Forging the Future: Pioneering Approaches in Business, Management and Economics Engineering to Overcome Emerging Global Challenges - 2024

https://doi.org/10.24867/FUTURE-BME-2024-077 Review paper

THE FUTURE OF AGRICULTURAL SPRAYING: AI AND UAVS FOR SMART AND SUSTAINABLE PRACTICES

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Abstract

Unmanned Aerial Vehicles (UAVs), commonly known as drones, paired with advanced artificial intelligence (AI) systems, are poised to transform agricultural spraying practices. Traditional spraying methods often face challenges in efficiency, precision, and environmental impact. UAVs equipped with AI-powered vision systems offer the potential to revolutionize crop protection by enabling targeted pesticide and fertilizer application, optimized flight paths, and real-time condition monitoring. AI algorithms analyze image and sensor data to detect pests, diseases, and nutrient deficiencies with remarkable accuracy. This precision targeting allows for a significant reduction in chemical usage, minimizing environmental impact and costs. Moreover, AI-controlled drones can operate autonomously, covering vast fields quickly and safely, even in challenging terrain. This study explores the cutting-edge advancements in UAV technology and AI for agricultural spraying. It highlights their potential to increase agricultural yields, improve resource management, and promote sustainable farming practices. Further research on regulatory frameworks, cost-effectiveness, and data privacy will be crucial in realizing the full potential of this transformative technology.

Key words: *UAVs, drones, precision agriculture, artificial intelligence, crop spraying, sustainability*

1. Introduction

The agricultural sector has witnessed significant transformations over the years, from the mechanized agriculture revolution in the early 20th century to the

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Green Revolution in the 1960s, which led to a substantial increase in food production. The latest revolution in agriculture is precision agriculture, which leverages advanced technologies such as GPS, satellite imaging, and data analytics to optimize crop yields and reduce environmental impact. Precision agriculture is crucial in addressing the growing global demand for food, as it enables farmers to manage their fields more efficiently and effectively, thereby increasing productivity while minimizing waste and environmental degradation. The need for precision agriculture is particularly pressing in the face of climate change, population growth, and the need for sustainable agricultural practices. As noted by Abobatta (2021), precision agriculture is essential for sustainable development and reducing poverty, especially in developing countries. The integration of precision agriculture tools and technologies is vital for ensuring a food-secure future and meeting the challenges posed by the increasing global demand for food (Mogili & Deepak, 2018).

Unmanned Aerial Vehicles (UAVs, drones) have emerged as a promising technology for various applications, including precision agriculture (Mogili & Deepak, 2018). Remote sensing is a powerful tool for monitoring crop health and detecting potential problems, such as pests, diseases, and nutrient deficiencies (Liaghat & Balasundram, 2010). UAVs equipped with AI-powered vision systems offer a solution to these challenges by enabling targeted pesticide and fertilizer application, optimized flight paths, and real-time condition monitoring (Kamilaris et al., 2017). AI algorithms can analyze image and sensor data to detect pests, diseases, and nutrient deficiencies with remarkable accuracy, allowing for precision targeting and a significant reduction in chemical usage (Kerkech et al., 2020). This precision targeting not only minimizes environmental impact but also reduces costs associated with excessive chemical application (Kouadio et al., 2023).

The integration of UAVs with advanced artificial intelligence (AI) systems has the potential to revolutionize agricultural spraying practices, addressing the challenges faced by traditional methods (Kouadio et al., 2023). Traditional spraying techniques often struggle with efficiency, precision, and environmental impact, leading to the overuse of pesticides and fertilizers (Giles, 2016). Moreover, AI-controlled drones can operate autonomously, covering vast fields quickly and safely, even in challenging terrain (Mogili & Deepak, 2018). This capability is particularly advantageous in areas with limited accessibility or where manual spraying is impractical (Kamilaris et al., 2017). Drones can also be used for aerial photography, providing detailed maps of fields and enabling farmers to assess crop conditions and identify problem areas (Giles, 2016).

As the agricultural landscape continues to evolve, producers are looking for new and exciting ways to increase their yields while also conserving resources and limiting their environmental impact. Drones and AI offer a promising solution, with the potential to transform every aspect of crop production from planting to harvest. By leveraging these cutting-edge technologies, farmers can optimize their operations, reduce costs, and promote sustainable farming practices (Kouadio et al., 2023).

This research contributes to the advancement of using drones and AI in agriculture in several key ways: crop protection, specialized payloads, optimizing operations, increasing yields, transforming crop production. In summary, this research highlights the transformative potential of drones and AI in revolutionizing modern agriculture, from enhancing crop protection to optimizing operations and promoting sustainability. These studies demonstrate the potential of computer vision in detecting weeds, pests, and diseases in crops. By using machine learning algorithms to analyze images, farmers can quickly and accurately identify potential issues and take action to prevent them from spreading.

2. Remote sensing

2.1 Soil Mapping

Remote sensing techniques can be used to map soil properties, such as texture, organic matter content, and nutrient levels, which are crucial for site-specific management (Surendran et al., 2024). Satellite-based remote sensing, such as Landsat and MODIS, can provide large-scale soil maps at relatively low cost (Shikha et al., 2007). Aerial-based remote sensing, using sensors mounted on aircraft or UAVs, can provide higher-resolution soil maps with more detailed information on spatial variability within fields (Stöcker et al., 2017).

2.2 Crop Monitoring

Remote sensing is a powerful tool for monitoring crop health and detecting potential problems, such as pests, diseases, and nutrient deficiencies (Liaghat & Balasundram, 2010). Multispectral and hyperspectral sensors can capture data across a wide range of wavelengths, allowing for the detection of subtle changes in plant reflectance that may indicate stress or disease (Adam et al., 2010). Thermal sensors can also be used to detect water stress in crops, enabling more efficient irrigation management (Schellberg et al., 2008).

2.4 Detecting weeds, pests and diseases

Computer vision has been increasingly used in agriculture to detect weeds, pests, and diseases. This technology uses machine learning algorithms to analyze images of crops and identify potential issues. Here are some recent studies on the use of computer vision in detecting weeds, pests, and diseases. Multispectral imaging has emerged as a powerful tool for detecting and monitoring weeds, pests, and diseases in precision agriculture. By providing valuable data on the spatial distribution of these threats, multispectral cameras can guide targeted interventions and optimize the use of herbicides and pesticides. Multispectral cameras can be used to detect, and map weed infestations in crop fields by exploiting differences in spectral reflectance between weeds and crops (Goel et al., 2003). Weeds often have distinct leaf pigments, canopy structure, and growth habits that result in unique spectral signatures that can be detected by multispectral sensors (Peña et al., 2013). By analysing multispectral data, algorithms can be developed to automatically identify, and map weed patches, enabling targeted application of herbicides and reducing the need for blanket spraying (Slaughter et al., 2008). Weed Detection: Computer vision can be used to detect weeds in crops by analyzing images of the field. This can be done using traditional image processing techniques or deep learning algorithms. For example, a study published in 2023 used a convolutional neural network (CNN) to detect weeds in corn fields with an accuracy of 95% (Chithambarathanu, 2023).

The latest advancements in multispectral camera technology for disease detection in precision agriculture are based on improved spectral resolution. Newer multispectral cameras are able to capture data in more spectral bands, providing more detailed information on plant reflectance and allowing for better discrimination between healthy and diseased plants (Mahlein et al., 2012). Higher resolution multispectral sensors, including those mounted on UAVs, can provide detailed maps of crop health at the individual plant level, enabling early detection of disease outbreaks (Peña et al., 2013). Combining multispectral data with thermal imaging allows for the detection of changes in leaf temperature associated with certain diseases, further improving diagnostic accuracy (Calderón et al., 2013).

Several machine learning algorithms can be trained on multispectral data to automatically identify disease symptoms in crops. **Convolutional Neural Networks** (CNNs): CNNs are a type of deep learning algorithm that can effectively process and classify multispectral images. A study used a CNN to detect weeds in corn fields from multispectral images with 95% accuracy. **You Only Look Once (YOLO)**: YOLO is a real-time object detection system that can be trained on multispectral datasets. Researchers trained YOLO v3 from scratch to detect objects in multispectral images, achieving an overall mean average precision (mAP) of 46.4%. **Support Vector Machines (SVMs**): SVMs are a traditional machine learning algorithm that can be used for multispectral image classification. SVMs are good at handling two-class problems and are easy to implement. **Linear Discriminant Analysis (LDA)**: LDA is a supervised dimensionality reduction technique that can be used for multispectral image classification. LDA is easy to implement but may lead to overfitting. **Random Forest**: Random Forest is an ensemble learning method that can be used for multispectral image classification. It is robust to overfitting and can handle high-dimensional data (Zeng et al., 2021).

These algorithms can be trained on multispectral datasets containing images of healthy and diseased crops. The models can then be used to automatically identify disease symptoms in new multispectral images, helping farmers detect and manage crop diseases more efficiently. Also, Hyperspectral cameras that capture data in hundreds of narrow spectral bands are becoming more affordable and accessible, providing even more detailed information on plant health and disease status (Mahlein et al., 2012). Low-cost multispectral sensors are being developed for use with smartphones and handheld devices, allowing farmers to quickly assess crop health in the field (Delalieux et al., 2007). Integrating multispectral data with other sources of information, such as weather data and historical disease records, can improve disease forecasting models and guide more targeted interventions (Sankaran et al., 2010). These advancements in multispectral camera technology, combined with improved data analysis capabilities, are making it easier and more cost-effective for farmers to detect and manage crop weeds, pests and diseases, reducing the need for broad-spectrum pesticide applications and promoting more sustainable agriculture.

3. UAV spraying

The effectiveness of UAV spraying is influenced by various factors, including droplet size, flight altitude, flight speed, and environmental conditions (Liu et al., 2022; Wang et al., 2018; Qin et al., 2018). Spray quality, characterized by droplet coverage and drift potential, is a critical aspect that requires attention to balance between coverage and drift risk (Dengeru et al., 2022). The size of droplets generated by UAVs and ground-based machinery plays a crucial role in spray quality, with smaller droplets having a higher risk of drift but better coverage (Yallappa et al., 2017; Ling et al., 2018).

In challenging environments such as orchards and tall trees, the application of UAV spraying becomes essential for achieving higher spray penetration and effectiveness (He, 2018). The optimization of UAV spraying techniques is vital for ensuring precise and effective pesticide application in modern commercial crop protection systems. Understanding the impact of downwash airflow on spray distribution and deposition is crucial for improving the uniformity and efficiency of multi-rotor UAV spraying (Boukhalfa et al., 2014).

The integration of remote sensing data with variable-rate application systems in precision agriculture requires careful coordination and data management (Schellberg et al., 2008). Satellite-based remote sensing may face limitations such as spatial resolution constraints and cloud cover issues, while aerial-based remote sensing can be impacted by weather conditions and flight schedules (Ehsani & Maja, 2013). Additionally, the use of UAVs for remote sensing in agriculture may be subject to regulatory and legal considerations, including airspace restrictions and privacy concerns (Stöcker et al., 2017).

Variable-rate application systems, which adjust input levels based on spatial and temporal variability within fields, can be guided by remote sensing data to ensure that inputs are applied where and when they are most needed (Schellberg et al., 2008). This approach can lead to significant savings in input costs and reduced environmental impact.

In conclusion, the evaluation of UAV spraying in precision agriculture underscores the need for continuous research and development to enhance the effectiveness, efficiency, and environmental sustainability of this technology. By addressing key factors influencing spray quality and deployment challenges, UAV spraying can significantly contribute to modern agricultural practices.

4. Benefits of Remote Sensing in Precision Agriculture

Remote sensing has been increasingly integrated into precision agriculture to enhance crop management and minimize environmental impacts. The benefits of remote sensing in precision agriculture include real-time crop monitoring, which provides data on crop health, soil conditions, water status, and yield, enabling farmers to make informed decisions about variable rate applications within fields (PointOneNav, 2024). This leads to improved crop yield by identifying areas of stress or growth, allowing farmers to optimize inputs like seeds, fertilizer, and water, resulting in higher yields and better-quality produce (Sangeetha et al., 2024). Additionally, precision agriculture reduces the need for pesticides and excessive fertilizer use, thereby preserving soil quality and promoting a healthier ecosystem (Sangeetha et al., 2024). Remote sensing also helps farmers optimize resource use by applying site-specific management practices, minimizing waste, and maximizing efficiency (Surendran et al., 2024). Furthermore, the integration of remote sensing data with other technologies like GPS, GIS, and machine learning enables farmers to make more informed decisions about crop management, reducing the farm's dependence on weather conditions (Ohio State University, 2017).

Remote sensing technology can automate many tasks, such as crop monitoring and data analysis, freeing up farmers to focus on more strategic and high-value activities (Ehsani & Maja, 2013). By optimizing crop management practices and reducing waste, remote sensing in precision agriculture can contribute to a more sustainable and environmentally friendly agricultural system (Khanal et al., 2020). Remote sensing data can help farmers identify areas of stress and optimize resource allocation, leading to reduced water and fertilizer usage (Schellberg et al., 2008). By identifying and addressing potential issues early on, remote sensing in precision agriculture can help farmers achieve higher crop yields and improve overall agricultural productivity (Sishodia et al., 2020). This technology can reduce the need for manual data collection and analysis, saving farmers time and resources (Giles, 2016). Remote sensing data can be used to create detailed maps of crop and soil variability, enabling farmers to implement site-specific management practices and optimize agronomic inputs (Liaghat & Balasundram, 2010). It can detect early signs of disease and pest infestations, enabling farmers to take targeted actions and reduce the need for chemical pesticides and fungicides (Ennouri et al., 2020).

Artificial intelligence (AI) is also being increasingly used in precision agriculture to analyze large amounts of data from remote sensing and other sources. AI algorithms can identify patterns and anomalies in the data, enabling farmers to predict and prevent crop diseases, pests, and other issues (Sangeetha et al., 2024). AI can also optimize crop yields by identifying the most effective irrigation and fertilization strategies, reducing waste and environmental impact (Surendran et al., 2024). Moreover, AI-powered decision support systems can provide farmers with personalized recommendations for crop management, taking into account factors like weather, soil type, and crop variety (PointOneNav, 2024). These AI-powered systems can significantly improve the efficiency and effectiveness of precision agriculture, enabling farmers to make data-driven decisions and achieve better outcomes.

5. Challenges and Limitations

While remote sensing offers numerous benefits in precision agriculture, there are also challenges and limitations to its widespread adoption, including: high initial investment costs, specialized expertise, data integration, spatial and temporal resolution, regulatory and legal considerations. The acquisition of remote sensing equipment and the development of data processing and analysis capabilities can require significant initial investments (Ehsani & Maja, 2013). Effectively using remote sensing in precision agriculture requires specialized expertise in data acquisition, processing, and interpretation, which may not be readily available in all farming communities (Adam et al., 2010). Integrating remote sensing data with other precision agriculture technologies, such as variable-rate application systems, requires careful coordination and data management (Schellberg et al., 2008). Satellite-based remote sensing may be limited by spatial resolution, cloud cover, and revisit frequency, while aerial-based remote sensing can be affected by weather conditions and flight schedules (Ehsani & Maja, 2013). The use of UAVs for remote sensing in agriculture may be subject to regulatory and legal considerations, such as airspace restrictions and privacy concerns (Stöcker et al., 2017). These challenges highlight the need for careful consideration of the potential benefits and limitations of AI in drone technology for agriculture, as well as the importance of addressing these hurdles to ensure effective and sustainable adoption.

6. Conclusions

UAV spraying has emerged as a powerful tool in precision agriculture, enabling farmers to optimize crop yields, reduce input costs, and promote sustainable farming practices. By providing valuable data on soil properties, crop health, and input needs, remote sensing can guide targeted interventions and optimize resource use efficiency. The integration of remote sensing with other precision agriculture technologies, such as variable-rate application systems, can further enhance the effectiveness of these practices.

However, the widespread adoption of remote sensing in precision agriculture faces challenges, including high initial investment costs, the need for specialized expertise, and the integration of data from various sources. Addressing these challenges will require collaboration among farmers, researchers, and technology providers to develop more accessible and user-friendly remote sensing solutions.

As precision agriculture continues to evolve, UAV sprayers will play an increasingly important role in enhancing crop production, improving resource use efficiency, and promoting sustainable farming practices through the use of artificial intelligence (AI) in agriculture drones as it revolutionizes farming practices.

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