A BIBLIOMETRIC-BASED ANALYSIS OF RESEARCH PROGRESS IN UNMANNED AERIAL REMOTE SENSING OF WHEAT
/
基于文献计量的小麦无人机遥感研究进展分析

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ABSTRACT
To gain a comprehensive understanding of the current status of unmanned aerial vehicle (UAV) technology in wheat crop growth monitoring and its development trajectory, this paper quantifies and visualizes the relevant literature published between 2015 and 2024 in the Web of Science database. By conducting a comprehensive analysis of high-frequency keywords, the article presents a summary of the prevailing research topics in this field. This can assist researchers in further familiarizing themselves with the relevant literature and providing a novel perspective on the utilization of UAV technology in wheat crop growth monitoring.

摘要
为深入探究无人机技术在小麦作物生长监测中的应用现状及其发展趋势，本文对 Web of Science 数据库中 2015 至 2024 年间发表的相关文献进行了量化与可视化分析。文章通过深入分析高频关键词等，归纳该领域的主流研究热点,可以帮助研究者进一步熟悉该领域相关文献，为理解无人机技术在小麦作物生长监测中的应用提供全新的视角。

INTRODUCTION
Wheat is the primary grain crop in China, comprising 25% of the total grain production area. China is the world's largest producer and exporter of wheat, and its production is closely linked to global food security. In 2023, wheat production decreased slightly by 0.9% to 134.53 million tons. The stable increase in production remains a significant challenge for China's agriculture sector. Standardized cultivation necessitates efficient monitoring and forecasting capabilities (*Andrés et al., 2023*). The conventional approach to measuring crop loss, relying on sampling, is limited in precision and lacks the necessary accuracy for precision agriculture. Consequently, the advancement of rapid and precise monitoring technology is vital for the progress of intelligent agriculture. At present, *Phang et al., (2023*), mainly discusses the differences between satellites and drones in data collection and introduces the advantages of drone remote sensing in data collection and analysis. *Maes et al., (2019),* focused on analyzing the research progress of drone remote sensing technology in the areas of drought stress, weed and pathogen detection, nutritional status and growth vigor assessment, and yield prediction. *Sishodia et al., (2020)*, based on the analysis of remote sensing systems and remote sensing technology applications in agriculture, studied vegetation indices commonly used in remote sensing analysis to help scientists understand the spatial and temporal variations of crops. Most of these reviews focus on the progress of UAV applications in agriculture, with fewer articles providing a systematic summary of the field of remote sensing extraction of wheat crops.

Scientific literature databases are collections of disciplinary knowledge constructed by scholars in related fields, which carry the recording and dissemination of disciplinary knowledge (*Bornmann et al., 2020; Garg et al., 2016*). Statistical analysis of literature data can reveal current research hotspots, quickly capture the latest research trends, and effectively predict future research trends. In recent years, scholars have conducted analyses on remote sensing research on crop growth monitoring (*Wang et al., 2019*), crop monitoring in smallholder farms using unmanned aerial vehicles (*Gokool et al., 2023*), and the application of machine learning methods in agricultural management *(Zhang et al., 2021)* based on bibliometric analysis. However, there are few reports on bibliometric analysis in the field of specific crop monitoring such as wheat.

In light of the aforementioned considerations, this paper utilizes a bibliometric methodology to categorize and examine the literature related to the monitoring wheat crops via unmanned aerial vehicles (UAVs). The number of countries of origin, authors, journals and keywords in this field over the past ten years are analyzed in order to offer a comprehensive overview of the development trajectory and evolution of research hotspots in the domain of remote sensing-based wheat crop extraction.

MATERIALS AND METHODS

Data source

This paper presents a specific search strategy constructed based on the Advanced search function in the WOS (Web of Science) core collection database, through which relevant literature can be filtered. Boolean logic operation rules were applied to construct the following search formula: The following search formula was constructed: “TS = (("UAV" OR "unmanned aerial vehicle" OR "remotely piloted aircraft") AND ("RGB*" OR "multispectral*" OR "hyperspectral*") AND ("winter wheat" OR "wheat culture" OR "wheat cereal" OR "wheat*"))”. The search was conducted between 1 January 2015 and May 2024, and only articles were included. After screening the search criteria, 548 literature records were initially obtained. The records were then subjected to further screening and cleaning in order to guarantee the accuracy and relevance of the data. By eliminating data that was unrelated to the topic and performing de-emphasis and merging processes, 347 valid documents were ultimately identified as the basis for subsequent analyses. These will provide a reference basis for future related studies.

Research tools and methods

In this paper, the research data were mapped and analyzed with the help of the VOSviewer and CiteSpace software. VOSviewer was utilized to map authorship and keyword co-occurrence due to its diversified visual functions in the areas of keywords, co-institutions, and co-authors, as well as its user-friendly mapping process and aesthetic image presentation. Meanwhile, the HistCite software was employed to categorize and extract data on a number of parameter indicators, including authors, countries, institutions, journals, and highly cited papers. Furthermore, an in-depth visualization and analysis of geographical collaboration networks among different countries were conducted in conjunction with VOSviewer and Scimago Graphica software.

Countries of citing papers analysis

The collaboration of national institutions in scientific research is increasingly recognized as a valuable avenue for accessing supplementary scientific resources, sharing, and the overall advancement of scientific research capabilities (*Han et al., 2022*). Using the VOSviewer software, a geographic network view of scientific research cooperation encompassing 42 countries was constructed (Figure 1).

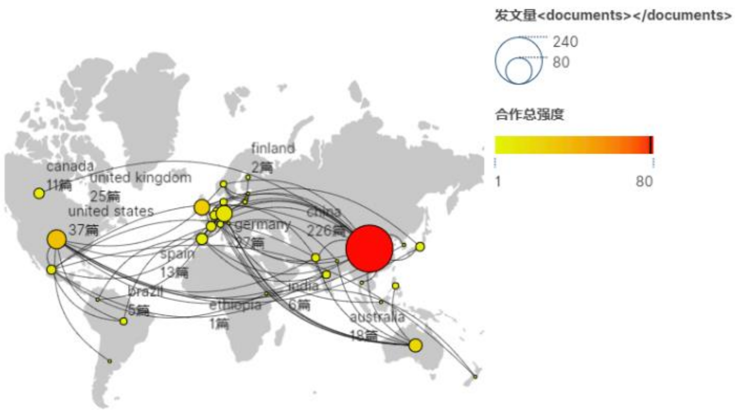

Fig. 1 - Network map of cooperation between the countries in the world in terms of publications

The size of the nodes is directly proportional to the quantity of articles sent by each country; thus, the larger the node, the greater the volume of articles. The thickness of the connecting line between nodes indicates the strength of the cooperation relationship between countries. A thicker line signifies a greater number of articles sent by the cooperating countries. Node color represents the level of intensity of the cooperation.

As illustrated in Figure 1, China and the United States demonstrate the most robust collaboration within the global scientific research network. The two countries have jointly published an impressive 30 papers, representing 13.27% and 81.08% of their respective total output. The two countries initially established a research partnership in 2017, subsequently reaching a peak in the number of co-authored papers in 2022.

Furthermore, China and the United Kingdom have also engaged in considerable scientific cooperation, with a total of 17 co-authored papers. Additionally, China and Germany have collaborated on nine scientific papers. These findings illustrate that China plays a pivotal role in international scientific research cooperation, maintaining active and frequent collaboration with numerous countries.

Authors of citing papers analysis

A comprehensive examination of the researcher community enables the identification of the most influential scholars and the primary research strengths in the field. In the domain of unmanned aerial vehicle wheat monitoring, there are 1,386 active authors. Of these, authors with only one paper account for 69.77% of the total, which is consistent with the Lotka-Price law (*Irene et al., 2013*).

Table 1 presents the ten most prolific authors in the field of unmanned aerial vehicle (UAV) applications in wheat research. Yan Zhu, a prominent researcher in the field, leads the ranking with her exceptional research output. The next most prolific researchers are Cao Satellite and Yang Guijun, who have published 23 and 18 articles, respectively. It is noteworthy that all of the top ten authors are based in China, with six of them affiliated with Nanjing Agricultural University. This observation suggests that Chinese scholars are at the forefront of academic research in the field of UAV remote sensing applied to wheat crops, and that Nanjing Agricultural University, as a leading agricultural university in China, has achieved significant advancements in this area.

Table 1

Top 10 authors in the world in terms of number of publications

Author	Institution	Papers	Local citation score / LCS	Global citation score / GCS
Zhu Yan	Nanjing Agricultural University	25	6	830
Cao Weixing	Nanjing Agricultural University	23	6	700
Tian Yongchao	Nanjing Agricultural University	18	1	710
Yang Guijun	Beijing Academy of Agricultural and Forestry Science	18	86	1258
Cheng Tao	Nanjing Agricultural University	17	5	563
Feng Haikuan	Nanjing Agricultural University	16	56	988
Yao Xia	Nanjing Agricultural University	15	1	594
Li Zhenhai	Technology Center for Information Agriculture	14	20	720
Liu Tao	Yangzhou University	10	1	64
Sun Chengming	Yangzhou University	10	1	49

Keywords of citing papers analysis

As the fundamental element of academic papers, the co-occurrence analysis of keywords can elucidate the research focal points and trends within particular scientific disciplines (*Dong et al., 2022*). In this study, the VOSviewer software was employed to map the keyword density of 347 documents. It should be noted that some keywords may not be fully represented in the images due to the scale. In order to provide a more accurate representation of the research focus, the keywords with a frequency of at least 5 were selected for visualization.

As illustrated in Figure 2, the brightness of a keyword is directly proportional to its frequency of occurrence in the literature. In other words, the higher the brightness, the higher the frequency of occurrence of the keyword. Through the graphical analysis, it was found that, with the exception of unmanned aerial vehicle, high-frequency keywords such as vegetation indexes, leaf area index, biomass, and chlorophyll content constituted the representative terms in the field. Therefore, the in-depth analysis and discussion of these keywords are of great significance for understanding the current research status and future directions in this field.

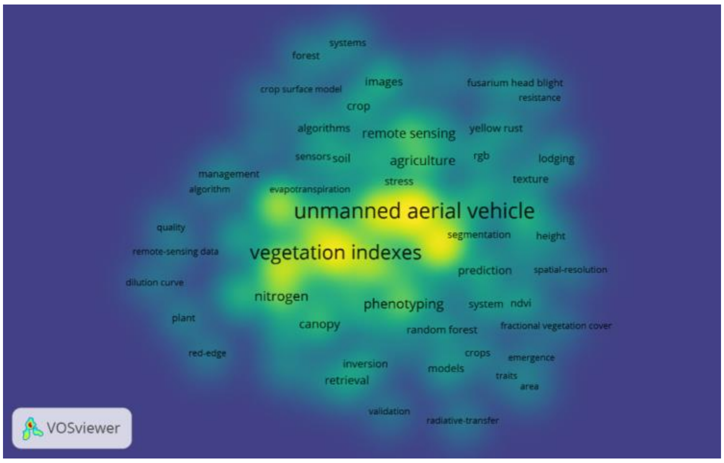

Fig. 2 – Keyword density map

The keyword density map intuitively reveals the research focus in this field. To deeply analyze the specific context of keywords, this paper selected the keywords with a frequency exceeding 15 in the map and organized them into Table 2. Through the detailed analysis of Table 6 and further research combined with the chart, it can be known that high-frequency keywords such as "prediction" and "classification" clearly highlight the core objectives of wheat remote sensing data research based on unmanned aerial vehicle technology. Specifically, that is, through the in-depth analysis and processing of unmanned aerial vehicle data, it is committed to achieving accurate prediction of wheat yield. The realization of this goal is of key significance for the scientific planning and rational allocation of resources in agricultural production, and is directly related to the improvement of agricultural economic benefits and the guarantee of national food security.

Table 2

High frequency keywords(frequencies≥15)

Sequence	Keyword	Keyword count	Sequence	Keyword	Keyword count
1	vegetation indexes	202	11	Nitrogen	50
2	Yield	116	12	Remote sensing	46
3	Unmanned aerial vehicle	111	13	Plant height	37
4	Leaf area index	109	14	Canopy	25
5	Biomass	91	15	Disease	24
6	Chlorophyll content	77	16	Algorithm	20
7	Reflectance	70	17	Prediction	20
8	Machine learning	64	18	Classification	16
9	Models	64			
10	Deep learning	57			

In addition, high-frequency keywords such as "Yield", "leaf area index", "biomass", "chlorophyll content", "nitrogen" and "disease" all clearly point to the key directions of unmanned aerial vehicle data research. The importance of wheat yield monitoring for agricultural management and national food security is self-evident. It is not only a key indicator for measuring the efficiency of agricultural production, but also directly affects the stability of national grain reserves and market supply. In actual production, accurate yield prediction helps farmers to reasonably arrange planting plans and optimize resource investment, and also provides an important basis for the government to formulate agricultural policies and ensure food security.

At the same time, keywords such as "machine learning" and "deep learning" clearly reflect the main methods of unmanned aerial vehicle remote sensing data analysis. Especially machine learning has gradually developed into the mainstream technology in this field in recent years.

This is mainly because machine learning algorithms have powerful pattern recognition and data mining capabilities when dealing with large-scale, high-dimensional unmanned aerial vehicle remote sensing data. It can automatically extract valuable information and features from complex data, thereby providing strong support for accurate wheat yield prediction and growth status assessment. Compared with traditional data analysis methods, machine learning methods show significant advantages in accuracy, generalization ability and adaptability, and can better cope with the diversity and complexity of unmanned aerial vehicle remote sensing data.

In order to gain a deeper understanding of the development process in this research area, this paper utilizes the CiteSpace software to analyze the evolution of keywords and to create a map of the keywords' time zones (Figure 3). Figure 3 illustrates the evolution of keywords over time. Each time period is represented by a vertical axis, and the keywords are displayed as annuli, with the size of the annulus indicates the frequency of keyword appearances and the color marking the time of keyword appearances. The connecting lines indicate the co-occurrence of keywords, thereby revealing the evolution of the research theme and the cross-disciplinary trend.

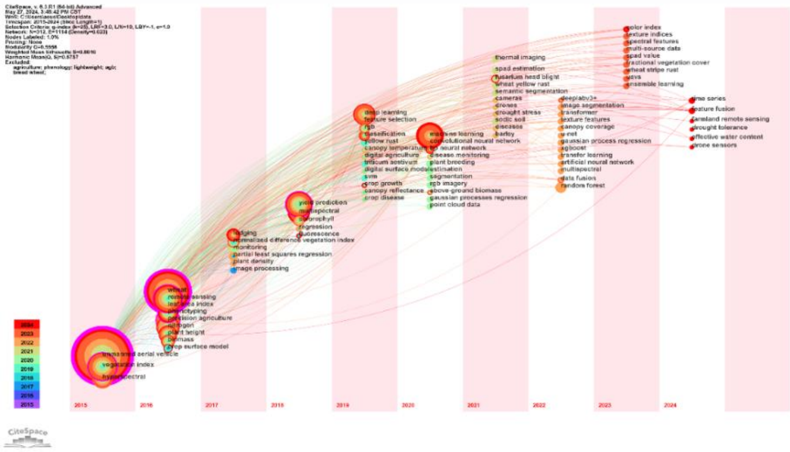

Fig. 3 - The mapping of keyword co-occurrence time zone

Figure 3 illustrates the uniform distribution of high-frequency keywords across time zones, which demonstrates the continuous development of this research field and the expansion of its scope. With regard to the acquisition of data, the initial focus was on hyperspectral, multispectral and RGB data (*Yang et al., 2022; Kang et al., 2024; Ma et al., 2023*), which subsequently gave way to the utilization of integrated multi-source remote sensing data, encompassing hyperspectral and multispectral, visible and hyperspectral, RGB and multispectral, and other combinations. etc. which reflects the increasing depth of research on the use of unmanned aerial vehicles (UAVs) for remote sensing data acquisition over the past decade (*Liu et al., 2023; Yue et al., 2021; Ding et al., 2022*). *Ding et al., (2020)*, employed a UAV to obtain multispectral, RGB, and thermal infrared images, subsequently constructing a multi-source fusion dataset to predict nitrogen content in wheat. Compare with traditional monitoring methods, unmanned aerial vehicle technology has higher precision in wheat growth monitoring and agricultural production management. Traditional manual monitoring methods are not only time-consuming and labor-intensive, but also prone to errors. While unmanned aerial vehicles can cover a wide area in a short time, and the obtained data is more accurate and comprehensive, which can provide a more reliable basis for agricultural production management.

The study of unmanned acquisition of information related to the growth process of wheat has emerged as a new and prominent area of research. The frequent appearance of keywords such as leaf area index, plant height, and nitrogen underscore the crucial role of wheat growth monitoring in attracting the attention of scholars (*Song et al., 2020; Yue et al., 2017; Liu et al., 2020*) making it a major focus of research. *Chen et al., (2019), Chen et al., (2020), Gao et al., (2016*) employed hyperspectral images to estimate the leaf area index. *Li et al., (2023); Wang et al., (2024),* employed multispectral images to estimate the leaf area index. *Tao et al., (2020*), gathered hyperspectral images from an unmanned aerial vehicle (UAV) to ascertain the yield and plant height of wheat. *Wang et al., (2020)*, monitored the nitrogen content of wheat with the aid of hyperspectral data. The research on these parameters can help researchers understand the growth mechanism of wheat, grasp the dynamic changes of wheat growth in real time, adjust field management strategies in a timely manner, and improve yield and quality.

With respect to the research objectives, phenotyping constituted an early and consistent research focus in the field (*Wan et al., 2021*). Since 2018, research has also gradually shifted towards prediction studies and inversion techniques (*Han et al., 2021*). *Zhu et al., (2024),* proposed a genetic algorithm-improved support vector machine algorithm for estimating wheat growth and yield in a trial of 12 wheat varieties and 3 levels of nitrogen fertilizer application, specifically Shannong 28. The yield model produced superior results (R^2=0.70). *Sangjan et al., (2024*), extracted satellite images in conjunction with UAV images for the purpose of comparing the wheat yield prediction models of the two sampling methods. The findings indicated that the accuracy of the two prediction models is comparable. Through in-depth research, it is found that these two prediction models are comparable in terms of accuracy, but each has its own advantages in different application scenarios. For example, in large-scale farmland monitoring, the model combined with satellite images may have more advantages; while in small-scale precision agriculture, the model mainly based on drone images may perform better. Among them, the prediction of wheat yield and above-ground biological indicators and the drawing of inversion maps have become the most common and crucial practical forms in prediction research. With the continuous innovation of technology and the increasing abundance of data, this field is expected to achieve greater breakthroughs in aspects such as multi-source data fusion, intelligent analysis, and precision agriculture applications, providing more scientific and efficient decision support for agricultural production management.

With regard to technological innovation, the field has been developing at a particularly rapid pace. The concept of Partial Least Squares Regression (PLSR) has been widely introduced since 2017 (*Zhang et al., 2022*), and subsequently, regression analysis has become a mainstream method for data analysis. *Guo et al., (2021), Fu et al., (2021*), proposed a multi-scale texture extraction method (GLCM). The extracted spectral features, multiscale texture features, and their combinations were analyzed using partial least squares regression (PLSR) and least squares support vector machine (LSSVM) regression models, which demonstrated high accuracy when based on multiscale texture. In recent years, the emergence of keywords such as support vector machine, random forest, and neural network reflects the extensive application of machine learning and deep learning techniques in this field (*Ji et al., 2024; Yang et al., 2021; Lucks et al., 2021)*. *Arshad et al.,* (*2023*), employed the vegetation index extracted from UAV images in conjunction with climate data, selected eight models in machine learning for combination, and found that the accuracy of the RF model was superior to that of the other models. *Amorim et al., (2022)*, utilized a drone to acquire multispectral images. The spectral images of wheat at three growth stages were extracted, and vegetation indices were then combined with three different machine learning models. It was found that the models were able to more accurately estimate the biomass of wheat at different periods. As technology advances and data collection becomes increasingly sophisticated, scholars are dedicating greater attention to data processing. Developing data analysis methods based on machine learning and deep learning can better mine and utilize monitoring data and provide more scientific decision support for agricultural production management.

RESULTS

The literature concentration in the field of unmanned aerial vehicles (UAVs) monitoring wheat crops is gradually increasing, forming two major global cooperation nodes with China and the United States as the cores. Chinese authors not only have a high output of papers but also pay attention to international exchanges and cooperation. They carry out cooperation with scholars from the United States, the United Kingdom and other countries. The number of co-authored papers accounts for 24.78% of China's total paper output. Chinese scholars are increasingly strengthening teamwork, promoting the optimal integration of research forces, and continuously broadening the breadth and depth of research.

The evolution of research hotspots in the field of UAV monitoring wheat is gradually becoming clear. Wheat, UAVs, yield, vegetation index, and machine learning are high-frequency keywords. However, as time goes by, keywords such as plant height, leaf area, nitrogen content, and deep learning continue to appear. The research hotspot has gradually shifted from the early single yield monitoring of wheat by UAVs to the direction of monitoring specific growth information of wheat. Through UAV monitoring means, researchers, on the one hand, pay attention to the nutritional components of wheat at different growth stages, and while maximizing the satisfaction of wheat growth needs, reduce fertilizer application; on the other hand, they pay attention to the relationship between indicators such as leaf area, plant height, nitrogen content and yield and quality, and more scientifically guide wheat production practice.

CONCLUSIONS

This paper takes the Web of Science database as the data source and selects relevant academic papers to conduct bibliometric analysis of the development trend of unmanned aerial vehicles for monitoring wheat crops. Due to the limited coverage of the database, a large number of high-quality journals are not retrieved. At the same time, due to the language limitations of the database, the vast majority of articles are mainly in English and cannot fully reflect the research situations in different language regions around the world. These limitations will have a certain impact when analyzing research hotspots.

In addition, this paper only screens for high-frequency words and does not consider a large number of low-frequency emergent words that appear at different time stages. These emerging fields that appear in the short term are not included in this analysis. When setting the co-occurrence intensity threshold for data visualization, some smaller research hotspots will be affected by the co-occurrence intensity and word frequency threshold selection of keywords.

Secondly, due to space limitations, this paper does not conduct citation analysis and journal analysis.

Finally, through bibliometric analysis, this paper analyzes and summarizes the time development trend of this discipline from three aspects: research field, research objective, and technological innovation, and does not conduct in-depth excavation and review from a disciplinary perspective. These limitations can be continuously studied and discussed in future work.

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