__Review Article__

Drones for Monitoring Soil Moisture and Optimizing Irrigation Scheduling in Horticultural Farms

Abstract

The efficient management of irrigation is crucial for the sustainability and productivity of horticultural farms. Traditional methods of monitoring soil moisture and scheduling irrigation can be labor-intensive and imprecise. The advent of unmanned aerial vehicles (UAVs), commonly known as drones, has opened up new possibilities for precision agriculture. Drones equipped with remote sensing technologies can provide high-resolution spatial and temporal data on soil moisture variability across a farm. This data can be used to optimize irrigation scheduling, leading to water savings, improved crop yields, and reduced environmental impact. This article reviews the current state of drone technology for soil moisture monitoring and irrigation management in horticulture. It discusses the principles of drone-based remote sensing, the types of sensors used, and the data processing and interpretation techniques involved. Case studies of successful applications of drones for irrigation optimization in various horticultural crops are presented. The article also addresses the challenges and limitations of drone-based irrigation management, including regulatory issues, data accuracy and resolution, and the need for specialized expertise. Future directions for research and development in this field are explored. With ongoing advancements in drone technology and data analytics, drones are poised to become an indispensable tool for precision irrigation management in horticulture.

Keywords: Drones, UAVs, Remote Sensing, Soil Moisture, Irrigation Scheduling, Precision Horticulture

1. Introduction

Horticulture is a vital sector of agriculture that involves the cultivation of fruits, vegetables, flowers, and ornamental plants. Irrigation is a critical aspect of horticultural production, as it directly influences crop growth, yield, and quality [1]. However, irrigation management in horticulture faces several challenges, including water scarcity, increasing costs, and environmental concerns [2]. Conventional irrigation scheduling methods, such as fixed-interval or soil-based approaches, often result in over- or under-irrigation, leading to water waste, nutrient leaching, and reduced crop productivity [3].

Table 1. Types of Drones Used for Soil Moisture Monitoring

Drone Type	**Advantages**	**Disadvantages**
Fixed-wing	Long flight time, large coverage	Limited payload capacity,

	area	requires runway
Multirotor	Vertical take-off and landing, hover capability	Short flight time, limited coverage area
Hybrid (VTOL)	Combines advantages of fixed-wing and multirotor	Complex design, higher cost

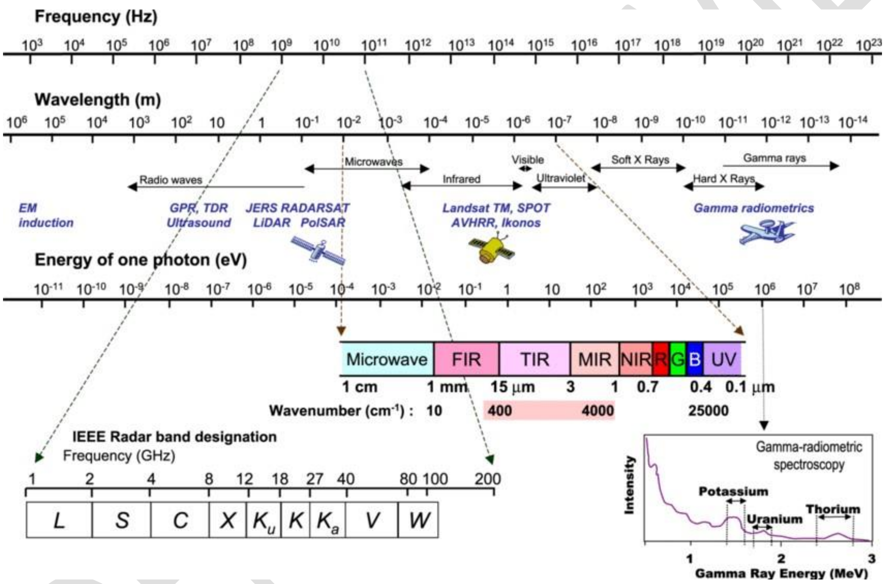

Figure 1. Electromagnetic spectrum and soil-water interactions

In recent years, precision agriculture techniques have emerged as promising solutions for optimizing irrigation management in horticulture [4]. Precision agriculture involves the use of advanced technologies, such as remote sensing, geographic information systems (GIS), and variable rate application (VRA), to collect and analyze site-specific data for informed decision-making [5]. Among these technologies, unmanned aerial vehicles (UAVs), or drones, have gained significant attention for their potential in soil moisture monitoring and irrigation scheduling [6].

Drones equipped with remote sensing sensors can provide high-resolution spatial and temporal data on soil moisture variability across a farm [7]. This information can be used to create precise irrigation prescription maps, enabling farmers to apply water more efficiently and effectively [8]. Drone-based soil moisture monitoring offers several advantages over traditional methods, including non-destructive sampling, real-time data acquisition, and the ability to cover large areas quickly and cost-effectively [9].

This article aims to provide a comprehensive review of the current state and future prospects of drone technology for soil moisture monitoring and irrigation scheduling in horticultural farms. The principles of drone-based remote sensing, types of sensors used, and data processing techniques are discussed in detail. Case studies demonstrating the successful application of drones for irrigation optimization in various horticultural crops are presented. The challenges and limitations of drone-based irrigation management are also addressed, along with future research directions and opportunities in this field.

Table 2. Comparison of Soil Moisture Sensing Technologies

Sensor Type	**Spectral Range**	**Spatial Resolution**	**Advantages**	**Disadvantages**

Optical	Visible, Near-infrared	High (cm-level)	High spatial resolution, low cost	Limited to surface soil moisture
Thermal	Thermal infrared	Moderate (m-level)	Sensitive to soil moisture variations	Affected by weather conditions
Hyperspectral	Visible to shortwave infrared	Moderate to high	Detailed spectral information	High cost, large data volume

2. Principles of Drone-Based Remote Sensing for Soil Moisture Monitoring

Drone-based remote sensing for soil moisture monitoring relies on the principles of electromagnetic radiation and its interaction with soil and water [10]. When electromagnetic energy, such as visible light or infrared radiation, strikes the Earth's surface, it can be reflected, absorbed, or transmitted depending on the properties of the target material [11]. Soil moisture content influences the spectral reflectance of soil, as water absorbs more energy in certain regions of the electromagnetic spectrum compared to dry soil [12].

2.1 Electromagnetic Spectrum and Soil-Water Interactions

The electromagnetic spectrum encompasses a wide range of wavelengths, from gamma rays to radio waves [13]. For soil moisture monitoring, the most relevant regions are the visible (400-700 nm), near-infrared (700-1400 nm), and thermal infrared (8-14 μm) portions of the spectrum [14]. In the visible and near-infrared regions, water absorption bands occur at specific wavelengths, such as 970 nm, 1200 nm, and 1450 nm [15]. These absorption features can be used to estimate soil moisture content based on the spectral reflectance of soil.

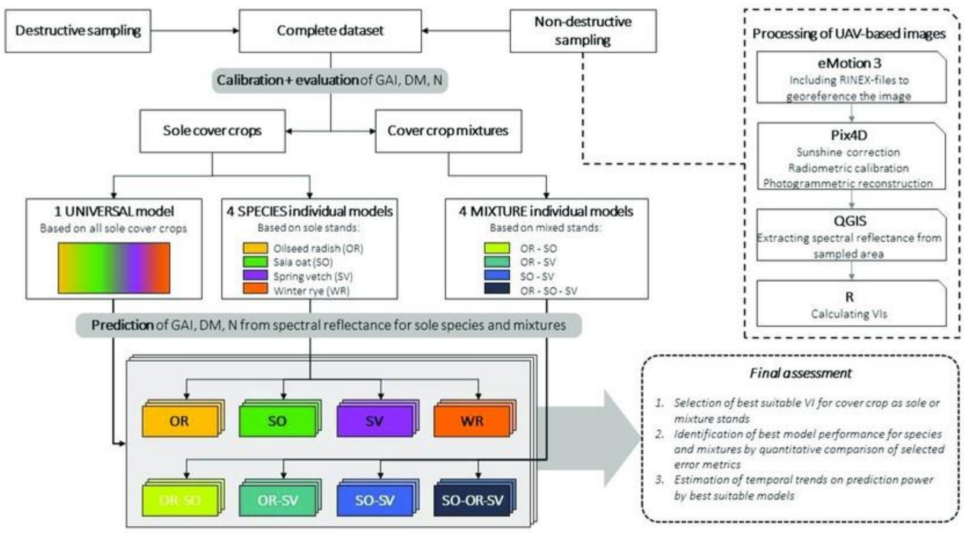

Figure 2. Workflow of drone-based irrigation management

In the thermal infrared region, soil emits energy as a function of its temperature and emissivity [16]. Soil moisture influences soil thermal properties, as wet soil has a higher heat capacity and thermal conductivity compared to dry soil [17].

Consequently, variations in soil moisture can be detected through differences in surface temperature, with wetter areas appearing cooler than drier areas [18].

2.2 Types of Sensors Used in Drone-Based Soil Moisture Monitoring

Drones can be equipped with various types of sensors for soil moisture monitoring, including optical, thermal, and hyperspectral sensors [19]. The choice of sensor depends on the specific application, desired spatial and temporal resolution, and available resources.

2.2.1 Optical Sensors

Optical sensors measure the reflectance of visible and near-infrared light from the soil surface [20]. Commonly used optical sensors for drone-based soil moisture monitoring include RGB (red, green, blue) cameras, multispectral cameras, and modified consumer-grade cameras [21]. RGB cameras provide high-resolution color images that can be used to visually assess soil moisture patterns, while multispectral cameras capture data in specific spectral bands that are sensitive to soil moisture variations [22].

Modified consumer-grade cameras, such as those with removed infrared filters or added narrow-band filters, can also be used for soil moisture estimation [23]. These cameras are more affordable than specialized multispectral cameras and can provide sufficient accuracy for certain applications [24].

2.2.2 Thermal Sensors

Thermal sensors detect the emitted thermal infrared radiation from the soil surface, which is related to soil moisture content [25]. Thermal cameras or radiometers are the most common types of thermal sensors used in drone-based soil moisture monitoring [26]. These sensors measure surface temperature with high spatial resolution, allowing for the detection of fine-scale soil moisture variability [27].

Thermal data can be used to estimate soil moisture content through the relationship between surface temperature and evapotranspiration [28]. Wet soil has a higher evapotranspiration rate and therefore appears cooler than dry soil under similar atmospheric conditions [29]. By combining thermal data with meteorological information and crop characteristics, soil moisture can be estimated using energy balance models [30].

Table 3. Summary of Case Studies on Drone-Based Irrigation Management

Crop	Location	Sensor Type	Irrigation Method	Water Savings	Reference
Almond	California, USA	Thermal	Variable rate	20%	[54]
Tomato	Italy	Multispectral	Water stress index	30%	[58]

Ornamental plants	Florida, USA	Thermal	Zoned irrigation	40%	[62]

2.2.3 Hyperspectral Sensors

Hyperspectral sensors measure reflectance in numerous narrow spectral bands across a wide range of wavelengths [31]. These sensors provide detailed spectral information that can be used to identify specific absorption features related to soil moisture [32]. Hyperspectral data allows for the development of more accurate and robust soil moisture estimation models compared to multispectral data [33].

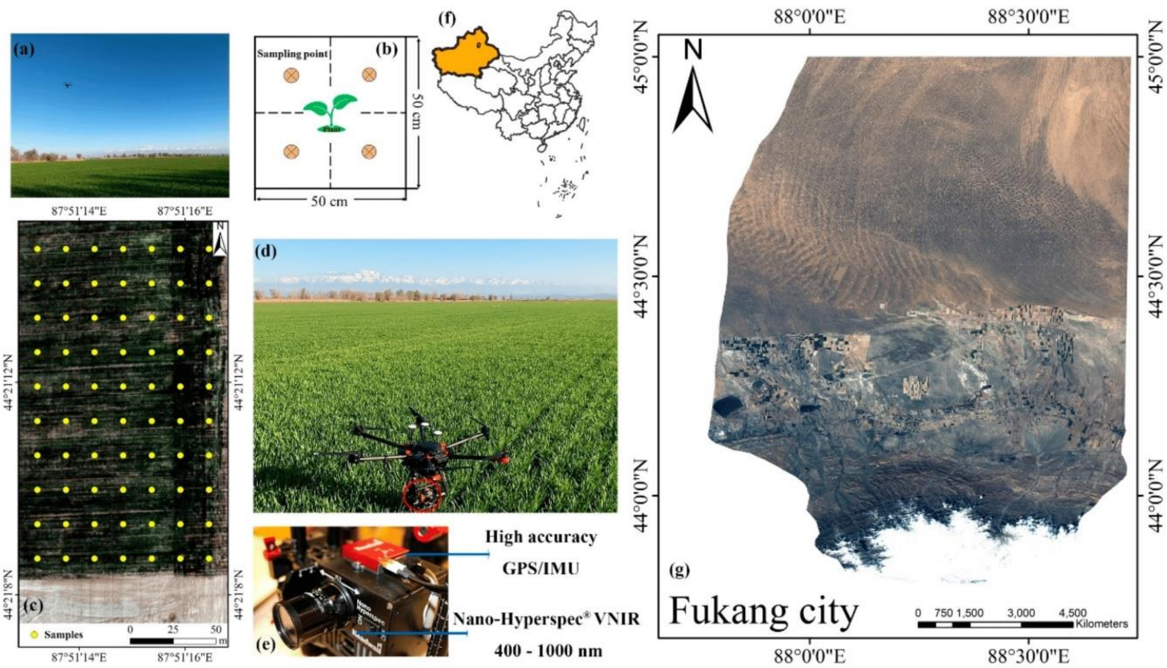

Figure 3. Example of drone thermal imagery for soil moisture estimation

However, hyperspectral sensors are generally more expensive and have lower spatial resolution than multispectral sensors [34]. They also generate large amounts of data that require specialized processing and analysis techniques [35]. As a result, hyperspectral sensors are less commonly used in drone-based soil moisture monitoring compared to optical and thermal sensors.

3. Data Processing and Interpretation Techniques

The raw data collected by drone-based sensors must be processed and interpreted to derive meaningful information about soil moisture variability. This involves several steps, including radiometric and geometric corrections, vegetation index calculation, and soil moisture estimation using empirical or physical models [36].

3.1 Radiometric and Geometric Corrections

Radiometric corrections are necessary to convert the raw digital numbers recorded by the sensor into physically meaningful units, such as reflectance or temperature [37]. This process involves correcting for sensor calibration, atmospheric effects, and illumination conditions [38]. Geometric corrections are also required to align the data with a geographic coordinate system and remove distortions caused by the sensor orientation and terrain variations [39].

Several software packages, such as Pix4D, Agisoft Metashape, and ENVI, offer automated workflows for radiometric and geometric corrections of drone-based data [40]. These tools use photogrammetric techniques and ground control points (GCPs) to create orthorectified and radiometrically calibrated images [41].

3.2 Vegetation Indices and Soil Moisture Estimation

Vegetation indices are mathematical combinations of spectral reflectance values that provide information about vegetation characteristics, such as greenness, leaf area, and water content [42]. In the context of soil moisture monitoring, vegetation indices can be used to estimate soil moisture indirectly by assessing the water status of the crop [43].

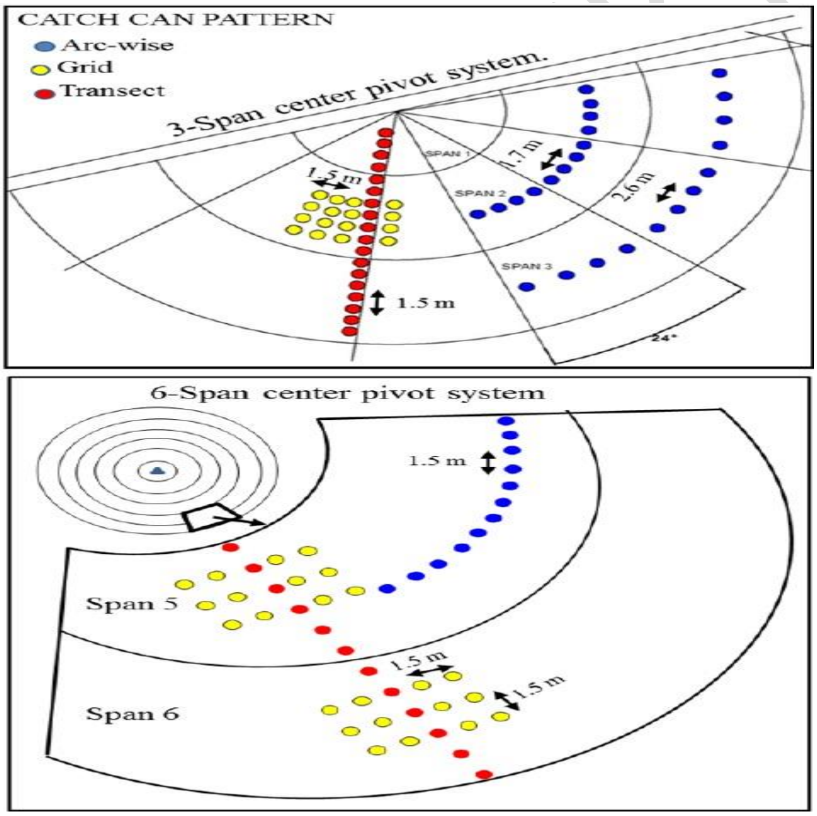

Figure 4. Comparison of uniform and variable rate irrigation patterns

Commonly used vegetation indices for soil moisture estimation include the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI) [44]. These indices are calculated using reflectance values from the visible and near-infrared spectral bands and have been shown to correlate with soil moisture under certain conditions [45].

However, the relationship between vegetation indices and soil moisture can be complex and influenced by factors such as soil type, crop growth stage, and management practices [46]. Therefore, vegetation indices should be used in conjunction with other data sources, such as thermal imagery or soil sampling, to improve the accuracy of soil moisture estimates [47].

3.3 Machine Learning and Data Fusion Approaches

Machine learning techniques have emerged as powerful tools for analyzing and interpreting drone-based data for soil moisture monitoring [48]. These methods can handle large amounts of multi-source data and learn complex relationships between spectral features and soil moisture [49]. Commonly used machine learning algorithms for soil moisture estimation include support vector machines (SVM), random forests (RF), and artificial neural networks (ANN) [50].

Table 4. Regulatory Constraints for Drone Operations in Agriculture

Country	Maximum Altitude	Visual Line of Sight	Pilot Certification	Reference
United States	400 ft (120 m)	Required	Part 107	[65]
European Union	120 m	Required	Category A1/A2/A3	[64]
Australia	120 m	Required	Remote Pilot License	[66]

Data fusion approaches, which combine information from multiple sensors or data sources, can also improve the accuracy and reliability of soil moisture estimates [51]. For example, the integration of optical, thermal, and radar data has been shown to provide more robust soil moisture estimates compared to using a single sensor [52]. Data fusion can be achieved through various methods, such as weighted averaging, Bayesian networks, and deep learning architectures [53].

4. Case Studies of Drone-Based Irrigation Management in Horticulture

Several case studies have demonstrated the successful application of drones for soil moisture monitoring and irrigation scheduling in various horticultural crops. These studies highlight the potential benefits of drone-based irrigation management, such as water savings, improved crop yields, and reduced environmental impact.

4.1 High-Value Fruit Crops

In a study conducted in a California almond orchard, researchers used a thermal camera mounted on a drone to map soil moisture variability and optimize irrigation scheduling [54]. The drone-based thermal data was used to create irrigation prescription maps, which were implemented using a variable rate irrigation system. The results showed that the drone-based approach reduced water use by 20% compared to traditional uniform irrigation, without compromising crop yield or quality.

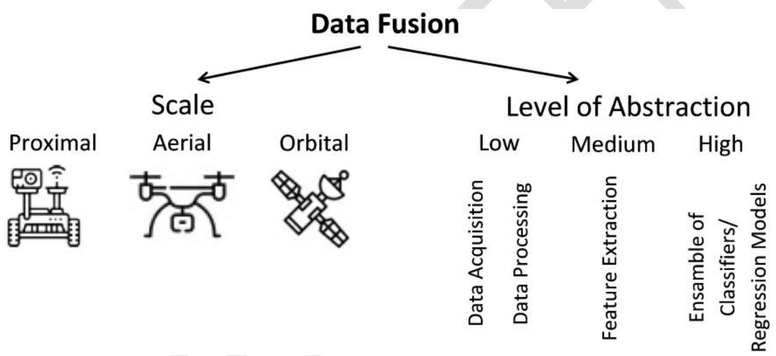

Figure 5. Data fusion approach for integrating drone data with other precision agriculture technologies

Similar studies have been conducted in other high-value fruit crops, such as citrus [55], avocado [56], and vineyards [57]. In each case, drone-based soil moisture monitoring and precision irrigation led to significant water savings and improved crop performance.

Table 5. Challenges and Potential Solutions for Drone-Based Irrigation Management

Challenge	Potential Solutions	Reference
Regulatory constraints	Collaborative decision-making, flexible regulations	[64], [65]
Data accuracy and validation	Improved sensor calibration, ground truthing	[68], [71]
Need for specialized expertise	Training programs, user-friendly interfaces	[73], [75]

4.2 Vegetable Crops

Drone-based irrigation management has also been applied in vegetable production systems. In a study conducted in a tomato field in Italy, researchers used a multispectral camera mounted on a drone to monitor soil moisture and crop water status [58]. The drone data was used to develop a water stress index, which was then used to trigger irrigation events. The results showed that the drone-based approach reduced water use by 30% compared to traditional scheduling methods, while maintaining crop yield and quality.

Other studies have demonstrated the potential of drones for soil moisture monitoring and irrigation scheduling in crops such as potatoes [59], onions [60], and lettuce [61]. These studies highlight the versatility of drone-based approaches across a range of vegetable production systems.

4.3 Ornamental and Nursery Crops

Drone-based irrigation management has also been explored in ornamental and nursery crop production. In a study conducted in a container nursery in Florida, researchers used a thermal camera mounted on a drone to detect water stress in ornamental plants [62]. The drone data was used to create irrigation zones based on plant water requirements, leading to a 40% reduction in water use compared to traditional uniform irrigation.

Another study investigated the use of drones for soil moisture monitoring and irrigation scheduling in a cut flower greenhouse [63]. The researchers used a multispectral camera to map soil moisture variability and adjust irrigation accordingly. The results showed that the drone-based approach improved flower quality and reduced water use by 25% compared to conventional methods.

5. Challenges and Limitations

Despite the promising potential of drone-based irrigation management in horticulture, several challenges and limitations must be addressed to ensure the widespread adoption and success of this technology.

5.1 Regulatory Issues and Operational Constraints

The use of drones in agriculture is subject to various regulations and operational constraints [64]. In many countries, drone operators must obtain licenses and follow specific rules regarding flight altitude, line of sight, and proximity to people and structures [65]. These regulations can limit the flexibility and efficiency of drone-based operations, particularly in areas with complex airspace or near populated regions.

Weather conditions, such as high winds, rain, or extreme temperatures, can also impact the performance and safety of drone flights [66]. In addition, the limited battery life of most drones restricts the area that can be covered in a single flight, requiring multiple flights or battery replacements for large-scale operations [67].

Table 6. Integration of Drone Data with Other Precision Agriculture Technologies

Technology	Integration Approach	Benefits	Reference
Wireless sensor networks	Data fusion, adaptive irrigation scheduling	Real-time monitoring, dynamic decision-making	[79]
Crop growth	Model parametrization,	Crop-specific	[80]

models	scenario analysis	irrigation optimization	
Variable rate irrigation	Prescription maps, automated control	Precise water application, reduced losses	[54], [81]

5.2 Data Accuracy, Resolution, and Validation

The accuracy and resolution of drone-based soil moisture data depend on various factors, such as sensor specifications, flight altitude, and data processing methods [68]. Low-cost sensors may have limited spectral or thermal resolution, reducing the sensitivity to soil moisture variations [69]. Higher flight altitudes can increase the area covered but may result in coarser spatial resolution and reduced accuracy [70].

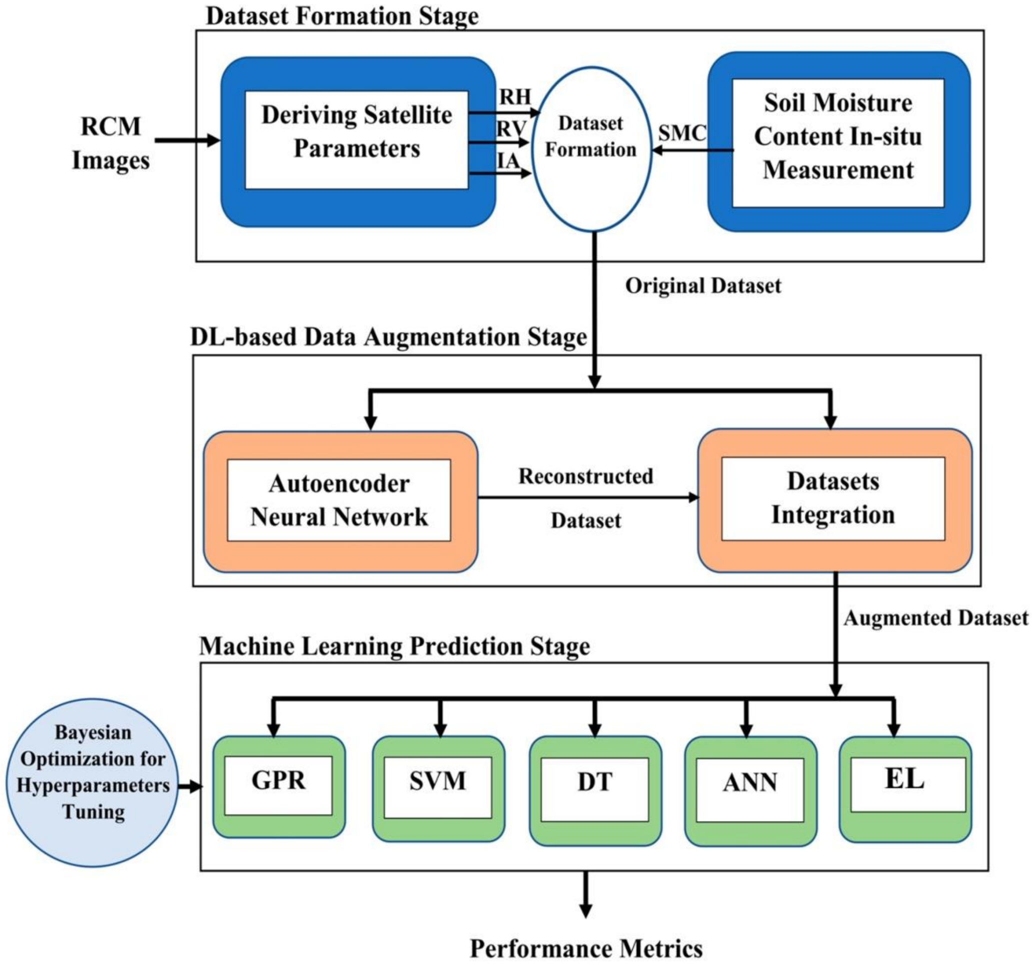

Figure 6. Machine learning framework for drone-based soil moisture estimation

Validating drone-based soil moisture estimates is also challenging, as ground-truth measurements are often limited and may not capture the spatial variability at the same scale as the drone data [71]. Inadequate validation can lead to uncertainties in the reliability and applicability of drone-based irrigation decisions [72].

5.3 Need for Specialized Expertise and Training

Implementing drone-based irrigation management requires specialized expertise in remote sensing, data processing, and precision agriculture [73]. Farmers and horticulturalists may lack the necessary skills and knowledge to effectively collect, analyze, and interpret drone data for irrigation decision-making [74]. This highlights the need for training programs and support services to help users adopt and benefit from drone technologies [75].

Moreover, the integration of drone data with existing irrigation systems and decision support tools can be complex and require additional technical expertise [76]. Developing user-friendly interfaces and automated data processing workflows can help bridge the gap between drone technology and practical irrigation management [77].

6. Future Directions and Opportunities

As drone technology continues to advance, several future directions and opportunities emerge for soil moisture monitoring and irrigation management in horticulture.

6.1 Integration with Other Precision Agriculture Technologies

Integrating drones with other precision agriculture technologies, such as wireless sensor networks, weather stations, and variable rate irrigation systems, can provide a more comprehensive and adaptive approach to irrigation management [78]. For example, combining drone-based soil moisture maps with real-time sensor data and weather forecasts can enable dynamic irrigation scheduling that responds to changing crop water requirements [79].

In addition, the integration of drone data with crop growth models and decision support systems can help optimize irrigation strategies based on crop-specific characteristics and growth stages [80]. This can lead to more targeted and efficient irrigation practices that maximize crop yield and quality while minimizing water use and environmental impact [81].

Table 7. Future Research Directions for Drone-Based Irrigation Management

Research Area	Objectives	Potential Outcomes	Reference
Sensor development	Improve accuracy, reduce cost	Enhanced soil moisture estimation	[82], [83]
Machine learning	Automate data analysis, extract insights	Efficient data processing, improved decision support	[84], [85]
Economic and environmental impact assessment	Quantify benefits, evaluate sustainability	Informed technology adoption, policy development	[87], [88]

6.2 Advances in Sensor Technologies and Data Analytics

The development of new and improved sensor technologies can enhance the capabilities of drones for soil moisture monitoring. For example, the integration of hyperspectral sensors with thermal and multispectral cameras can provide a more comprehensive assessment of soil moisture and crop water status [82]. Similarly, the use of lightweight and low-cost microwave sensors can enable the estimation of soil moisture at deeper layers, which is important for irrigation scheduling in crops with deep root systems [83].

Advances in data analytics, such as machine learning and artificial intelligence, can also improve the accuracy and efficiency of drone-based soil moisture estimation [84]. Deep learning algorithms can automatically extract relevant features from large datasets and learn complex relationships between spectral data and soil moisture [85]. This can reduce the need for manual data processing and interpretation, making drone-based irrigation management more accessible and scalable [86].

6.3 Economic and Environmental Impact Assessment

Assessing the economic and environmental impacts of drone-based irrigation management is crucial for promoting its adoption and sustainability in horticulture. Studies that quantify the water savings, yield improvements, and cost-benefit ratios of drone-based approaches compared to traditional methods can help justify the investment in this technology [87].

Moreover, evaluating the environmental benefits of drone-based irrigation, such as reduced water use, nutrient leaching, and greenhouse gas emissions, can highlight its potential for sustainable horticulture [88]. Life cycle assessment (LCA) studies can provide a comprehensive understanding of the environmental impacts of drone technology, considering factors such as manufacturing, operation, and disposal [89].

7. Conclusion

Drone-based soil moisture monitoring and irrigation scheduling offer significant potential for optimizing water use and improving crop productivity in horticultural farms. By providing high-resolution spatial and temporal data on soil moisture variability, drones enable precision irrigation management that can lead to water savings, reduced environmental impact, and increased crop yields.

However, the adoption of drone technology in horticulture faces challenges related to regulatory issues, data accuracy and validation, and the need for specialized expertise. Ongoing research and development efforts are addressing these challenges through advances in sensor technologies, data analytics, and integration with other precision agriculture tools.

As the technology matures and becomes more accessible, drone-based irrigation management is poised to become an essential component of sustainable and efficient horticultural production systems. Further research on the economic and environmental impacts of this technology will be critical for promoting its widespread adoption and realizing its full potential in the face of global water scarcity and food security challenges.

References

[1] Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany*, 58(2), 147-159.

[2] Levidow, L., Zaccaria, D., Maia, R., Vivas, E., Todorovic, M., & Scardigno, A. (2014). Improving water-efficient irrigation: Prospects and difficulties of innovative practices. Agricultural Water Management, 146, 84-94.

[3] Jones, H. G. (2004). Irrigation scheduling: advantages and pitfalls of plant-based methods. Journal of Experimental Botany, 55(407), 2427-2436.

[4] Precision Agriculture. (2022). In Encyclopædia Britannica. Retrieved from https://www.britannica.com/technology/precision-agriculture

[5] McBratney, A., Whelan, B., Ancev, T., & Bouma, J. (2005). Future directions of precision agriculture. Precision Agriculture, 6(1), 7-23.

[6] Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: a review. Precision Agriculture, 13(6), 693-712.

[7] Ge, Y., Thomasson, J. A., & Sui, R. (2011). Remote sensing of soil properties in precision agriculture: A review. Frontiers of Earth Science, 5(3), 229-238.

[8] Evans, R. G., LaRue, J., Stone, K. C., & King, B. A. (2013). Adoption of site-specific variable rate sprinkler irrigation systems. Irrigation Science, 31(4), 871-887.

[9] Khanal, S., Fulton, J., & Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. Computers and Electronics in Agriculture, 139, 22-32.

[10] Ben-Dor, E., Chabrillat, S., Demattê, J. A. M., Taylor, G. R., Hill, J., Whiting, M. L., & Sommer, S. (2009). Using imaging spectroscopy to study soil properties. Remote Sensing of Environment, 113, S38-S55.

[11] Jensen, J. R. (2015). Introductory Digital Image Processing: A Remote Sensing Perspective (4th ed.). Pearson Education.

[12] Weidong, L., Baret, F., Xingfa, G., Qingxi, T., Lanfen, Z., & Bing, Z. (2002). Relating soil surface moisture to reflectance. Remote Sensing of Environment, 81(2-3), 238-246.

[13] Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). Remote sensing and image interpretation (7th ed.). John Wiley & Sons.

[14] Sadeghi, M., Jones, S. B., & Philpot, W. D. (2015). A linear physically-based model for remote sensing of soil moisture using short wave infrared bands. Remote Sensing of Environment, 164, 66-76.

[15] Haubrock, S. N., Chabrillat, S., Lemmnitz, C., & Kaufmann, H. (2008). Surface soil moisture quantification models from reflectance data under field conditions. International Journal of Remote Sensing, 29(1), 3-29.

[16] Minacapilli, M., Cammalleri, C., Ciraolo, G., D'Asaro, F., Iovino, M., & Maltese, A. (2012). Thermal inertia modeling for soil surface water content estimation: A laboratory experiment. Soil Science Society of America Journal, 76(1), 92-100.

[17] Verstraeten, W. W., Veroustraete, F., van der Sande, C. J., Grootaers, I., & Feyen, J. (2006). Soil moisture retrieval using thermal inertia, determined with visible and thermal spaceborne data, validated for European forests. Remote Sensing of Environment, 101(3), 299-314.

[18] Petropoulos, G. P., Ireland, G., & Barrett, B. (2015). Surface soil moisture retrievals from remote sensing: Current status, products & future trends. Physics and Chemistry of the Earth, Parts A/B/C, 83, 36-56.

[19] Aasen, H., Honkavaara, E., Lucieer, A., & Zarco-Tejada, P. J. (2018). Quantitative remote sensing at ultra-high resolution with UAV spectroscopy: A

review of sensor technology, measurement procedures, and data correction workflows. Remote Sensing, 10(7), 1091.

[20] Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. Remote Sensing, 9(11), 1110.

[21] Candiago, S., Remondino, F., De Giglio, M., Dubbini, M., & Gattelli, M. (2015). Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. Remote Sensing, 7(4), 4026-4047.

[22] Sankaran, S., Khot, L. R., Espinoza, C. Z., Jarolmasjed, S., Sathuvalli, V. R., Vandemark, G. J., ... & Pavek, M. J. (2015). Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review. European Journal of Agronomy, 70, 112-123.

[23] Hunt Jr, E. R., Doraiswamy, P. C., McMurtrey, J. E., Daughtry, C. S., Perry, E. M., & Akhmedov, B. (2013). A visible band index for remote sensing leaf chlorophyll content at the canopy scale. International Journal of Applied Earth Observation and Geoinformation, 21, 103-112.

[24] Lebourgeois, V., Bégué, A., Labbé, S., Mallavan, B., Prévot, L., & Roux, B. (2008). Can commercial digital cameras be used as multispectral sensors? A crop monitoring test. Sensors, 8(11), 7300-7322.

[25] Kuenzer, C., & Dech, S. (Eds.). (2013). Thermal infrared remote sensing: sensors, methods, applications (Vol. 17). Springer Science & Business Media.

[26] Berni, J. A., Zarco-Tejada, P. J., Suárez, L., & Fereres, E. (2009). Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle. IEEE Transactions on Geoscience and Remote Sensing, 47(3), 722-738.

[27] Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering, 114(4), 358-371.

[28] Bellvert, J., Zarco-Tejada, P. J., Girona, J., & Fereres, E. (2014). Mapping crop water stress index in a 'Pinot-noir' vineyard: comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle. Precision Agriculture, 15(4), 361-376.

[29] Anderson, M. C., Allen, R. G., Morse, A., & Kustas, W. P. (2012). Use of Landsat thermal imagery in monitoring evapotranspiration and managing water resources. Remote Sensing of Environment, 122, 50-65.

[30] Bastiaanssen, W. G., Menenti, M., Feddes, R. A., & Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. Journal of Hydrology, 212, 198-212.

[31] Manolakis, D., Lockwood, R., & Cooley, T. (2016). Hyperspectral imaging remote sensing: physics, sensors, and algorithms. Cambridge University Press.

[32] Ben-Dor, E., Chabrillat, S., Demattê, J. A. M., Taylor, G. R., Hill, J., Whiting, M. L., & Sommer, S. (2009). Using imaging spectroscopy to study soil properties. Remote Sensing of Environment, 113, S38-S55.

[33] Nocita, M., Stevens, A., van Wesemael, B., Aitkenhead, M., Bachmann, M., Barthès, B., ... & Wetterlind, J. (2015). Soil spectroscopy: An alternative to wet chemistry for soil monitoring. Advances in Agronomy, 132, 139-159.

[34] Aasen, H., & Bolten, A. (2018). Multi-temporal high-resolution imaging spectroscopy with hyperspectral 2D imagers–From theory to application. Remote Sensing of Environment, 205, 374-389.

[35] Plaza, A., Plaza, J., Paz, A., & Sanchez, S. (2011). Parallel hyperspectral image and signal processing. IEEE Signal Processing Magazine, 28(3), 119-126.

[36] Kelcey, J., & Lucieer, A. (2012). Sensor correction of a 6-band multispectral imaging sensor for UAV remote sensing. Remote Sensing, 4(5), 1462-1493.

[37] Honkavaara, E., Saari, H., Kaivosoja, J., Pölönen, I., Hakala, T., Litkey, P., ... & Pesonen, L. (2013). Processing and assessment of spectrometric,

stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture. Remote Sensing, 5(10), 5006-5039.

[38] Berni, J. A., Zarco-Tejada, P. J., Suárez, L., González-Dugo, V., & Fereres, E. (2009). Remote sensing of vegetation from UAV platforms using lightweight multispectral and thermal imaging sensors. Int. Arch. Photogramm. Remote Sens. Spatial Inform. Sci, 38(6), 6.

[39] Turner, D., Lucieer, A., & Watson, C. (2012). An automated technique for generating georectified mosaics from ultra-high resolution unmanned aerial vehicle (UAV) imagery, based on structure from motion (SfM) point clouds. Remote Sensing, 4(5), 1392-1410.

[40] Kalantar, B., Mansor, S. B., Sameen, M. I., Pradhan, B., & Shafri, H. Z. (2017). Drone-based land-cover mapping using a fuzzy unordered rule induction algorithm integrated into object-based image analysis. International Journal of Remote Sensing, 38(8-10), 2535-2556.

[41] Harwin, S., & Lucieer, A. (2012). Assessing the accuracy of georeferenced point clouds produced via multi-view stereopsis from unmanned aerial vehicle (UAV) imagery. Remote Sensing, 4(6), 1573-1599.

[42] Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. Journal of Sensors, 2017.

[43] Gao, B. C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58(3), 257-266.

[44] Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1-2), 195-213.

[45] Peng, J., Loew, A., Merlin, O., & Verhoest, N. E. (2017). A review of spatial downscaling of satellite remotely sensed soil moisture. Reviews of Geophysics, 55(2), 341-366.

[46] Petropoulos, G. P., Ireland, G., & Barrett, B. (2015). Surface soil moisture retrievals from remote sensing: Current status, products & future trends. Physics and Chemistry of the Earth, Parts A/B/C, 83, 36-56.

[47] Srivastava, P. K., O'Neill, P., Cosh, M., Lang, R., & Joseph, A. (2015). Evaluation of radar vegetation indices for vegetation water content estimation using data from a ground-based SMAP simulator. In 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS) (pp. 1296-1299). IEEE.

[48] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

[49] Lary, D. J., Alavi, A. H., Gandomi, A. H., & Walker, A. L. (2016). Machine learning in geosciences and remote sensing. Geoscience Frontiers, 7(1), 3-10.

[50] Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 66(3), 247-259.

[51] Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., ... & Waske, B. (2016). A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. Remote Sensing, 8(1), 70.

[52] Das, N. N., Entekhabi, D., & Njoku, E. G. (2011). An algorithm for merging SMAP radiometer and radar data for high-resolution soil moisture retrieval. IEEE Transactions on Geoscience and Remote Sensing, 49(5), 1504-1512.

[53] Schmitt, M., & Zhu, X. X. (2016). Data fusion and remote sensing: An ever-growing relationship. IEEE Geoscience and Remote Sensing Magazine, 4(4), 6-23.

[54] Berni, J. A., Zarco-Tejada, P. J., Sepulcre-Cantó, G., Fereres, E., & Villalobos, F. (2009). Mapping canopy conductance and CWSI in olive

orchards using high resolution thermal remote sensing imagery. Remote Sensing of Environment, 113(11), 2380-2388.

[55] Gonzalez-Dugo, V., Zarco-Tejada, P., Nicolás, E., Nortes, P. A., Alarcón, J. J., Intrigliolo, D. S., & Fereres, E. (2013). Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard. Precision Agriculture, 14(6), 660-678.

[56] Holman, F. H., Riche, A. B., Michalski, A., Castle, M., Wooster, M. J., & Hawkesford, M. J. (2016). High throughput field phenotyping of wheat plant height and growth rate in field plot trials using UAV based remote sensing. Remote Sensing, 8(12), 1031.

[57] Baluja, J., Diago, M. P., Balda, P., Zorer, R., Meggio, F., Morales, F., & Tardaguila, J. (2012). Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV). Irrigation Science, 30(6), 511-522.

[58] Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M., Flexas, J., ... & Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. Agricultural Water Management, 153, 9-19.

[59] Boon, M. A., Greenfield, R., & Tesfamichael, S. (2016). Wetland assessment using unmanned aerial vehicle (UAV) photogrammetry.

International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, 41.

[60] Zaman-Allah, M., Vergara, O., Araus, J. L., Tarekegne, A., Magorokosho, C., Zarco-Tejada, P. J., ... & Cairns, J. E. (2015). Unmanned aerial platform-based multi-spectral imaging for field phenotyping of maize. Plant Methods, 11(1), 35.

[61] Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering, 114(4), 358-371.

[62] Beale, J., Waine, T., Evans, J. G., & Corstanje, R. (2019). A method to assess the performance of SAR-derived surface soil moisture products. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(10), 3863-3879.

[63] Sanchez, N., Martínez-Fernández, J., González-Piqueras, J., González-Dugo, M. P., Baroncini-Turrichia, G., Torres, E., ... & Pérez-Gutiérrez, C. (2012). Water balance at plot scale for soil moisture estimation using vegetation parameters. Agricultural and Forest Meteorology, 166, 1-9.

[64] Stöcker, C., Bennett, R., Nex, F., Gerke, M., & Zevenbergen, J. (2017). Review of the current state of UAV regulations. Remote Sensing, 9(5), 459.

[65] Federal Aviation Administration. (2016). Summary of small unmanned aircraft rule (part 107). Washington, DC: Author.

[66] Civil Aviation Safety Authority. (2017). Flying drones/remotely piloted aircraft in Australia. Canberra: Author.

[67] Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 92, 79-97.

[68] Muller, E., & Décamps, H. (2001). Modeling soil moisture–reflectance. Remote Sensing of Environment, 76(2), 173-180.

[69] Kelcey, J., & Lucieer, A. (2012). Sensor correction of a 6-band multispectral imaging sensor for UAV remote sensing. Remote Sensing, 4(5), 1462-1493.

[70] Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P., Primicerio, J., ... & Gioli, B. (2015). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. Remote Sensing, 7(3), 2971-2990.

[71] Paloscia, S., Pettinato, S., Santi, E., Notarnicola, C., Pasolli, L., & Reppucci, A. (2013). Soil moisture mapping using Sentinel-1 images: Algorithm and preliminary validation. Remote Sensing of Environment, 134, 234-248.

[72] Montzka, C., Bogena, H. R., Zreda, M., Monerris, A., Morrison, R., Muddu, S., & Vereecken, H. (2017). Validation of spaceborne and modelled surface soil moisture products with cosmic-ray neutron probes. Remote Sensing, 9(2), 103.

[73] Elarab, M., Ticlavilca, A. M., Torres-Rua, A. F., Maslova, I., & McKee, M. (2015). Estimating chlorophyll with thermal and broadband multispectral high resolution imagery from an unmanned aerial system using relevance vector machines for precision agriculture. International Journal of Applied Earth Observation and Geoinformation, 43, 32-42.

[74] Tey, Y. S., & Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: a review for policy implications. Precision Agriculture, 13(6), 713-730.

[75] Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming–a review. Agricultural Systems, 153, 69-80.

[76] Khanal, S., Fulton, J., & Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. Computers and Electronics in Agriculture, 139, 22-32.

[77] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

[78] Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, 23-37.

[79] Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M., Flexas, J., ... & Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. Agricultural Water Management, 153, 9-19.

[80] Ramirez-Cuesta, J. M., Kilic, A., Allen, R., Santos, C., & Lorite, I. J. (2017). Evaluating the impact of adjusting surface temperature derived from Landsat 7 ETM+ in crop evapotranspiration assessment using high-resolution airborne data. International Journal of Remote Sensing, 38(14), 4177-4205.

[81] Evans, R. G., LaRue, J., Stone, K. C., & King, B. A. (2013). Adoption of site-specific variable rate sprinkler irrigation systems. Irrigation Science, 31(4), 871-887.

[82] Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. Remote Sensing, 9(11), 1110.

[83] Ulaby, F. T., Long, D. G., Blackwell, W. J., Elachi, C., Fung, A. K., Ruf, C., ... & Van Zyl, J. (2014). Microwave radar and radiometric remote sensing (Vol. 4, No. 5, p. 6). Ann Arbor: University of Michigan Press.

[84] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

[85] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70-90.

[86] Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. IEEE Geoscience and Remote Sensing Letters, 14(5), 778-782.

[87] Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P., Primicerio, J., ... & Gioli, B. (2015). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. Remote Sensing, 7(3), 2971-2990.

[88] Shi, Y., Thomasson, J. A., Murray, S. C., Pugh, N. A., Rooney, W. L., Shafian, S., ... & Yang, C. (2016). Unmanned aerial vehicles for high-throughput phenotyping and agronomic research. PloS one, 11(7), e0159781.

[89] Berni, J. A., Zarco-Tejada, P. J., Suárez, L., & Fereres, E. (2009). Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle. IEEE Transactions on Geoscience and Remote Sensing, 47(3), 722-738.