

[14] D. B. Lobell, M. B. Burke, C. Tebaldi, , M. D. Mastrandrea, W. P. Falcon, & R. L. Naylor, “Prioritizing climate change adaptation needs for food security in 2030,” *Science*, 319(5863), 607–610, 2007. https://doi.org/10.1126/science.1152339

[15] A. K. Mahlein,, T. Rumpf, P. Welke, H. W. Dehne, L. Plümer, U. Steiner,, & E. C. Oerke, “Development of spectral indices for detecting and identifying plant diseases, *Remote Sensing of Environment*, 128, 21–30, 2012. https://doi.org/10.1016/j.rse.2012.09.019

[16] J. Pretty, “Agricultural sustainability: Concepts, principles, and evidence, *Philosophical Transactions of the Royal Society B: Biological Sciences*, 363(1491), 447–465, 2008. https://doi.org/10.1098/rstb.2007.2163

[17] P. S. Thenkabail, J. G. Lyon, & A. Huete, “Biophysical and Biochemical Characterization and Plant Species Studies,” 2018. https://doi.org/10.1201/9780429431180

[18] Y. Wang,, H. Zhang,, & X. Li, “Urban Tree Canopy Mapping Based on Double-Branch Convolutional Neural Network and Multi-Temporal High Spatial Resolution Satellite Imagery,” 2023. https://doi.org/10.3390/rs15030765

[19] H. Petersson, D. Gustavsson, and D. Bergstrom, “Deep learning approaches for hyperspectral image analysis: A review. Remote Sensing,” 2016 Sixth International Conference on Image Processing Theory, Tools and Applications (IPTA), 2016. https://doi.org/10.1109/IPTA.2016.7820963

[20] J. Xue, & B. Su, “Significant remote sensing vegetation indices: A review of developments and applications,” Sensors, 2017. https://doi.org/10.1155/2017/1353691

[21] Lin Ke, Gong Liang, Huang Yixiang, Liu Chengliang, and Pan Junsong, “Deep learning-based segmentation and quantification of cucumber powdery mildew using convolutional neural networks, *Computers and Electronics in Agriculture*, vol. 10, 2019. https://doi.org/10.3389/fpls.2019.00155

[22] R. Gebbers and V. Adamchuck, “Precision Agriculture and Food Security,” vol. 327, no. 5967, 828–831, 2010, https://doi.org/10.1126/science.1183899

[23] C. Toth, and G. Jóźków, “Remote sensing platforms and sensors: A survey,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 115, pp. 22–36, May 2016, https://doi.org/10.1016/j.isprsjprs.2015.10.004

[24] R. Martínez-Peña, S. Vélez, R. Vacas, H. Martín, and S. Álvarez, “Remote Sensing for Sustainable Pistachio Cultivation and Improved Quality Traits Evaluation through Thermal and Non-Thermal UAV Vegetation Indices,” *Appl. Sci.*, 13(13), 7716, 2023, https://doi.org/10.3390/app13137716

[25] Anne M. Thompson, Herman G. J. Smit, Debra E. Kollonige, Ryan M. Stauffer, *Field Measurements for Passive Environmental Remote Sensing*, Instrumentation, Intensive Campaigns, and Satellite Applications 2023, pp. 57–78. https://doi.org/10.1016/B978-0-12-823953-7.00011-3

[26] S. P. Mohanty, D. P. Hughes, & M. Salathé, “Using deep learning for image-based plant disease detection,” *Frontiers in Plant Science*, 7, 1419. 2016. https://doi.org/10.3389/fpls.2016.01419

[27] A. Kamilaris, &, F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, April 2018. https://doi.org/10.1016/j.compag.2018.02.016

[28] M. Dyrmann, H. Karstoft, & H. S. Midtiby, “Plant species classification using deep convolutional neural networks,” *Biosystems Engineering*, 151, pp. 72–81, 2016. https://doi.org/10.1016/j.biosystemseng.2016.08.024

[29] J. G. A. Barbedo, “Plant disease identification from individual lesions and spots using deep learning,” *Biosystems Engineering*, vol. 180, pp. 96–107, ref. 22. 2019, https://doi.org/10.1016/j.biosystemseng.2019.02.002

[30] NASA. Harmonized Landsat and Sentinel-2 (HLS) Dataset. https://hls.gsfc.nasa.gov/ . 2021.

[31] ESA. Sentinel-2 User Handbook. European Space Agency. 2021.

[32] USGS. Landsat 9 Mission Overview. United States Geological Survey. 2021.

[33] Planet. PlanetScope Imagery. 2023. https://www.planet.com/products/satellite-monitoring/

[34] Sinergise. EO Browser. 2023. https://apps.sentinel-hub.com/eo-browser/

[35] DJI. Phantom 4 Multispectral. 2021. https://www.dji.com/global/support/product/p4-multispectral

[36] Parrot. Sequoia Multispectral Sensor. 2021. https://www.parrot.com/global/drones/parrot-sequoia

[37] MicaSense. Altum Multispectral Camera. 2021. https://www.micasense.com/altum

[38] Pix4D. Drone mapping software. 2023. https://www.pix4d.com/

[39] DroneDeploy. Cloud-based drone software. 2023. https://www.dronedeploy.com/

[40] ASD. FieldSpec Handheld 2 Spectroradiometer. 2021. https://www.malvernpanalytical.com/en/products/product-range/asd-range/fieldspec-range/fieldspec-handheld-2

Received December 25, 2024

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В. М. Синєглазов, Р. С. Конюшенко, С. О. Долгоруков. Проблеми багатоспектральної обробки зображень у сільському господарстві

Це дослідження надає комплексний порівняльний аналіз супутникових та дронових платформ для агромоніторингу, з особливим акцентом на можливості мультиспектральної зйомки. Наш аналіз показує, що супутникові системи забезпечують широке покриття та є економічно вигідними для моніторингу великих територій, тоді як дрони пропонують вищу просторову роздільну здатність (до 2,5 см/піксель) і більшу гнучкість у збиранні цільових даних, що робить їх ідеальними для середніх за розміром сільськогосподарських угідь. Дослідження розглядає ключові технології та платформи дистанційного зондування, зокрема супутникову систему Sentinel-2 та сенсори, встановлені на дронах, такі як MicaSense RedEdge-MX, оцінюючи їх ефективність у критично важливих сільськогосподарських застосуваннях. У статті також досліджується застосування згорткових нейронних мереж для обробки мультиспектральних даних, демонструючи їх виняткову здатність до вирішення важливих аграрних завдань, зокрема класифікації культур, виявлення хвороб та оцінки стресу рослин. Включаючи до навчання нейромереж спектральні індекси теплові індекси та біофізичні параметри (LAI, вміст хлорофілу), розробляємо надійну систему для агромоніторингу та прогнозування врожайності. Це дослідження робить внесок як у теоретичне розуміння дистанційного зондування в сільському господарстві, так і в розробку практичних рекомендацій для впровадження рішень точного землеробства, що сприяють підвищенню продуктивності та сталому розвитку сучасних агросистем.

Ключові слова: гіперспектральна зйомка; точне землеробство; прогнозування врожайності; супутниковий моніторинг; моніторинг за допомогою дронів; спектральні індекси; згорткові нейронні мережі.

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