Journal of Computer Science and Electrical Engineering
ISSN: 2663-1946
DOI: 10.61784/jcsee240118

UAV LOW-ALTITUDE AGRICULTURAL INFORMATION REMOTE SENSING MONITORING

Jen-Chia Hsiao
National Penghu University of Science and Technology, Makong, Taiwan, China.

Abstract: Timely and accurate acquisition of field crop growth status and environmental information is the premise and foundation for precise crop management. UAV low-altitude remote sensing technology has incomparable advantages in obtaining crop images of different scales, and has become an important means and method for agricultural information monitoring. This article mainly focuses on the composition of UAV low-altitude remote sensing systems, crop growth monitoring, and yield prediction. The research and application of nutrition diagnosis, pest and disease monitoring, crop lodging, growth stress diagnosis, etc. were summarized and analyzed. The problems of UAV low-altitude remote sensing in agricultural information monitoring were analyzed. Finally, the application prospects and development were proposed. Trend. Future research should focus on the continuous expansion of the breadth and depth of remote sensing monitoring of agricultural conditions, the continuous development of intelligence, and the exploration of low-cost, micro-miniature sensing equipment, and use the integration and complementarity of multi-source data to form a highly versatile system, easy-to-operate solution, further expanding the application scope of UAV low-altitude remote sensing in the acquisition and analysis of crop phenotypic information in precision agriculture.
Keywords: UAV; Low-altitude remote sensing; Agricultural conditions monitoring; Information precision

1 INTRODUCTION

UAV remote sensing is an organic combination of unmanned aircraft technology, remote sensing technology, sensor technology, remote control technology, positioning technology and communication technology. It combines to realize a new comprehensive application technology of remote sensing data acquisition, modeling and analysis[1]. The images acquired by drone remote sensing are processed by splicing, geometric correction, etc. After analyzing the data, crop growth monitoring, yield estimation, etc. can be realized. Nutritional diagnosis and growth stress monitoring have become important tasks in precision agriculture. It is an important means to provide information on spatiotemporal changes in fields such as physical conditions and environmental factors[2-3]. In the past ten years, with the rapid development of microcomputers and communication technology, wireless Research on human-machine remote sensing monitoring of agricultural information has grown exponentially. Many scholars at home and abroad have used UAV remote sensing to obtain and analyze field crop phenotypic information, and have achieved impressive results. This article provides an overview of UAV low-altitude remote sensing platforms, introduces commonly used drones and sensor types, remote sensing of drones The progress and shortcomings of monitoring in the extraction, analysis and application of agricultural information are discussed. On this basis, low-altitude remote sensing monitoring of agricultural information by UAV is proposed. It provides technical ideas for agricultural mechanization and informatization practitioners, and further promotes the application and application of UAV remote sensing in precision agriculture. develop.

2 OVERVIEW OF UAV LOW-ALTITUDE REMOTE SENSING

2.1 UAV Low-Altitude Remote Sensing

UAV low-altitude remote sensing agricultural condition monitoring is based on an unmanned aerial vehicle as a platform, equipped with different types of image acquisition equipment according to mission requirements, to quickly obtain agricultural condition data in high-resolution target areas, and to obtain specific results with the help of certain image analysis technology. The UAV remote sensing system mainly consists of UAV, flight control system, positioning system, sensing equipment, stable gimbal (sensor support equipment), communication system, image processing platform (such as MATLAB, Pix4D, ENVI, PhotoScan), etc.[4] .

2.2 Types of Drones

According to different structures, UAVs can be divided into four categories: fixed wing, multi-rotor, helicopter and airship. Fixed-wing aircraft are fast and have long flight times, but they are expensive, have poor hovering capabilities, and are prone to blurry images at high speeds. Small multi-rotor drones can achieve fixed-point hovering, medium and slow speed navigation and It is easy to carry and suitable for fixed-point, high-repeatability, multi-scale, and high-resolution farmland information collection. It is more widely used in remote sensing monitoring of agricultural conditions[5]. None Human helicopters have large rotors, stable flight, and can carry larger equipment, but they are complex to operate, noisy, and costly. Airship drones have It has good hovering ability and load capacity, but its size and weight are large, its stability is poor under windy conditions, and it has few applications in agricultural information monitoring[6].

2.3 Types of Airborne Sensors for Remote Sensing of Agricultural Conditions

As the main component of information acquisition, the performance and quality of airborne sensors are important factors affecting the acquisition and analysis of high-precision crop information[7]. After nearly ten years of development, the performance and quality of airborne sensors used in UAV low-altitude remote sensing agricultural monitoring There are many types of sensors, such as RGB cameras, multispectral cameras, hyperspectral cameras, thermal imagers and lidar[8]. In the initial stage of using drone images to monitor crop growth, due to the limited carrying capacity of drones, most of the research carried out at that time used digital images or multispectral images as data sources. Although images with fine spectral characteristics could not be obtained, But the spatial resolution can reach centimeter level. With the increasing maturity of UAV technology, UAV hyperspectral remote sensing has been used by many scholars to study crop growth monitoring in the agricultural field due to its advantages of strong band continuity, large amount of spectral data and nanometer-level resolution[9], and has become a powerful tool for observing surface crops. The thermal imager receives infrared radiation information of crops through sensors, and can quickly extract large-area crop canopy temperature information, and is mostly used in research on crop drought stress and moisture content analysis[10]. Using lidar to obtain remote sensing point cloud data can also invert ground agricultural information[8].

2.4 Advantages of UAV remote sensing monitoring of agricultural conditions

UAV remote sensing monitoring has fast, maneuverable and strong response capabilities, is suitable for farmland scenes with different planting structures and different terrains, and can provide real-time and accurate remote sensing data to agricultural growers, managers and decision-makers in emergency or non-emergency situations; The cost of UAV remote sensing is low, there is no need to consider the safety of the pilot, there is little cloud interference, and the operating conditions are low; multi-angle aerial photography is used to obtain centimeter-level resolution data in different directions, which can effectively combine three-dimensional canopy height and orthophoto information to improve reflection. The performance accuracy; the strong autonomy of UAV remote sensing can be equipped with different resolutions and different types of sensing equipment according to different requirements, and an efficient remote sensing data information analysis model can be established; UAV remote sensing is correspondingly sensitive to spatially heterogeneous information. In different situations Under the influence of crop and climate conditions, human management conditions and other factors, there are regional differences in farmland on a macro scale. Satellite remote sensing is difficult to overcome the impact of the above factors on the inversion accuracy[11], while UAV remote sensing can be used in low-altitude ranges, conduct research on a small scale and obtain a large amount of high-quality image data.

3 APPLICATION OF UAV LOW-ALTITUDE REMOTE SENSING IN AGRICULTURAL INFORMATION MONITORING

3.1 Crop Growth Monitoring

Growth reflects the status and trend of crop growth in the field. Quickly obtaining crop growth information can provide an important basis for field management decisions. Crop coefficient, Leaf Area Index (LAI), vegetation index, biomass, plant height, photosynthetic pigments Content, etc. are commonly used parameters[12]. In terms of inverting crop growth parameters, analytical methods mainly include methods based on empirical statistical regression and machine learning; image morphological features and spectral features are used for analysis. Analytical methods for pattern recognition; model analysis methods for simulating reflectance using leaf canopy structure and biochemical parameters, and analysis methods based on the combination of multi-source data Method. Gao Lin et al.[13] used remote sensing data to obtain high-precision soybean LAI prediction values. According to the physiological characteristics of the crop, in the red band, red edge band and near-infrared Band, its spectral reflection characteristics are significantly correlated with growth, so regression can be established through multispectral image data and ground measurement data The model inverts crop phenotypic parameters. Chen Peng et al.[14] used UAV multi-spectral images to integrate the spectral information and texture information in the images into a new comprehensive index. The chlorophyll content of potatoes was estimated using the standard. The root mean square error of the comprehensive index model was 2.3% lower than that of the single vegetation index model. Bian et al.[15] used drones Using multispectral cameras and thermal infrared cameras as sensors, a variety of vegetation indices and water stress rates were obtained to provide scientific basis for precise irrigation. Hassan et al.[16] mounted a micro-sequoia sensor on a drone, studied 32 wheat varieties and breeding conditions under different irrigation conditions, and monitored the entire production of wheat. NDVI of the life cycle. The high resolution of hyperspectral can provide richer and continuous data information. Pei Haojie et al.[17] used hyperspectral cameras as sensors to A new index inversion model based on five indicators: leaf area index, leaf chlorophyll content, plant nitrogen content, plant water content and biomass. The accuracy is high, and the standard root mean square error of the model is as low as 0.038. Gao Lin et al.[18] used Cubert UHD185 Firefly imaging in winter wheat experimental fields. The spectrometer conducted a joint air-ground experiment to estimate the

LAI of winter wheat and obtained detailed spectral characteristic information. The study found that the spectral quality in the 458-830 nm band was better. excellent. Tao Huilin et al.[19] used UAV hyperspectral data to analyze the correlation between indices and growth monitoring indicators in different growth periods, and successfully inverted winter Xiaoxiao data. Wheat growth monitoring chart. Hyperspectral imaging and parameter mapping technology can realize the inversion of the spatial distribution of biophysical and chemical parameters of crops at a regional scale, which is more accurate. It provides a reliable basis for agricultural decision-making, but the current parameter map is a prediction model based on semi-empirical relationships, which has certain spatiotemporal limitations; in addition, UAVs carrying hyperspectral data need to weigh the relationship between space, spectral resolution and coverage to obtain Subtle feature information of the target.

3.2 Crop Yield Estimates

Timely prediction of crop yield can provide reliable support for operators to manage planting patterns and formulate crop policies, and has become one of the urgent needs for the development of precision agriculture[20]. UAV low-altitude remote sensing estimates of crop yield are mainly based on obtaining key growth conditions of crops. This can be achieved by establishing a regression model based on period vegetation index, moisture content, height information, etc.[21]. Zhao Xiaoqing et al.[22] used a multi-rotor drone equipped with an imaging hyperspectral sensor monitoring system to obtain soybean hyperspectral data at different spectral spatial scales at different growth stages to construct a vegetation index, and used the least squares method to establish the relationship between yield and vegetation index. The regression model has a correlation as high as 0.811 7. In terms of winter wheat yield estimation, Zhu Wanxue et al.[23] used the least squares method to construct 9 linear models based on different vegetation indexes and winter wheat measured yields. The correlation is good and the optimal The estimated index is EVI2. Md et al.[24] used UAV remote sensing to obtain rice RGB images, used a variety of image processing methods to segment and extract rice, and estimated the rice yield in the area through the area of rice grains. This method manually extracted features. The error is large. Zhang Meina et al.[25] proposed a method to predict cotton yield by merging RGB and CIR spectral images. Based on the panoramic image, they extracted and calculated three characteristic parameters: chroma, plant coverage and normalized vegetation index. Build a predictive model with an average absolute error percentage of 4.0% between estimates and actual values. At present, in terms of crop yield estimation, there are fewer crops involved, mostly concentrated on crops such as rice, wheat, and soybeans. Most of them are estimated by establishing regression models to analyze correlations. There are differences in the different growth stages of crops. Obviously, the accuracy is relatively low. In future research, it is necessary to integrate multiple aspects of crop growth parameters and establish an estimation model suitable for specific crops.

3.3 Crop Nitrogen Diagnosis

The normal growth of crops is inseparable from nutrients such as nitrogen, phosphorus, and potassium. Nitrogen in particular determines the photosynthetic ability and assimilation product ability of crops. Therefore, nitrogen Fertilizer management is one of the important processes to increase crop yield and enhance quality. UAV hyperspectral remote sensing monitors crop nitrogen mainly by retrieving leaf color. Canopy spectral differences caused by changes in color, chlorophyll level, moisture content, etc. can be used to obtain the spatial distribution of crop biophysical and chemical parameters. In nitrogen diagnosis The research focuses on food crops such as rice, winter wheat and corn. In terms of precise fertilization management of rice fields, Qin Zhanfei et al.[26] used imaging hyperspectral data Combining statistical analysis and remote sensing parameter mapping technology to invert the spatial distribution of rice nitrogen content at the regional scale, the root mean square error is only 0.329. In the process of rapid nutrition diagnosis of crops such as corn and wheat, Wei Pengfei et al.[27] collected drone multispectral images and measured leaf nitrogen content in corn planting bases. The data and the established regression model R2 were both higher than 0.5, achieving high-precision monitoring of nitrogen content in summer corn leaves. Liu et al.[28] based on UAV hyperspectral The system acquires wheat canopy images, and combines the artificial neural network method to establish a wheat leaf nitrogen inversion model, which can predict the leaf nitrogen concentration of wheat in different periods. Degree. Jay et al.[29] used UAV spectra to obtain sugar beet canopy images and invert the nitrogen content of the sugar beet canopy. At present, most research on nutrient monitoring focuses on On the construction of the inversion model of crop nitrogen nutrition indicators, and on the basic inversion of crop nitrogen nutrition indicator information and how to judge the nitrogen deficit status There are few studies on the design of variable fertilization methods based on UAV images. Therefore, nitrogen fertilization recommendation methods and models based on UAV images are still needed. Further exploration; complex biochemical components such as lignin, starch, etc. in the process of crop nitrogen retrieval based on UAV hyperspectral imaging remote sensing lead to light Overlapping spectral absorption characteristics will also affect the estimation of nitrogen content.

3.4 Monitoring of crop Diseases, Pests and Weeds

According to statistics from the Food and Agriculture Organization of the United Nations, more than 30% of crop yields are lost every year due to pests, diseases, and weeds, and in severe cases, crops may even fail[30]. It is particularly important to quickly monitor large-scale pests, diseases, and weeds and take effective remedial measures. UAV low-altitude remote sensing has the characteristics of low operating cost, high flexibility and strong real-time ability to obtain data, which gives it incomparable advantages in the rapid detection of crop diseases, insect pests and weeds over a large area[31]. Xue Jinli et al.[32] The UAV carried spectra to acquire cotton seedling images with different low-altitude resolutions, and used the YOLOv3 model to identify weeds in cotton fields, with a recognition rate as high as 94.06%. Gome et al.[33] used UAV remote sensing images to identify weeds in wheat growing areas and control weeds based on the identification results. In agricultural remote sensing, many scholars analyze the sensitive bands of crop growth information and use Use the characteristics of multispectral near-infrared region and red edge region to monitor crop diseases and pests[34]. Hunt et al.[35] used a six-rotor drone equipped with a multispectral camera to obtain potato canopy image information, and used an object-oriented analysis method to accurately determine the degree of potato beetle damage. The principle of hyperspectral remote sensing to detect pests and diseases is to analyze the occurrence of pests and diseases To achieve this, Lan Yubin et al.[36] obtained the UAV low-altitude citrus orchard hyperspectral images and processed the area of interest in the canopy of healthy plants and plants infected with Huanglongbing. For the diagnosis of Huanglongbing, the misjudgment rate on the test set is only 3.36%. Most research on crop diseases and pests information using UAV remote sensing technology focuses on analyzing the relationship between image spectral characteristics and the occurrence degree of pests and diseases. There are few reports on the early diagnosis of crop diseases and pests using UAV remote sensing. If it is to be used in actual agricultural production Promotion and application also need to combine image data with meteorological, water resources and other information, analyze it into operational prescription maps that can guide drone aerial plant protection, and formulate different precise spraying plans according to the characteristics of different regions .

3.5 Crop Lodging Status Monitoring

Crop lodging caused by climate change and disastrous weather will reduce crop photosynthesis and seed setting rates, significantly reducing crop yields[37]; in addition, plant damage caused by lodging provides conditions for the spread of diseases, which will again increase disaster losses[38], so effective monitoring of plant lodging is crucial to reducing plant lodging. It is of great significance to reduce crop losses. The spectral, color and texture characteristics of UAV low-altitude remote sensing images open up new opportunities for lodging monitoring and lodging area calculation. New ideas. Li Zongnan et al.[39] obtained RGB images of lodging corn through drone remote sensing, and analyzed features such as color and texture to calculate the lodging area. Dong Jinhui et al.[40] used machine learning for image classification and estimated the lodging area of wheat using spliced digital images, with a minimum error of 0.3%. Dai Jianguo[41] used UAV multispectral images to analyze spectral reflectance and established a cotton field lodging disaster loss assessment model. The classification results were accurate on the test set. The rate is 91.30% and the AUC value is 0.80. Han et al.[42] used a drone to obtain multispectral and visible light images of lodging corn, and extracted texture and canopy structure. In order to improve the calculation accuracy of corn lodging area, Zhang Xinle et al.[43] used UAV multi-spectral data to gradually extract features and analyze differences, and constructed two types of logistic models based on five types of lodging area extraction. The lodging area extraction method based on typical feature combinations is used to extract the lodging area in the mature stage. The identification of late corn has important reference significance.

3.6 Crop Water Stress Diagnosis

Images obtained by UAV remote sensing at appropriate spatial and temporal resolutions play a very important role in accurately analyzing the spatial variability and interrelationships of agrometeorological conditions, soil moisture content, stress parameters, etc. where crops are located, and can provide a Provide a basis for sensing the spatial variability of crop water shortage within the farmland area. Research in this area at home and abroad is mainly divided into water stress diagnosis methods based on crop parameters and diagnosis methods based on soil moisture content[44]. In terms of UAV remote sensing monitoring of soil moisture, multispectral, hyperspectral remote sensing and multi-spectral remote sensing are used. It is a common method to build a vegetation index model by acquiring single or multiple bands from various sensors. Wang Jingzhe et al.[45] used the image data acquired by hyperspectral drones to establish the difference index, ratio index, normalized index and vertical vegetation index. The relationship with soil moisture content provides reference for the moisture content of oasis farmland in arid areas. Zhang Zhitao et al.[46] used UAV multispectral remote sensing to obtain canopy multispectral orthographic images of corn and winter wheat, and simultaneously collected different root areas. Deep soil moisture content, a machine learning-based relationship model between vegetation index and soil moisture content was constructed. The model R2 was higher than 0.851, and the root mean square error was only 0.7%. For research based on the perception of crop water stress, it has been implemented Monitoring of water stress in cotton[47], tomatoes[48], orchards[49] and vineyards[50]. Using thermal infrared remote sensing to obtain the temperature index of crops can also accurately represent the temperature index or indicator of crop water stress. Some scholars have established vegetation indexes based on specific multispectral bands to monitor crop physiological characteristics and water stress variation information[51]. Commonly used ones include lutein, chlorophyll and canopy structure indexes. Research on water stress based on these three types of indices The stability of its field effect still deserves further exploration. In the process of applying UAV low-altitude remote sensing to crop water stress monitoring, it is necessary to combine the effects of ground observations to improve the accuracy and real-time performance of multi-source spatio-temporal information fusion.

4 SHORTCOMINGS AND FUTURE DEVELOPMENT TRENDS IN UAV LOW-ALTITUDE REMOTE SENSING MONITORING OF AGRICULTURAL INFORMATION

4.1 Shortcomings in Current Research on UAV Low-Altitude Remote Sensing Monitoring of Agricultural Information

Research on UAV low-altitude remote sensing in agricultural conditions monitoring has shown exponential growth in the past decade. Generally speaking, UAV remote sensing systems have achieved many significant results in the promotion and application of agricultural conditions monitoring, but current research still has deficiencies, there are mainly the following problems: (1) Although UAV flight control technology has made great progress in recent years, the flight stability and intelligence level in the UAV remote sensing monitoring process are faced with complex problems. There are certain limitations in the operating environment. On the one hand, UAVs cannot withstand large load capacity, and factors such as the sensor accuracy, battery life and communication distance they carry will affect the practicality of UAV remote sensing monitoring[52] On the other hand, UAVs are greatly affected by the external environment, and it is difficult to carry out corresponding flight monitoring work in rainy and windy weather, resulting in reduced applicability. Although the flight control uses synovial membrane variable structure control and anti-interference technology The algorithm can cope with the influence of wind to a certain extent[53 ¡ 54], but the remote sensing image information obtained by UAVs has a lot of jitter and noise information, and needs to go through a highly professional and cumbersome pre-processing process[55]. The processing results have a greater impact on the accuracy of subsequent data analysis and model inversion. large impact, which also limits its wide applicability in agriculture.
(2) A single sensor mounted on a UAV low-altitude remote sensing system cannot fully reflect field and crop phenotypic information. How to comprehensively use different remote sensing information to improve monitoring accuracy and expand monitoring scope requires further thinking. With the miniaturization and intelligence of airborne sensors, some scholars have studied multi-source data to simultaneously monitor farmland information. For example, Gao Lin et al.[56] used a combination of digital images and hyperspectral imaging data to comprehensively estimate corn biomass. However, current research on multi-source data fusion to analyze crop phenotypic information is still limited. In complex agricultural environments, the combination of data should not be limited to the fusion of two or more sensors. Research by Han Wenting et al.[57] shows that Changes in spatial relationships will affect the specificity of target analysis. Field spatial changes can be obtained through a variety of methods, especially nanosatellites. Information such as soil fertility can also be extracted through historical yield maps, soil conductivity measurements, or tractor-based Remote sensing, combining information from all these resources, can provide certain assistance for the management decision-making process. How to efficiently integrate imaging spectral data with spatial configuration data, as well as UAV remote sensing data, satellite remote sensing data and ground monitoring data, etc. The application of fusion of space-sky-earth integrated data still requires further research.
(3) In the research on agricultural information monitored by UAV remote sensing, the impact of spatiotemporal transformation on the acquisition and analysis of crop phenotypic information was not considered. In crop production At different stages of growth, the spectral and texture characteristics are also different. Current agricultural information monitoring research based on UAV remote sensing is mostly based on single It is rare to obtain crop phenotypic data for multiple consecutive growth periods. There are few inversion parameters and insufficient representativeness, making it difficult to accurately express the true characteristics of crops. Parameters such as real growth trend and index. Therefore, it is necessary to continuously monitor the crop growth process and explore periodic and dynamic monitoring models for agricultural information.[58]. After obtaining data from UAV low-altitude remote sensing, the establishment of crop index inversion, yield estimation, nitrogen assessment and crop growth stress model are often based on experience. It is mainly based on experience, and separate modeling is needed to analyze different types of crop phenotypic information. Currently, no one has developed a universal method for UAV remote sensing monitoring research. model or parameter library for adjusting crops[6]. Although many scholars use indicators such as vegetation index and growth parameters to use empirical statistical regression and machine learning to The method[8] has been successfully used to analyze agricultural information such as crop coverage, plant height, lodging area, biomass, leaf area index, canopy temperature, water stress, etc. However, for most crops and their indicators, the model's Stability, accuracy and universality still need to be further studied. In addition, for remote sensing information acquisition There are few subsequent studies on precise management applications such as target distribution maps and nitrogen monitoring level maps. Therefore, there is an urgent need to develop efficient surface object recognition and information Extract and analyze models to form certain standards and common methods.

4.2 UAV Low-Altitude Remote Sensing Application Prospects and Development Trends

4.2.1 The breadth and depth of remote sensing monitoring applications of agricultural conditions continue to expand

UAV remote sensing monitoring technology has significant advantages and broad application prospects in obtaining agricultural information, and has become one of the important means to efficiently obtain field and crop phenotypic information and carry out modern agricultural management. Current UAV remote sensing monitoring Most of the research objects are concentrated on crops such as corn, wheat, rice, cotton, and soybeans. There are fewer studies on potatoes, vegetables, and forestry and fruit industries. Moreover, the number of crop varieties included in the research is small, and it is impossible to achieve comprehensive analysis only by relying on single crop information. Information analysis of complex agricultural conditions. Therefore, in the future development process, the depth and breadth of UAV remote sensing in agricultural information monitoring should be continuously broadened to provide more theories and technologies for low-altitude remote sensing to obtain and analyze precise agricultural information. support.

4.2.2 Research and development direction of low-cost and miniaturized airborne sensing equipment

Low-altitude remote sensing based on UAVs has great advantages in acquiring and analyzing agricultural information, such as rapid field sampling, high-throughput and high-resolution Data types, rapid acquisition of growth parameters, rapid image synchronization, high-efficiency operation methods, etc. However, current UAV low-altitude remote sensing equipment such as high-speed Spectrometers, thermal imagers, etc. are expensive, which greatly limits the application and promotion of low-altitude remote sensing information acquisition by UAVs. The size of airborne sensing equipment is difficult for unmanned aerial vehicles. The endurance and flexibility of UAVs during flight are greatly affected. There is an urgent need to develop airborne sensing equipment with low cost, small size, light weight and strong versatility to promote the promotion of UAV low-altitude remote sensing technology in agriculture.

4.2.3 The exploration of drone multi-source data fusion technology continues to deepen

Sensors in different bands have different capabilities and characteristics in obtaining information. UAV multi-load sensors perform collaborative observation and data fusion processing. Technology is of great significance for efficiently retrieving crop information and applying it to the daily practice of precision agriculture. Taking crop disease information monitoring as an example, remote sensing data The data can provide surface continuous data. Combined with UAV multi-spectral data in key areas, it can provide point-like continuous phase data[58]. Therefore, future research should focus on utilizing the complementarity of spectral data and thermal data, the coupling of remote sensing data and ground observation data, the matching of high-altitude satellite and low-altitude spectral data, and continuously exploring the fusion technology of multi-source data to integrate Observe data and build a crop information analysis model with strong versatility, high accuracy and wide application to provide more solid guarantee for precision management of modern agriculture.

4.2.4 Standardization of remote sensing monitoring technology and promotion of easy-to-operate solutions

UAV agricultural condition remote sensing information monitoring requires professional skills in flight control technology, data analysis and modeling and other operations, especially the processing capabilities of thermal data and hyperspectral data, which places high demands on technical personnel. Therefore, it is necessary to research and promote standardized and easy-to-operate full-process technical solutions for processing procedures, so that users can independently obtain and analyze agricultural information, and allow non-expert users to control drones, hyperspectral and thermal sensors, etc. Data processing is used in daily operations to further expand the application scope of UAV low-altitude remote sensing platforms in precision agriculture.

5 CONCLUSION

As an important information acquisition method for modern precision agriculture, UAV low-altitude remote sensing can carry a variety of different sensing loads at the same time and is often used in agriculture. Airborne sensing equipment for remote sensing monitoring mainly includes RGB cameras, multispectral cameras, hyperspectral cameras, thermal imagers, and lidar. Their characteristics of high timeliness, high resolution, and low cost make them useful in monitoring agricultural information. The unique advantage has become the perception and analysis of crop phenotypic information in precision agriculture. Research hotspots. In remote sensing agricultural monitoring, through crop growth monitoring, yield estimation, nitrogen diagnosis, pests and diseases monitoring, lodging monitoring, crop water Stress analysis can formulate precise operation plans for field management, which has important theoretical support and technical application value for promoting modern agricultural production.

Although the current agricultural monitoring operations based on drone remote sensing have achieved certain results, there are still difficulties in meeting the diverse needs of users, including the difficulty in covering the complex agricultural reality in terms of breadth and depth of research; the high cost and versatility of sensors Low promotion rate due to low; remote sensing data The single nature of the data cannot fully represent the crop growth information; the data analysis process is highly professional and has not yet formed a highly versatile and easy-to-operate solution. There is no doubt that UAV remote sensing technology will continue to develop and further expand its application areas in precision agriculture. UAV sensor quality and performance The trend of improving performance and user-friendliness will continue, and a complete set of technical solutions that are easy to operate, highly versatile, and high-precision will be promoted to ordinary people. users, enabling non-expert users to apply UAV remote sensing monitoring systems to daily operations.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] He Yong, Cen Haiyan, He Liwen. Agricultural UAV technology and its applications. Beijing: Science Press, 2018: 232-233.

[2] Huang Yiqi, Liu Qi, Zhao Jianye. Research on mangrove drone monitoring based on convolutional neural network. Chinese Journal of Agricultural Mechanization, 2020, 41(2): 141-146+189.
[3] SIEBERTH T, WACKROW R, CHANDLER J H. Automatic detection of blurred images in UAV image sets. ISPRS Journal of Photogrammetry and Remote Sensing, 2016, 122: 1-16.
[4] Wang Pei, Luo Xiwen, Zhou Zhiyan. Review of key technologies for remote sensing information acquisition based on micro-UAVs. Chinese Journal of Agricultural Engineering, 2014, 30(18): 1-12.
[5] Li Xiaopeng, Hu Pengcheng, Xu Zhaoli. Method and application of rapidly acquiring field plant images based on quad-rotor drones. Journal of China Agricultural University, 2017, 22(12): 131-137.
[6] Liu Jiangang, Zhao Chunjiang, Yang Guijun. Research progress in analyzing field crop phenotypic information using UAV remote sensing. Chinese Journal of Agricultural Engineering, 2016, 32(24): 98-106.
[7] Zhao Peng, Shen Tingzhi, Shan Baotang. Design of micro-UAV remote sensing system based on CMOS image sensor. Acta Photonics, 2008(8): 1657-1661.
[8] Liu Zhong, Wan Wei, Huang Jinyu. Research progress on inversion of key parameters of crop growth based on UAV remote sensing. Chinese Journal of Agricultural Engineering, 2018, 34(24): 60-71.
[9] AASEN H, BURKART A, BOLTEN A. Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance. ISPRS Journal of Photogrammetry and Remote Sensing, 2015, 108: 245-259.
[10] SANTESTEBAN LG, DI SF, HERRERO A. High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard. Agricultural Water Management, 2017, 183: 49-59.
[11] Han Wenxuan, Arifu Kurban, Huang Zitong. Rapid detection of small targets in remote sensing images based on improved SSD algorithm. Journal of Xinjiang University (Natural Science Edition) (Chinese and English), 2020, 37(2): 163-169.
[12] Shao Guomin. Research on field corn crop coefficient estimation method based on UAV multispectral remote sensing. Yangling: Northwest A&F University, 2018.
[13] Gao Lin, Li Changchun, Wang Baoshan. Comparison of soybean leaf area index estimation accuracy based on multi-source remote sensing data. Journal of Applied Ecology, 2016, 27(1): 191-200.
[14] Chen Peng, Feng Haikuan, Li Changchun. Estimating chlorophyll content of potato leaves using spectral and texture fusion information from drone images. Transactions of the Chinese Society of Agricultural Engineering, 2019, 35(11): 63-74.
[15] BIAN J, ZHANG Z, CHEN J. Simple evaluation of cotton water stress using high resolution unmanned aerial vehicle thermal imagery. Remote Sensing, 2019, 11(3): 267.
[16] HASSAN MA, YANG MJ, RASHEED AY. A rapid monitoring of NDVI across the wheat growth cycle for grain yield prediction using a multi-spectral UAV platform. Plant science: an International Journal of Experimental Plant Biology, 2019, 282: 95-103.
[17] Pei Haojie, Feng Haikuan, Li Changchun. UAV remote sensing monitoring of winter wheat growth based on comprehensive indicators. Chinese Journal of Agricultural Engineering, 2017, 33(20): 74-82.
[18] Gao Lin, Yang Guijun, Yu Haiyang. Winter wheat leaf area index inversion based on UAV hyperspectral remote sensing. Chinese Journal of Agricultural Engineering, 2016, 32(22): 113-120.
[19] Tao Huilin, Xu Liangji, Feng Haikuan. Winter wheat growth monitoring based on UAV hyperspectral growth indicators. Journal of Agricultural Machinery, 2020, 51(2): 180-191.
[20] NEUMANN K, VERBURG PH, STEHFEST E. The yield gap of global grain production: A spatial analysis. Agricultural Systems, 2010, 103(5): 316-326.
[21] TEWES A, SCHELLBERG J. Towards remote estimation of radiation use efficiency in maize using UAV-based low-cost camera imagery. Agronomy, 2018, 8(2): 16.
[22] Zhao Xiaoqing, Yang Guijun, Liu Jiangang. Soybean breeding yield estimation based on UAV-borne hyperspectral spatial scale optimization. Chinese Journal of Agricultural Engineering, 2017, 33(1) 110-116.
[23] Zhu Wanxue, Li Shiji, Zhang Xubo. Field-scale winter wheat yield estimation based on UAV remote sensing vegetation index optimization. Chinese Journal of Agricultural Engineering, 2018, 34(11): 78-86.
[24] MD NR, SEOP N, SUN W B. Rice yield estimation based on K-means clustering with graph-cut segmentation using low-altitude UAV images. Biosystems Engineering, 2019, 177: 109-121.
[25] ZHANG MN, FENG AJ, ZHOU JF. Cotton yield prediction using remote visual and spectral images captured by UAV system. Transactions of the Chinese Society of Agricultural Engineering, 2019, 35(5): 91-98.
[26] Qin Zhanfei, Chang Qingrui, Xie Baoni. Estimation of total nitrogen content of rice leaves in the Yellow River irrigation area based on UAV hyperspectral images. Transactions of the Chinese Society of Agricultural Engineering, 2016, 32(23): 77-85.
[27] Wei Pengfei, Xu Xingang, Li Zhongyuan. Remote sensing estimation of summer corn leaf nitrogen content based on UAV multispectral images. Chinese Journal of Agricultural Engineering, 2019, 35(8): 126-133.
[28] LIU HY, ZHU HC, WANG P. Quantitative modeling for leaf nitrogen content of winter wheat using UAV-based hyper-spectral data. International Journal of Remote Sensing, 2017, 38(8/9/10): 2117-2134.
[29] JAY S, MAUPAS F, BENDOULA R. Retrieving LAI, chlorophyll and nitrogen contents in sugar beet crops from multi-angular optical remote sensing: Comparison of vegetation indices and PROSAIL inversion for field phenotyping. Field Crops Research, 2017, 210: 33-46.

[30] Jia Shaopeng, Gao Hongju, Hang Xiao. Research progress in image recognition technology of crop diseases and pests based on deep learning. Journal of Agricultural Machinery, 2019, 50(S1): 313-317.
[31] Tian Zhiwei, Xue Xinyu, Li Lin. Research status and prospects of plant protection drone pesticide application technology. Chinese Journal of Agricultural Mechanical Engineering, 2019, 40(1): 37-45.
[32] Xue Jinli, Dai Jianguo, Zhao Qingzhan. Weed detection in cotton fields based on low-altitude drone images and YOLOv3. Journal of Shihezi University (Natural Science), 2019, 37(1): 21-27.
[33] GOME Z-CAND ND, CASTRO AID, LPEZ-GRANADOS F. Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat. Precision Agriculture, 2014, 15(1): 44-56.
[34] JINYA S, CUNJIA L, MATTHEW C. Wheat yellow rust monitoring by learning from multispectral UAV aerial imagery. Computers and Electronics in Agriculture, 2018, 155: 157-166.
[35] HUNT ER, HIVELY WD, FUJIKAWA SJ. Acquisition of NIR green-blue digital photographs from unmanned aircraft for crop monitoring. Remote Sensing, 2010, 2(1): 290-305.
[36] Lan Yubin, Zhu Zihao, Deng Xiaoling. Monitoring and classification of citrus Huanglongbing plants based on UAV hyperspectral remote sensing. Chinese Journal of Agricultural Engineering, 2019, 35(3): 92-100.
[37] Zhou Ping, Zhou Kai, Liu Tao, etc. Research progress on rice lodging monitoring. Chinese Journal of Agricultural Mechanization, 2019, 40(10): 162-168.
[38] Zhao Lixin, Li Fanmao, Li Yan. Research prospects on upright crop lodging monitoring based on UAV platform. Chinese Journal of Agricultural Mechanization, 2019, 40(11): 67-72.
[39] Li Zongnan, Chen Zhongxin, Wang Limin. Extraction of corn lodging area based on small UAV remote sensing. Chinese Journal of Agricultural Engineering, 2014, 30(19): 207-213.
[40] Dong Jinhui, Yang Xiaodong, Gao Lin. Extraction of winter wheat lodging area information based on UAV remote sensing images. Heilongjiang Agricultural Sciences, 2016(10): 147-152.
[41] Dai Jianguo, Zhang Guoshun, Guo Peng. Cotton lodging information extraction based on UAV remote sensing multispectral images. Chinese Journal of Agricultural Engineering, 2019, 35(2): 63-70.
[42] HAN L, YANG G, FENG H. Quantitative identification of maize lodging-Causing feature factors using unmanned aerial vehicle images and a nomogram computation. Remote Sensing, 2018, 10(10): 3-19.
[43] Zhang Xinle, Guan Haixiang, Liu Huanjun. Extraction of corn lodging area at mature stage based on UAV multispectral images. Chinese Journal of Agricultural Engineering, 2019, 35(19): 98-106.
[44] Han Wenting, Zhang Liyuan, Niu Yaxiao. Research progress on the application of UAV remote sensing technology in precision irrigation. Journal of Agricultural Machinery, 2020, 51(2): 1-14.
[45] Wang Jingzhe, Ding Jianli, Ma Xuankai. UAV hyperspectral detection of soil moisture content in oasis farmland based on spectral index. Journal of Agricultural Machinery, 2018, 49(11): 164-172.
[46] Zhang Zhitao, Tan Chengxuan, Xu Chonghao. Research on corn root soil moisture content based on UAV multispectral remote sensing. Journal of Agricultural Machinery, 2019, 50(7): 246-257.
[47] COHEN Y, ALCHANATIS V, SELA E. Crop water status estimation using thermography: multi-year model development using ground-based thermal images. Precision Agriculture, 2015, 16(3): 311-329.
[48] EGEA G, PADILLA-DIAZ C M, MARTINEZ-GUANTER J. Assessing a crop water stress index derived from aerial thermal imaging and infrared thermometry in super-high density olive orchards. Agricultural Water Management, 2017, 187: 210-221.
[49] BERNI J A J, ZARCO-TEJADA P J, SEPULCRE-CANT G. Mapping canopy conductance and CWSI in olive orchards using high resolution thermal remote sensing imagery. Remote Sensing of Environment, 2009, 113(11): 2380-2388.
[50] ESPINOZA CZ, KHOT LR, SANKARAN S. High resolution multispectral and thermal remote sensing-based water stress assessment in subsurface irrigated grapevines. Remote Sensing, 2017, 9(9): 961.
[51] DANGWAL N, PATEL NR, KUMARI M. Monitoring of water stress in wheat using multispectral indices derived from Landsat-TM. Geocarto International, 2015, 31(6): 682-693.
[52] Ji Jingchun, Zhao Yuan, Zou Xiaojuan. Application progress of UAV remote sensing in farmland information monitoring. Acta Soil Science, 2019, 56(4): 773-784.
[53] Zhang Zhili. Simulation research on flight stability control model of UAV with wind resistance. Computer Simulation, 2017, 34(2): 115-118.
[54] Shi Tengfei. Research on wind resistance performance of quad-rotor UAV based on automatic disturbance rejection algorithm. Baoding: North China Electric Power University, 2017.
[55] Sun Gang, Huang Wenjiang, Chen Pengfei. Application progress of multispectral remote sensing technology of light and small UAVs. Journal of Agricultural Machinery, 2018, 49(3): 1-17.
[56] Gao Lin, Yang Guijun, Li Changchun, etc. Application of UAV frame hyperspectral remote sensing based on leaf area index fitting method combining spectral characteristics and PLSR. Journal of Crop Science, 2017, 43(4): 549-557.
[57] Han Wenting, Zhang Liyuan, Zhang Haixin. Extraction of field canal distribution information based on UAV remote sensing and object-oriented method. Journal of Agricultural Machinery, 2017, 48(3): 205-214.
[58] ZHANG J, PU R, HUANG W. Using in-situ hyperspectral data for detecting and discriminating yellow rust disease from nutrient stresses. Field Crops Research, 2012, 134(A203): 165-174 .