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Trend analysis of the application of multispectral technology in plant yield prediction: a bibliometric visualization analysis (2003–2024)

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Multispectral imaging technology uses sensors capable of detecting spectral information across various wavelength ranges to acquire multi-channel target data. This enables researchers to collect comprehensive biological information about the observed objects or areas, including their physical and chemical characteristics. Spectral technology is widely applied in agriculture for collecting crop information and predicting yield. Over the past decade, multispectral image acquisition and information extraction from plants have provided rich data resources for scientific research, facilitating a deeper understanding of plant growth mechanisms and ecosystem function. This article presents a bibliometric analysis of the relationship between multispectral imaging and crop yield prediction, reviewing past studies and forecasting future research trends. Through comprehensive analysis, we identified that research using multispectral technology for crop yield prediction primarily focuses on key areas, such as chlorophyll content, remote sensing, convolutional neural networks (CNNs), and machine learning. Cluster and co-citation analyses revealed the developmental trajectory of multispectral yield estimation. Our bibliometric approach offers a novel perspective to understand the current status of multispectral technology in agricultural applications. This methodology helps new researchers quickly familiarize themselves with the field's knowledge and gain a more precise understanding of development trends and research hotspots in the domain of multispectral technology for agricultural yield estimation.

KEYWORDS
multispectral technique, VOSviewer, CiteSpace, bibliometrics, yield forecast

1 Introduction

Agriculture serves as the basis for all agricultural production. It is the most important source of food for human survival and a critical backbone of the global economy that sustains human life and livelihoods (Friha et al., 2021). The advancement of technology in agricultural production is pivotal for the transformation of modern agriculture, necessitating further improvement in crop yields and enhanced resource efficiency in areas with limited production

(Godfray et al., 2010). The concepts of Precision Agriculture (Feng et al., 2019; Khanna and Kaur, 2019) and Smart Agriculture (Brewster et al., 2017; Tang et al., 2021) have emerged to enhance crop yields more efficiently and to promote the technological advancement of modern agriculture. These concepts focus on improving the sustainability and efficiency of agricultural production using advanced technologies and management methods. Yield prediction, a fundamental aspect of Precision Agriculture, plays a crucial role in improving agricultural sustainability and efficiency and is also an effective method for addressing food security challenges (Bongiovanni and Lowenberg-DeBoer, 2004; Gebbers and Adamchuk, 2010). Yield prediction aims to accurately assess future crop yields and provide a scientific basis for planting decisions, resource allocation, and farm management strategies.

Multispectral imaging technology, which uses spectral information at various wavelengths to analyze object properties, has received considerable attention and research in agricultural monitoring over the past decade (Zhu et al., 2022; Zhang K. et al., 2022). By capturing the distinct spectral reflectance characteristics of crops at various growth stages, this technology provides crucial insights into crop growth conditions (El-Shikha et al., 2007), pest and disease occurrences, water management, and other significant factors. Using spectral reflectance characteristics for crop yield assessment has immense application prospects. Multispectral imaging technology can monitor subtle changes in crop growth, enabling precise yield prediction, and facilitating more refined and efficient agricultural production management (Diacono et al., 2013). The application of multispectral technology to crop yield prediction has become increasingly comprehensive. Over many years, relevant literature has accumulated significantly, leading to a substantial increase in data volume. Therefore, summarizing existing literature is necessary to reveal the knowledge structure in this field. Regular literature reviews using bibliometric tools are essential for continuously evolving technological domains (Song et al., 2021; Rejeb et al., 2022). CiteSpace and VOSviewer are visualization analysis tools that can analyze the relationships between research topics within a specific field by analyzing a large amount of literature data. These tools can be used to trace the development of research topics and identify current research trends and frontiers (Jia et al., 2019). This study conducted a systematic review and analysis of existing research using CiteSpace and VOSviewer software to summarize the current status of multispectral imaging technology for predicting agricultural yields. Additionally, this study explored the primary challenges associated with multispectral imaging technology, including issues related to the cost of data acquisition, the complexity of processing and analyzing huge amounts of data, and the accuracy and reliability of technical implementation (Magney et al., 2017). Furthermore, this study provides insights into future trends, such as advancements in algorithms and models, advancements in hardware technology, and the integration of data from multiple sources, all of which are expected to enhance the potential application and practical effectiveness of multispectral imaging technology in agricultural yield prediction. Moreover, this study provides a comprehensive analytical framework for understanding the value and potential of multispectral imaging technology in modern precision agriculture and has significant implications for promoting the development and application of related technologies.

An analysis of the determinants influencing agricultural productivity requires a precise evaluation of crop yields (Lobell et al., 2020). The ability to predict crop yields enables scientifically sound post-harvest crop management and rotation practices to ensure optimal productivity. Inadequate crop yields can significantly affect food security, whereas excessive yields may lead to price disparities and resource wastage. The origin of crop yield prediction can be traced back to the early stages of statistical modeling in the last century (Glad and Hjort, 2016). Panse et al. (1966) were among the pioneers who used statistical principles to estimate crop yields, substantiating the feasibility of statistical models through survey results. However, owing to their reliance on historical data and statistical methods, these approaches are often limited in terms of their comprehensiveness and accuracy. In 1990, the widespread application of satellite remote-sensing technology marked a significant advancement. Clevers (1994) and others began using optical remote sensing data (e.g., reflectance) to periodically estimate the Leaf Area Index (LAI) during growing seasons (Clevers, 1994). The estimated LAI time series were then used to calibrate the growth models, yielding optimal results. Remote sensing data offers detailed, real-time information on crop growth, significantly improving the accuracy and timeliness of predictive models (Kanemasu et al., 1985). In 1990, because of the widespread application of satellite remote sensing technology, Clevers (1994) and others used (reflective) optical remote sensing data (e.g., various change indices) to periodically estimate LAI during the growing season. Subsequently, by calibrating the growth models based on the time series of the estimated LAIs, optimal results have been achieved. The integration of remote sensing technologies has significantly enhanced the accuracy and timeliness of predictions. Since the beginning of the 21st century, the emergence of Geographic Information Systems (GIS) has enhanced crop yield prediction accuracy. Lei et al. (2008) used a spatial crop growth model based on GIS and multispectral technology. This model divides the simulation area into multiple crop growth elements, calculates each element using a specific set of parameters, and then achieves aggregation of spatial crop yields and other related results for administrative regions. The simulation results demonstrate the effectiveness of the model in representing regional yield spatial diversity. It has been proposed that developing a spatial crop growth model that combines GIS, multispectral technology, and physiological process orientation would be feasible. GIS integrates spatial and geographic data, enabling the analysis of factors such as land use, soil type, and topography, thereby improving the accuracy and reliability of the predictions. The latest research (2010 to present) has significantly advanced crop yield prediction with the widespread application of machine learning and artificial intelligence technologies in the field of crop yield prediction. Wang Jing, who integrated HJ-LAI into the WOFOST model to estimate regional rice yields, along with others, combined modified HJ-LAI and WOFOST-simulated LAI (Wang et al., 2016). They used the Ensemble Kalman Filter (EnKF) algorithm to assimilate the time-series LAI. Using EnKF to integrate remote sensing data into crop growth models offers a reliable method for regional crop yield estimation. Machine learning algorithms, such as neural networks and random forests, can learn from large amounts of data and predict crop yields, thereby improving the accuracy and consistency of predictions.

Multispectral imaging captures images at various wavelengths and provides relevant information about the health and physiological conditions of plants, which are subsequently analyzed. Compared with traditional Red, Green, Blue (RGB) imaging, multispectral imaging provides more comprehensive data on vegetation indices, such as normalized difference vegetation index (NDVI), thereby improving the accuracy of biomass and yield estimation. Recent studies have focused on the use of drones equipped with multispectral cameras to enhance the flexibility and efficiency of data collection (Khan et al., 2017). Research on crop yield prediction based on multispectral techniques is an emerging field (Paudel et al., 2021).

This study aimed to conduct a visual analysis of the literature on crop yield prediction using comprehensive bibliometric techniques. We aimed to achieve the following research objectives:

1. Analysis of publication trends over the past 20 years**: Examine trends in publications to reveal the development and hotspots of multispectral technology in crop yield prediction.
2. Cluster analysis of keywords and co-citation**: Identify core research themes and key technologies in multispectral technology for crop yield prediction. The focus includes chlorophyll content detection, remote sensing applications, and the use of machine-learning models.
3. Analysis of research hotspots in China**: Analyze research trends in China and compare them with global research to forecast future developments in crop yield prediction in China.

In summary, this study used bibliometric methods to analyze the application of multispectral technology in crop yield prediction, revealing research hotspots and development trends in the field. This study provides important insights for future research and collaboration.

2 Research methods

Bibliometric mapping involves transforming traditional textual data into computationally interpretable patterns. It encompasses the integration and visualization of information from a specific field in diverse graphical formats. Widely used in publishing statistics and research institution impact assessments (Silva et al., 2022), bibliometric mapping organizes and visualizes data related to publishing authors, institutions, and hotspots. Typical visual representations include collaboration networks, relationship webs, and time-series charts, which facilitate data integration, information retrieval, decision support, language processing, and educational outreach (Farias da Cruz et al., 2022).

2.1 Co-citation analysis

Co-citation analysis is a bibliometric technique used to establish connections between documents based on their co-citations in other studies. In this study, focusing on crop yield prediction through multispectral technology, co-citation analysis plays a crucial role in the following aspects:

1. Identifying key publications: discovering influential publications that are frequently cited together, highlighting their significance in the field.
2. Mapping research themes: revealing clusters of research themes and methodologies related to the application of multispectral technology, including chlorophyll content detection, remote sensing, and machine learning models.
3. Understanding intellectual structure: provides insights into the intellectual structure of the field by identifying the key concepts and approaches that are central to research discussions.

Co-citation analysis aids in understanding the landscape of crop yield prediction research by highlighting pivotal studies and emerging trends within the domain.

2.2 Material collection

Web of Science data retrieval and search formula:

TS = ("leaf green" OR "chlorophyllin" OR "pheophytin") AND TS = ("plant growth model" OR "growing model of plant" OR "model of plant development" OR "plants developing model" OR "the model of the plant" OR "plant growth modeling" OR "plants' growth model") AND TS = ("multi-spectral imaging" OR "multispectral remote sensing images" OR "multi-spectrum image" OR "multispectral imaging technique" OR "multi-image" OR "panchromatic and multispectral images").

Keywords search: ARTIFICIAL NEURAL NETWORK, CHLOROPHYLL, CONVOLUTIONAL NEURAL NETWORK, CONVOLUTIONAL NEURAL NETWORK CNN, MULTISPECTRA, DEEP LEARNING, FEATURE EXTRACTION, PREDICTION, PREDICTION MODEL, PREDICTIVE MODELS, PLANT, and ESTIMATE.

To enhance the relevance of the literature on agricultural plants and yield prediction it is essential to include keywords such as "plant," "estimate," and "multispectral."As of March 1 2024 2,530 relevant documents were retrieved of which 2,480 were obtained after screening irrelevant documents. Among these 2,417 papers comprised 63 reviews 43 conference records and 4 book publications. These data were organized and imported into the widely used visualization software, VOSviewer and CiteSpace for visual analysis.

3 Results

3.1 Trend and forecast of number of documents published in the past year

After reviewing the retrieved literature, an analysis was conducted using the visualization software, CiteSpace. By examining publication patterns within a specific research domain, valuable insights into the research status and developmental trajectory of the target field can be obtained (Cui et al., 2018). A comprehensive analysis of the relevant literature was conducted and the annual publication volume trend over the past two decades was plotted, as depicted in Figure 1. This visualization offers a clear representation of the evolution of the field, enabling the identification of key periods of growth, potential turning points, and overall research momentum. The graph serves as a valuable tool for comprehending the historical context and current state of research on agricultural plant yield prediction using multispectral technology. Through an examination of this trend, it is possible to discern periods of heightened interest, potential technological advancements, and shifts in research focus over time.

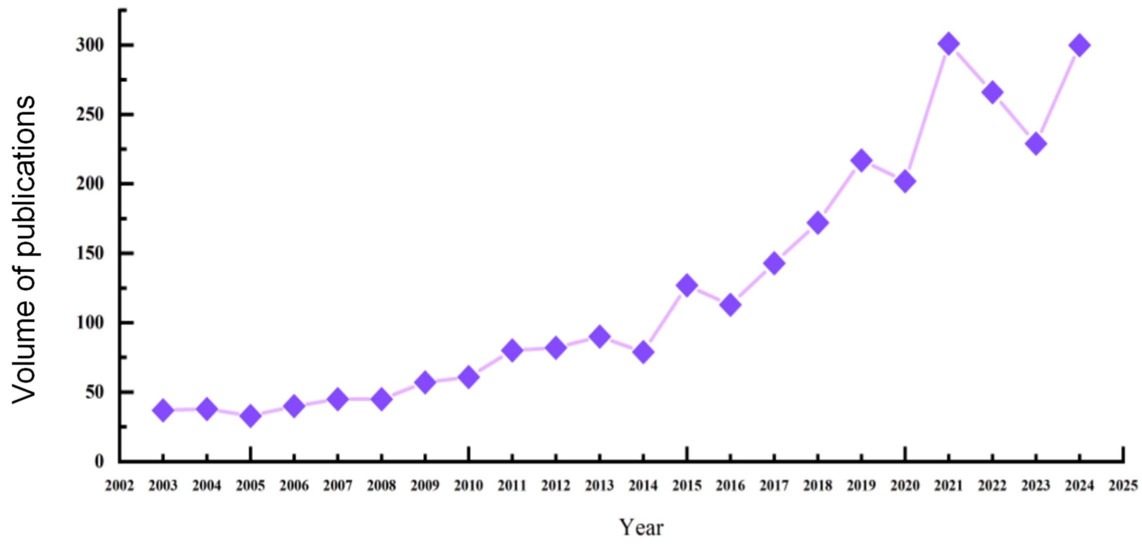

FIGURE 1
Annual publication volumes from 2002 to 2024.

Global research on the application of multispectral technology for agricultural yield prediction began in 2002. The study by Hoel and Bernt Olav, published in Acta Agriculturae Scandinavica, titled "Chlorophyll meter readings in winter wheat: cultivar differences and prediction of grain protein content," addresses the use of optical information for yield prediction (Hoel, 2002). Although this study did not specifically investigate the use of multispectral technology for yield prediction, the leaf chlorophyll measuring tool, the Hydro N-Tester (HNT), a tool for measuring leaf chlorophyll, operates on the fundamental principle of extracting plant data through optical reflectance of leaves. This approach can be viewed as a method of using spectral data for yield prediction. The number of publications in this field remained relatively steady from 2003 to 2009, with an annual growth rate of <10 papers, indicating a gradual initial development phase. After 2015, there was a significant increase in the annual publication output, consistently maintaining a three-digit count. In 2021, there was a peak in publications, underscoring the growing interest in yield prediction research by leveraging multispectral and associated technologies. Based on the trend observed from 2003 to 2023 and early 2024 data, it is projected that the number of publications will peak at 300 between 2024 and 2025. Based on the analysis of publication trends since 2000, there has been a consistent increase in the number of research papers dedicated to yield predictions using spectral information. This indicates increasing interest over the last two decades in the application of spectral imaging technology for agricultural monitoring and yield prediction. This trend reflects the growing academic attention to precision agriculture, particularly the importance of multispectral imaging technology in enhancing agricultural productivity efficiency.

3.2 Analysis of countries and regions

Using the VOSviewer software, a regional analysis was conducted on the literature retrieved from the Web of Science. By conducting a country-based literature analysis, we can identify the scientific research strengths and academic collaborations of various countries in this field (Liao et al., 2019). Considering the publication status of 87 countries in the field of multispectral yield measurement, countries with a minimum of five publications were selected as nodes for visualization analysis to create an international collaboration network map in the field of multispectral yield measurement. This map highlights that research in this field of multispectral yield measurement is predominantly concentrated in Asia, North America, and Central Europe. Notably, China (567 publications) and the United States (572 publications) have emerged as leaders in the development and application of multispectral yield measurements, indicating a clear dominant position. This dominance can be attributed to the vast market scale and advanced technological level of these two countries in terms of agricultural production and multispectral technological development. The data generated by the VOSviewer software were further utilized to create a geographic visualization map of the multispectral yield prediction-related literature using Scimago Graphics software. The results are shown in Figure 2.

In Figure 2, colors and numbers 1–15 denote 15 distinct country subgroups within the literature collaboration network, indicating collaborative connections among different countries. As two major core countries, China and the United States play crucial roles in international research on multispectral yield measurements. Countries such as Brazil (179 publications), Germany (178 publications), Australia (130 publications), and France (121 publications) formed a secondary core group, each making significant contributions to this research domain. The formation of this international publication relationship network signifies cooperation and knowledge exchange among diverse countries in the field of multispectral yield measurement, thus providing valuable insights for further development and collaboration in this field.

From a geographical distribution perspective, research has primarily concentrated in North America, Europe, and Asia. This spatial distribution trend can be attributed to three primary factors: substantial populations driving high market demand for agricultural products, advanced levels of agricultural technological development,

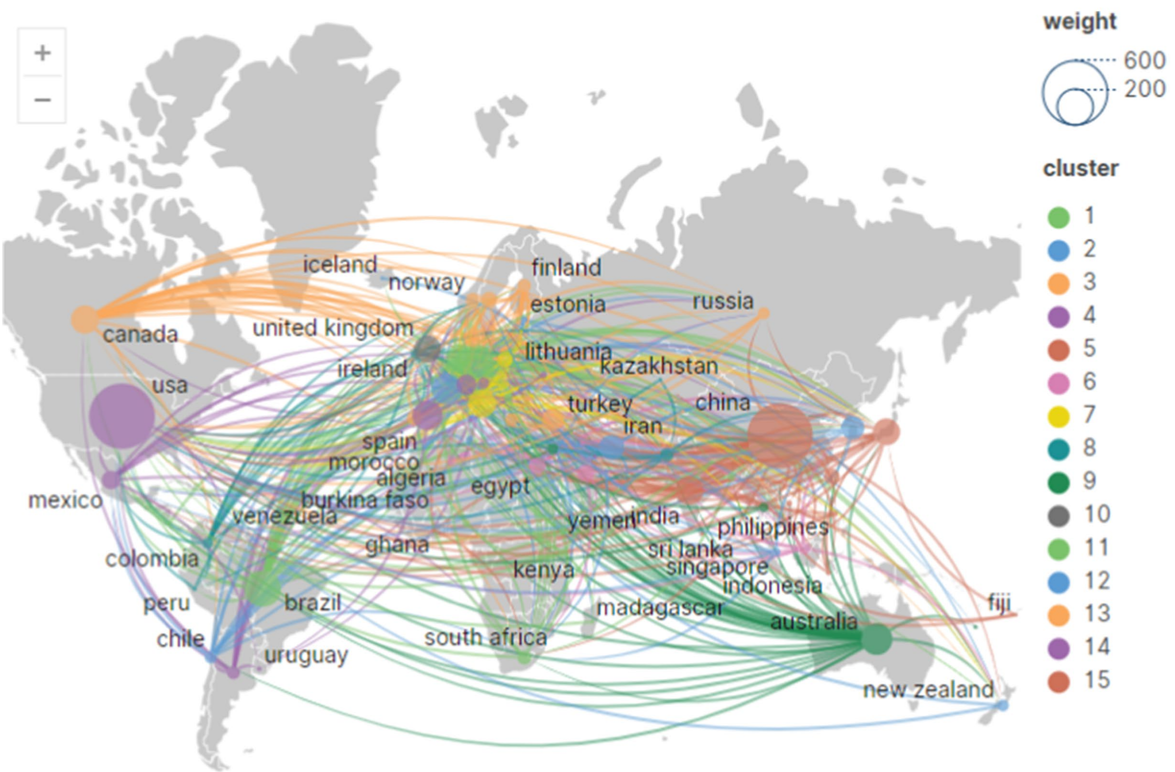

FIGURE 2
Geographic visualization of literature related to multispectral yield prediction.

and significant investments in scientific research (Wang et al., 2014). In Europe, especially Germany and the Netherlands, there has been significant progress in the application of machine learning techniques in agriculture. Machine learning is a promising approach, especially when it comes to collecting and publishing large amounts of data. We combine agronomic principles of crop modeling with machine learning to establish a machine learning baseline for large-scale crop yield prediction (Paudel et al., 2021). By analyzing big data extracted from multispectral images, the researchers developed high-precision models capable of predicting crop yield and water use efficiency. Researchers in Japan and South Korea used CNNS to process multispectral data to identify the growth stage and health status of crops (Kumar et al., 2020). These advanced image analysis techniques allow agricultural producers to accurately assess crop health and adjust management strategies accordingly to optimize output.

The increasing investment in precision agriculture technology research has led to a noticeable temporal trend of growing interest in precision agriculture among new researchers in the field of agricultural digitalization. This emphasis has fostered the further implementation and application of multispectral imaging technologies within agricultural production systems (Mahlatse et al., 2024). This distribution not only reflects the current state of research but also highlights potential areas for future development and collaboration in the realm of multispectral yield measurement and precision agriculture. Through comparative analysis of the application of technology in different countries, we can not only see the actual impact of each technology in global agriculture, but also understand how countries choose and adjust corresponding technological strategies according to their own agricultural development needs and scientific and technological levels. This kind of transnational technology impact analysis is helpful to predict the development direction of agricultural technology in the future, and also provides a valuable reference for global agricultural science and technology cooperation.

3.3 Analysis of the author's cooperative scientific knowledge map

Author collaboration networks are graphical methods used to analyze and visualize relationships among researchers. This approach not only assists researchers in comprehending collaboration and communication patterns within academic communities but also supports scientific decision-making (Chu et al., 2022). Tools such as CiteSpace and VOSviewer were used to draw network graphs illustrating the origins and developmental patterns of knowledge. These tools reveal structural relationships and evolutionary trends in related fields of knowledge (Chen et al., 2021).

The documents retrieved were imported into CiteSpace for visualization. To improve the graphical clarity, the nodes were adjusted, and only authors with more than five publications were selected as display nodes. The resulting author collaboration network diagram is shown in Figure 3. Figure 3 shows 409 nodes and 539 co-authorship connections. Network visualization reveals that within the field of multispectral yield measurement research, certain scholars have formed stable collaborative clusters. Notably, Zhu Yan and Cao Weixing have emerged as highly productive authors, each with more

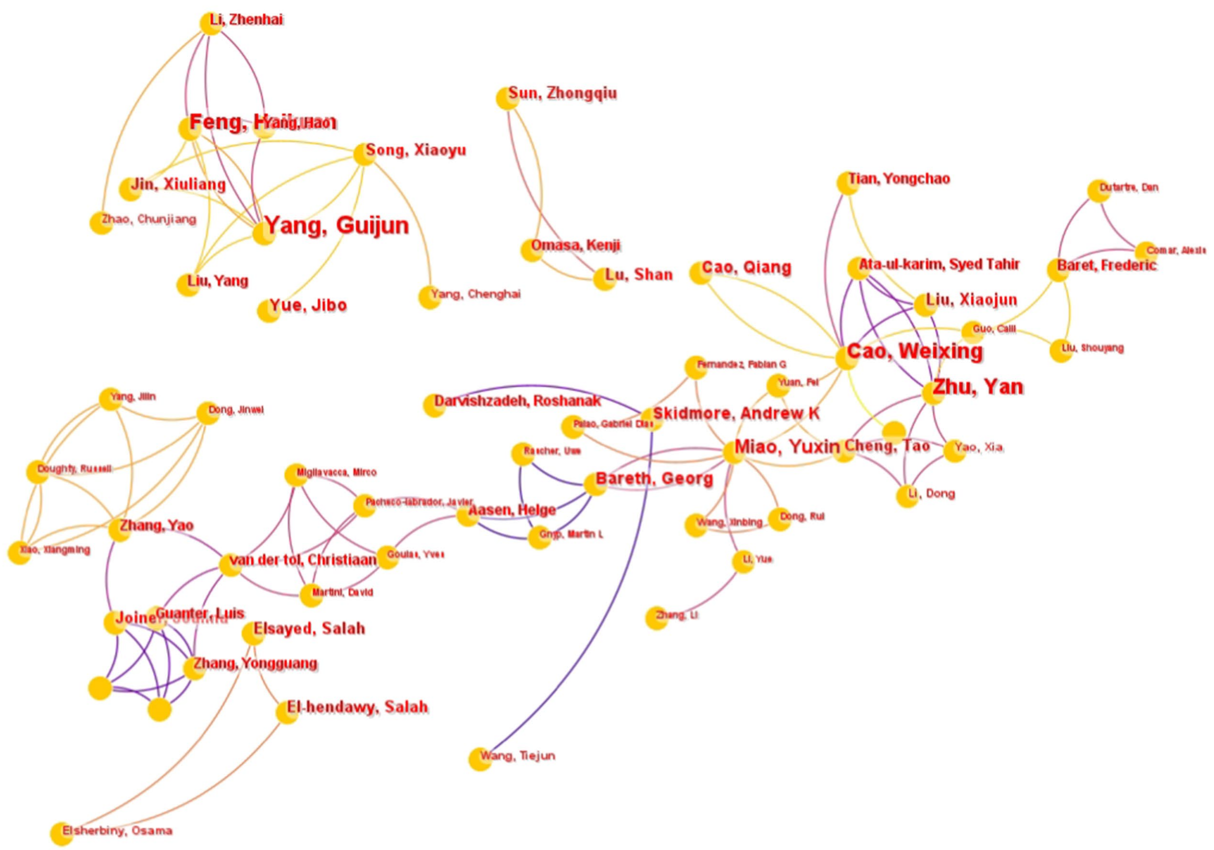

FIGURE 3
Illustration of author collaboration.

than ten publications. Both researchers are associated with Nanjing Agricultural University. The research cluster that revolves around these two scholars forms the largest collaborative community within the co-authorship network. This network analysis highlights the centrality of Nanjing Agricultural University's research team, with Zhu Yan and Cao Weixing as the key nodes in the collaborative landscape of multispectral yield measurement research. Their team represents the most substantial co-authorship cluster in the network diagram.

CiteSpace was used to generate a timeline illustrating authors' co-citation (Figure 4) based on the literature from the past decade. Co-citation refers to instances in which two or more authors are cited simultaneously in other publications. The simultaneous citation of multiple authors in various papers suggests a level of collaboration, mutual assistance, and shared research interest among these authors.

The timeline illustrated in Figure 4 depicts the progression from 2014 to 2024. Various colors are used to represent different years: nodes closer to the red end signify more recent publications, whereas those toward the blue-green end represent earlier publications. The lines connecting the nodes signify co-citation relationships, indicating publications that cite the same authors. Each node represents a publication with larger nodes, which indicates a higher citation count. The color of each node corresponds to the publication year of each paper.

The analysis of the evolution of agricultural and ecological research, as depicted in Figure 4, shows a significant transition from fundamental science to applied technology. Early research (2014–2017) focused on measuring plant biomass and cotton seedling growth, and analyzing chlorophyll fluorescence parameters, establishing a basis for comprehending plant physiological processes and ecosystem functions. Subsequently, the research focus shifted toward more practical applications, such as crop yield prediction (#0), determination of the above-ground biomass of rice (#1), and genomic selection (#10). These studies not only improve agricultural productivity but also promote sustainability. Notably, there has been a substantial increase in crop yield predictions in recent years (2021–2024), likely driven by global climate change and the challenges posed by population growth to food security. Similarly, the attention given to aboveground biomass in rice reflects the urgent need to enhance yield and resource-use efficiency in this crucial staple crop. Furthermore, an increase in genomic selection signifies a revolution in breeding methods, enabling scientists to select and cultivate crops with desirable traits more efficiently, thereby improving agricultural productivity. This evolution underscores the field's adaptation from basic research to impactful applications, addressing contemporary agricultural challenges while fostering sustainability and efficiency in food production.

3.4 Keyword analysis of plant yield prediction based on multispectral technology

Keywords are central to an academic paper, as they enable readers to promptly understand the fundamental aspects of the

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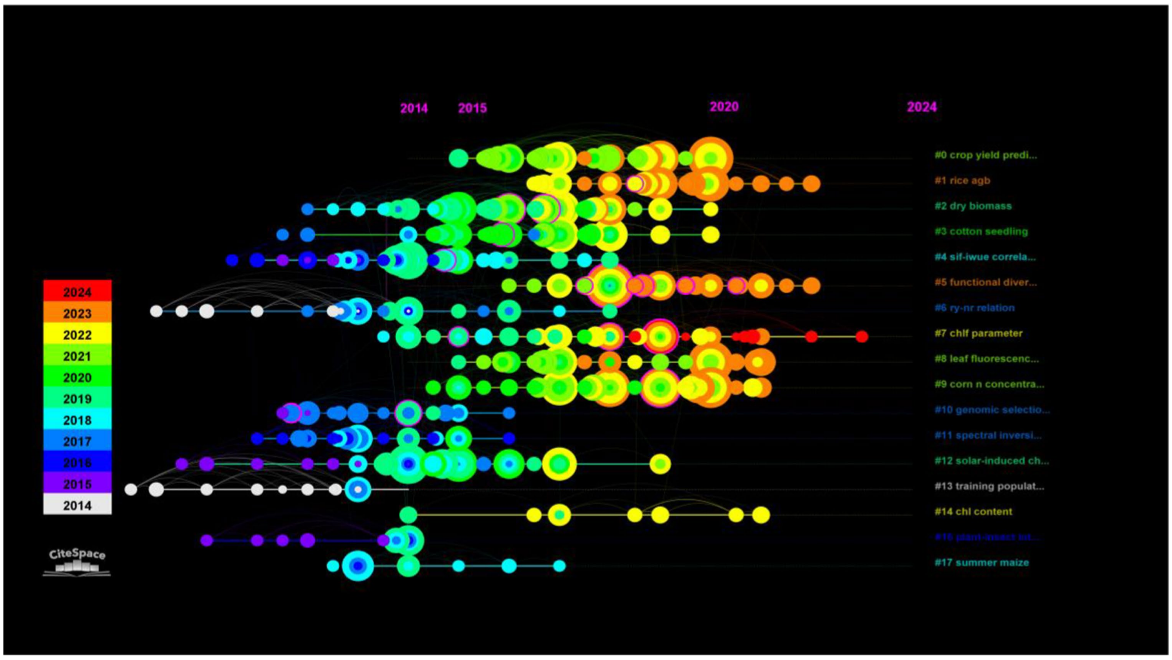

FIGURE 4
Illustration of author co-drawing time.

research beforehand, serving as a crucial basis for comprehending the papers (Ribeiro et al., 2022). Conducting keyword frequency analysis on multispectral yield prediction can rapidly reveal hotspots within the field. When integrated with timeline data, this analysis provides insights into the overall development trends in this area.

The retrieved literature was imported into VOSviewer where nodes were designated keywords with a threshold of ≥6 occurrences. Default settings were maintained for the other parameters. Each node represents a keyword with larger nodes indicating higher frequency of occurrence. The nodes were connected by lines with thicker lines denoting stronger associations. A total of 7,621 keywords were used to form 188 nodes and 1,500 connections which were further organized into nine main clusters and ranked by keyword total in descending order (Figure 5). Table 1 lists the top 30 high-frequency keywords used. Preliminary analysis of high-frequency keywords revealed that 'remote sensing,' 'machine learning,' and 'deep learning' appeared 109,103 and 66 times, respectively, ranking among the top three. This indicates that multispectral yield prediction focuses on remote sensing and machine learning advancing toward intelligent development. This aligns with core technologies for yield prediction using multispectral techniques whereas remote sensing equipment such as drones and satellites collects and extracts data. Image processing techniques calibrate segment and denoise multispectral images (Magney et al., 2017). Feature extraction includes parameters such as the NDVI enhanced vegetation index (EVI) chlorophyll content moisture index and temperature which are subsequently analyzed using statistical or machine learning methods. Common prediction models include regression analysis decision trees random forests support vector machines and neural networks. Recent advancements such as the Improved Particle Swarm Optimization-Extreme Learning Machine (IPSO-ELM) have gained popularity (Anderson and Walsh, 2022; Bobelyn et al., 2010; Fan et al., 2019; Zhang Y. Z. et al., 2022)

3.4.1 Multi-spectral imaging

Multispectral imaging has revolutionized the way agricultural data is collected, enabling detailed analysis of crop health and environmental interactions. For example, research by Dey et al. (2022) documented significant improvements in the technology's accuracy in detecting nutritional deficiencies and pest infestation-critical for yield forecasting. Being able to collect data in different spectral bands allows for a more nuanced understanding of crop stress and growth vitality, which are closely related to yield outcomes.

3.4.2 Machine learning

The integration of machine learning techniques has greatly improved the prediction accuracy of yield models. By processing large data sets from multispectral images, machine learning algorithms are able to identify complex patterns that human analysts cannot recognize. For example, Lobell et al. (2020) show that machine learning models are able to predict yield outcomes under changing weather conditions with significantly higher accuracy than traditional statistical methods.

3.4.3 Convolutional neural networks (CNN)

CNN has played a key role in advancing spatial data analysis to predict crop yields. Their ability to process pixel-based images and identify spatial layers and patterns makes it possible to assess the condition of crops over large areas in detail. DeepYield's combined architecture, which integrates convolutional neural networks (CNNS) and convolutional Long and short term memory networks (ConvLSTM) to accurately predict crop yield based on remote sensing data, combines CNNS for spatial feature extraction and LSTM for

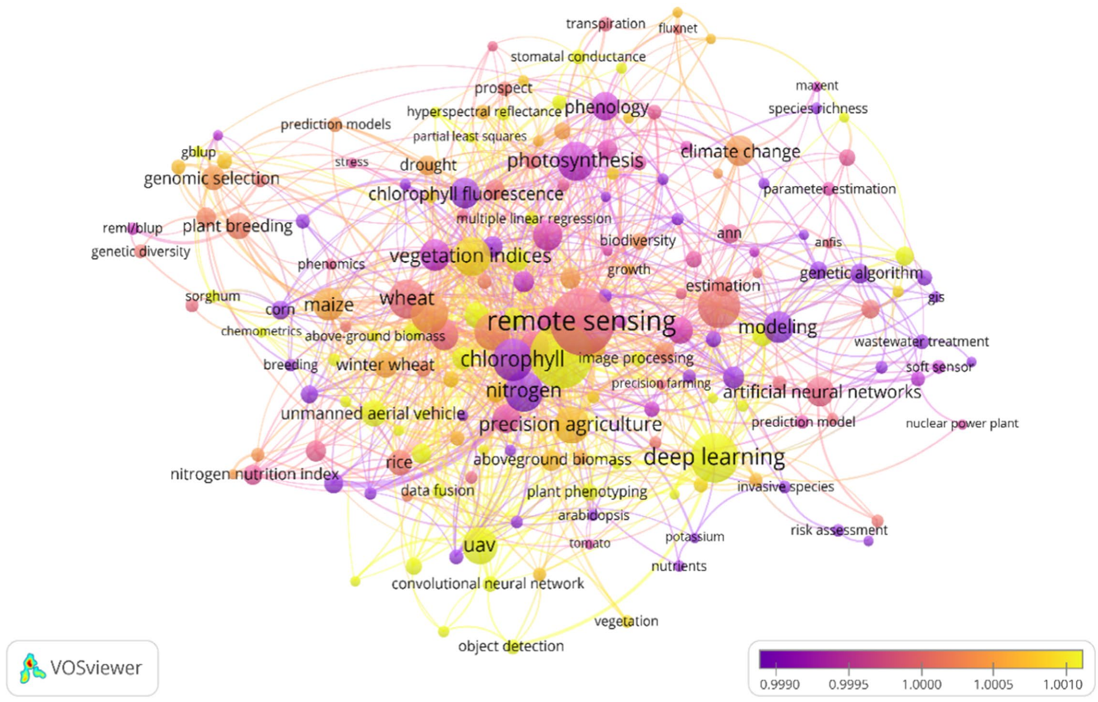

FIGURE 5
Illustration of multispectral keyword analysis.

capturing time dependence. Provides A comprehensive framework that significantly improves the accuracy and reliability of crop yield forecasts (Khan et al., 2017). Work by Zhu et al. (2022) shows that CNNS, applied to drone and satellite imagery, are able to identify subtle changes in crop health that can be sensed long before they are visible to the naked eye, allowing for timely interventions to maintain or increase yields.

In our analysis, we carefully assess the impact of specific techniques such as multispectral imaging, machine learning, and convolutional neural networks (CNN) on the field of crop yield prediction. This analysis not only allows us to track the trajectory of these technologies, but also quantifies their transformative impact on agricultural practices. The increasing reliance of yield forecasting on these advanced analytical techniques is consistent with the broader trend of precision and smart agriculture. Bibliographic insight shows a shift in agricultural research from observational to predictive analysis, a shift driven by advances in imaging and data processing techniques. Accurate and timely forecasting can lead to better resource management, optimized crop insurance and effective market planning.

3.5 Research hotspot analysis: keyword cluster analysis

Keyword clustering analysis is a data mining technique that uses clustering algorithms to organize keywords and extract valuable information from the clustering analysis. This analysis method effectively reduces the workload of extensive textual data analysis, enabling researchers to quickly identify trends and explore new research topics (Farias da Cruz et al., 2022; Kuo et al., 2005; Vrahatis et al., 2002). The selection of keywords in a paper significantly affects its presentation and dissemination within the scientific community (Rejeb et al., 2022). By examining the keywords of a paper, researchers can determine the research theme and ascertain its potential success (Mlambo et al., 2016; Uddin et al., 2015).

3.5.1 Study on yield prediction based on the multispectrum (cluster 0 cluster 1 cluster 2 cluster 3 cluster4 and cluster 6)

Based on the existing literature, multispectral-based yield prediction has been identified as a highly effective and promising method. Using CiteSpace, a keyword clustering diagram (Figure 6) was generated through an extensive review of the literature. The main clusters in the diagram include the chlorophyll content, artificial neural networks, remote sensing, and models. Chlorophyll content is a crucial indicator of plant growth and is a core component of photosynthesis, reflecting the synthesis of organic compounds by plants. Being the most abundant pigment in plant chloroplasts, chlorophyll significantly influences the photosynthetic efficiency. Diamond-shaped symbols identify various research topics or keywords and are color-coded to indicate the year of study they correspond to. The color variation of each diamond shows the activity of the study subject in different years. The colored bubbles around the topic show the interrelationships and time evolution of the different research areas, while the interconnected lines indicate how closely the different topics reference each other or relate to each other. This visual representation helps to analyze trends, evolution, and interactions between topics within the academic field.

In plant yield prediction research and application, chlorophyll content is often used as an important input parameter to estimate crop growth status, biomass, and potential yield. Remote sensing and spectral technologies are frequently used to acquire essential plant

TABLE 1 Description of heat frequency keywords.

Order	Keyword	Occurrences	Total link strength
1	Remote sensing	109	90.00
2	Machine learning	100	77.00
3	Deep learning	66	51.00
4	Vegetation indices	47	44.00
5	Vegetation index	47	44.00
6	Nitrogen	48	43.00
7	Precision agriculture	43	41.00
8	Chlorophy	52	41.00
9	Uav	42	39.00
10	Wheat	46	38.00
11	Photosynthesis	46	38.00
12	Hyperspectra	43	36.00
13	Artificial neural network	57	36.00
14	Maize	35	33.00
15	Chlorophy11 content	34	28.00
16	Yield	31	25.00
17	Leaf area index	30	24.00
18	Reflectance	29	22.00
19	Unmanned aerial vehicle	25	22.00
20	Biomass	28	22.00
21	Random forest	21	22.00
22	Phenology	28	21.00
23	Rice	24	21.00
24	Chlorophll fluorescence	22	20.00
25	Winter wheat	24	19.00
26	Partial lenst squares regression	20	19.00
27	Artificial intelligence	20	18.00
28	Plant breeding	26	17.00
29	Genomic selection	23	17.00
30	Sentinel-2	20	17.00

information, such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge Index (NDRE). These technologies capture relevant plant data by processing remote-sensing images and transmitting this information to the subsequent processing stages. The integration of chlorophyll content, remote sensing, and spectral data offers a comprehensive approach to accurately monitor and predict plant yields.

Artificial neural networks (ANNs) are widely used tools to predict plant yield. These networks can process a variety of plant physiological parameters and environmental factors, including chlorophyll content, and predict future yields by establishing correlations between these data and the actual yields. Through continued enhancement and refinement of these models, it is possible to equip them to recognize the complex relationships between input data (including chlorophyll content obtained through remote sensing techniques) and output data (i.e., crop yield). The prediction model is trained and validated using actual production data to ensure that it remains stable in a specific environment after multiple iterations, thus allowing it to be used to predict future crop yields.

By comprehensively utilizing remote sensing technology and machine learning models, such as artificial neural networks, it is possible to examine the potential correlation between data to develop models that accurately predict crop yields. The interdisciplinary application of these technologies has significant potential in various fields including facility agriculture, precision agriculture, crop monitoring, and resource management.

3.5.2 Cluster keyword #0: chlorophyll content

This is the largest clustering, emphasizing a significant trend in yield prediction technology based on multispectral technology for the detection and utilization of chlorophyll content. Chlorophyll serves as the primary pigment for plant photosynthesis, absorbing light energy and converting it to chemical energy for the synthesis of organic compounds. Consequently, chlorophyll content plays a crucial role in photosynthetic efficiency, thereby affecting crop yield. In recent years, it has been found that reducing chlorophyll to increase canopy photosynthesis could be a promising optimization strategy, as summarized by Laisk (1982) and Osborne and Raven (1986). Clustering contained 26 keywords and was conducted in 2009. Key terms, such as "chlorophyll meter," "Soil Plant Analysis Development readings," "ascorbic acid," "light-adapted state," and "Solar-Induced chlorophyll Fluorescence field measurements" highlight important tools and methods for assessing chlorophyll content in plants through the use of multispectral technology. The "chlorophyll meter" and "SPAD readings" play a crucial role in agricultural yield prediction because they measure the ratio of light transmitted and reflected by leaves to estimate chlorophyll content. These data are essential for understanding plant growth conditions and nutritional requirements and serve as key indicators in agricultural management. The analysis of "ascorbic acid" is related to the study of plant antioxidant mechanisms, providing insights into crop health and resilience against environmental stress. The concept of the "light-adapted state" pertains to how plants adjust to specific light conditions, which can be assessed by measuring photosynthetic parameters (such as photosynthetic rate and fluorescence) and is essential for understanding photosynthetic performance. The term, "SIF field measurements" refers to Sun-Induced Chlorophyll Fluorescence field measurements, which provide a non-invasive method for monitoring plant photosynthetic activity. Together, these indicators support the application of multispectral technology for agricultural yield prediction. Ascorbic acid, also known as vitamin C, is involved in the synthesis and regeneration of chlorophyll and serves as an important electron donor in photosynthesis. It plays a crucial role in the antioxidant systems of plants and protects chlorophyll from degradation under environmental stress. This is essential for the study of crop health and resilience to adverse conditions. The "light-adapted state" refers to the physiological condition of plants under specific lighting conditions. It encompasses

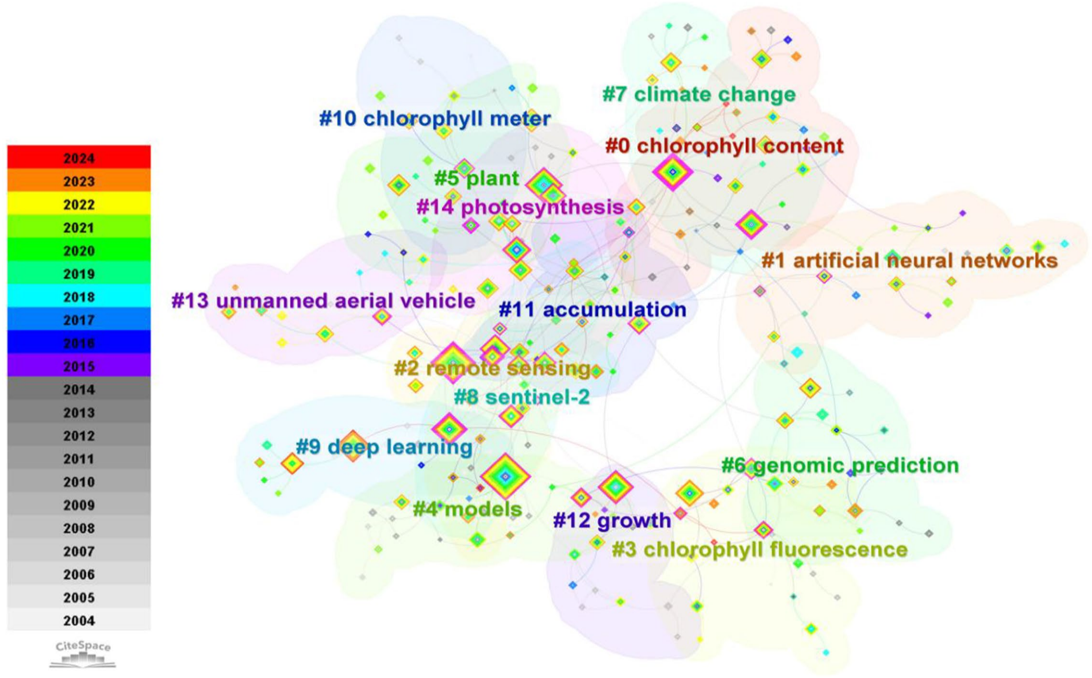

FIGURE 6
Illustration of keyword cluster analysis.

the process by which plants adjust to varying light intensities and spectral compositions, thereby affecting their photosynthetic efficiency and overall growth. Assessing this state is the key to understanding how plants perform photosynthesis. "SIF field measurements" involve the identification of chlorophyll fluorescence triggered by sunlight, which serves as a non-destructive approach for monitoring the photosynthetic activity of plants. Fluorescence signals can offer insights into the photosynthetic efficiency, photosystem II function, and energy equilibrium within plants. These parameters collectively support the utilization of multispectral technology for predicting agricultural yields by providing valuable information on plant health, photosynthetic efficiency, and stress tolerance.

3.5.3 Clustering keyword #1: artificial neural network

Artificial Neural Network (ANN) is a computational modeling tool characterized by densely interconnected adaptive simple processing units referred to as artificial neurons or nodes. These units are capable of performing large-scale parallel computations, enabling the processing of intricate nonlinear relationships and execution of pattern-recognition tasks. In the field of agriculture, ANN have extensive applications in crop growth prediction, pest detection, and soil quality assessment. Its advantage lies in its ability to learn from extensive multispectral data and extract features, thereby supporting tasks, such as crop yield prediction and health status analysis. The structure and functionality of ANNs render them effective tools for data processing and knowledge learning and have significant prospects for applications in the agricultural sciences (Schalkoff, 1997). In the context of clustering analysis, key terms pertain to the application of computational models and technological tools for simulating plant physiological states and transpiration processes. ANN refers to a biomimetic computational model capable of learning from extensive data to match the optimal model, which is applicable to modeling and predictive tasks involving complex datasets. In the current learning process, methodologies can be "supervised," "unsupervised," or a combination of both (Liao and Wen, 2007). Neural networks such as multi-layer perceptrons, typically use backpropagation algorithms for supervised training (Rumelhart et al., 1986). Terms such as "greenhouse gases," "urban vegetation," and others are related to the use of artificial neural networks and meteorological models to predict and analyze plant transpiration (Griffani et al., 2024). Transpiration is the primary physiological process through which crops regulate their temperature. Numerous plants maintain relatively stable tissue temperatures through transpiration in response to ambient temperatures. Both photosynthesis and transpiration are indispensable physiological processes in plants, with a significant effect on the synthesis and utilization of organic matter. Consequently, it is essential to consider these processes when predicting plant yields.

3.5.4 Cluster keyword #2: remote sensing

This clustering included 18 relevant keywords that focused on remote sensing imagery and spectral data, along with closely associated terms, such as drones and hyperspectral sensors. Remote sensing information is collected by drones and satellites equipped with remote sensing technologies. Hyperspectral imaging, which captures images at numerous wavelengths, has significantly enhanced traditional imaging techniques by providing higher information content and more efficient images. These advancements serve as the basis for subsequent phases of deep learning, using the powerful flexibility and nonlinear data-processing capabilities of artificial neural networks for accurate yield predictions. The integration of drones, machine learning, deep learning, wireless sensor networks, and big data has fundamentally transformed the field of agriculture. Efficient remote sensing image processing is a crucial prerequisite for further advancements in deep learning.

3.5.5 Cluster keyword #3: chlorophyll fluorescence

In clustering, keywords such as "chlorophyll fluorescence," "plum rainy season," "stomatal conductance," "non-photochemical energy dissipation," and "ferutic acid" were used to study the factors related to plant photosynthesis, stomatal conductance, and chlorophyll fluorescence. These factors, particularly photosynthesis and stomatal conductance, are crucial for plant growth and yield (Christina et al., 2020). "Chlorophyll fluorescence" is essential for studying photosynthetic efficiency and chlorophyll fluorescence characteristics of plants. "Stomatal conductance" involves the opening and closing process of plant stomata. "Non-photochemical energy dissipation" is related to the dissipation of non-photochemical energy in plants. These findings offer significant theoretical support for predicting crop yields and nitrogen managing. Accurate and timely estimation of these photosynthetic functional traits is essential for reliably predicting crop productivity and providing feedback regarding climate change (Walker et al., 2014; Rogers et al., 2017; Yu et al., 2020).

3.5.6 Clustering keyword #6: gene prediction

This cluster consisted of 16 keywords, primarily focusing on developments in 2013, particularly emphasizing "genomic selection" and "linear mixed model." These advancements are crucial in modern agriculture, serving as essential methodologies for enhancing crop growth and improving the precision of yield prediction. This quantitative analytical approach, which incorporates genetic information, has significantly increased the efficiency and effectiveness of crop improvement programs, rendering the prediction of crop yields and optimization of breeding strategies more scientifically robust and precise. Furthermore, "reciprocal recurrent selection" has been recognized as an effective methodology for improving the performance of hybrid progenies from diverse populations. This technique can be used to improve yield, disease resistance, and other agronomic traits, thereby accelerating hybrid optimization. The term "elapsed time" typically pertains to the consideration of project cycles in agricultural research and breeding domains. This highlights the need to consider plant growth cycles when conducting yield predictions, which is of paramount importance. These keywords have significant implications in improving the accuracy of crop yield predictions and optimizing breeding strategies. They offer advanced technological support for agricultural scientific research and innovative methods for improving the precision of crop yield predictions and the efficiency of breeding processes. This cluster represents a pivotal advancement in agricultural science and technology.

3.5.7 Clustering keyword#9: deep learning: clustering keywords #4 model

Cluster #9 is characterized by keywords such as "deep learning," "machine learning," and "feature fusion," with a primary focus on efficiently collecting information on crop growth status and making precise yield predictions using advanced technology. This cluster, primarily focusing on the period around 2018, represents the application of the recent advances in agricultural research. "Deep learning" and "machine learning" algorithms are used for data analysis to predict crop yields. These technological advancements have the potential to significantly improve the technical capabilities of crop management and yield prediction. The incorporation of "feature fusion" methods further enhances the accuracy of predictions by integrating multiple data sources to extract more comprehensive insights into crop conditions. This cluster highlights the increasing use of advanced computational techniques in agriculture to enhance crop production and predict yields. Cluster #4, which revolves around predictive modeling, with keywords such as "vegetation indices," "prediction model," "crop surface model," "satellite imagery," and "crop monitoring" all central to the development and application of predictive models in agriculture. The main focus of this cluster is the use of these models to monitor crop growth and predict crop yields. The cluster was formed in 2013, preceding Cluster 9, and aligns with the chronological advancement of technology in the field. The "prediction model" is a mathematical theoretical framework used to forecast plant growth, estimate yield, and assess health status. Within this context, the "crop surface model" has emerged as an innovative technical approach for analyzing and characterizing plant surface structures and for facilitating the examination of plant physical morphology. Consequently, it serves as a valuable technical parameter for the prediction models. From a macroscopic perspective, "satellite imagery" is an effective method for obtaining plant-related information. This approach involves the collection of vegetation image data via satellite technology, enabling the large-scale analysis of crop growth patterns and health conditions across extensive areas. The concept of "crop monitoring" encompasses the utilization of the aforementioned tools and techniques for continuous observation and analysis of crops.

The integration of multispectral technology in modern agricultural research combines remote sensing, data science, and agronomics, highlighting the interdisciplinary nature of the field. This integration of diverse technological approaches signifies the advancement of precision agriculture toward more sophisticated, data-driven methodologies. The development of ultra-efficient and highly accurate deep learning models for agricultural yield prediction represents a frontier in agricultural science with potential implications for global food security, resource management, and sustainable farming practices. This research direction aligns with broader efforts to leverage advanced computational techniques to address the complex agricultural challenges in the era of climate change and increasing food demand. This integrated approach exemplifies the synergistic application of advanced modeling techniques, remote sensing technologies, and data analytics in modern precision agriculture. This underscores the evolution of agricultural practices toward more data-driven, technologically sophisticated methodologies aimed at optimizing crop management and enhancing overall agricultural productivity.

3.6 Keyword co-citation time analysis

The retrieved literature was imported into CiteSpace for keyword analysis, and the keyword analysis and co-citation timeline were then drawn. The images (Figure 7) were analyzed using these data. The following conclusions were drawn.

Based on the frequency and centrality of keywords, we identified the "prediction" (337 occurrences) and "model" (253 occurrences) as central to research on yield prediction using multispectral measurements. This highlights the importance of a robust model for precise yield predictions. Additionally, the high centrality of the "chlorophyll content" (166 occurrences) and "LAI" (114 occurrences) highlights their significant impact on studies using multispectral techniques for yield prediction. Subsequently, the focus was directed toward the temporal trends of these keywords. We have conducted a phase summary and discussion. This methodological approach provides insights into the evolving research emphasis and trends in multispectral-based yield prediction research. Plant growth and yield predictions have evolved significantly in methodology and technology over the last two decades. Initially (2003–2005), predictive analyses primarily relied on traditional data-collection methods. Subsequently, the research focus (2006–2012) shifted toward the quantification of plant physiological indicators, such as the measurement and analysis of key parameters, including chlorophyll content, chlorophyll fluorescence, and leaf area index. Concurrently, artificial neural networks have been used to develop predictive models. Between 2009 and 2011, researchers initiated an exploration of the application potential of remote sensing technology for plant information extraction, laying the foundation for subsequent studies through this interdisciplinary approach. From 2012 to 2017, significant progress has been made in prediction techniques at the microscopic level, facilitated by advancements in biochemical technologies. The integration of multispectral techniques for plant yield prediction with plant nitrogen element inversion has significantly enhanced the prediction accuracy, exemplifying the trend toward multidisciplinary research integration. Recently (2018 to present), advanced computational technologies, such as artificial intelligence and machine learning, along with optimized predictive models, have propelled multispectral-based yield-prediction techniques. These improved multispectral models have increased prediction accuracy and expanded the application scope, supporting precision in agricultural development. In conclusion, through a CiteSpace keyword analysis, we identified the "prediction," "model," "chlorophyll content," and "LAI" as critical keywords in crop yield research based on multispectral technology. These keywords exhibit close collaborative relationships, focusing on predictive models, chlorophyll content, and leaf area index, which play pivotal roles in plant growth and crop yield prediction. Research has gradually shifted from plant growth to aspects such as chlorophyll content, LAI, and remote sensing technology driven by deep learning applications. These research outcomes offer vital theoretical foundations and methodological support for monitoring crop growth and yield predictions with significant implications for improving agricultural production efficiency.

3.7 Analysis of Chinese literature

3.7.1 Data sources and research methods

In this study, Web of Science, Scopus, and the China National Knowledge Infrastructure databases were used to search for relevant Chinese literature data sources until February 22, 2024. Searching literature through databases, such as Web of Science and Scopus, is a common method used to systematically evaluate the research development. Our research team searched for literature using keywords such as "multispectral imaging," "agricultural yield," and "plant monitoring," which summarize academic works on using multispectral imaging in agricultural yield prediction and plant

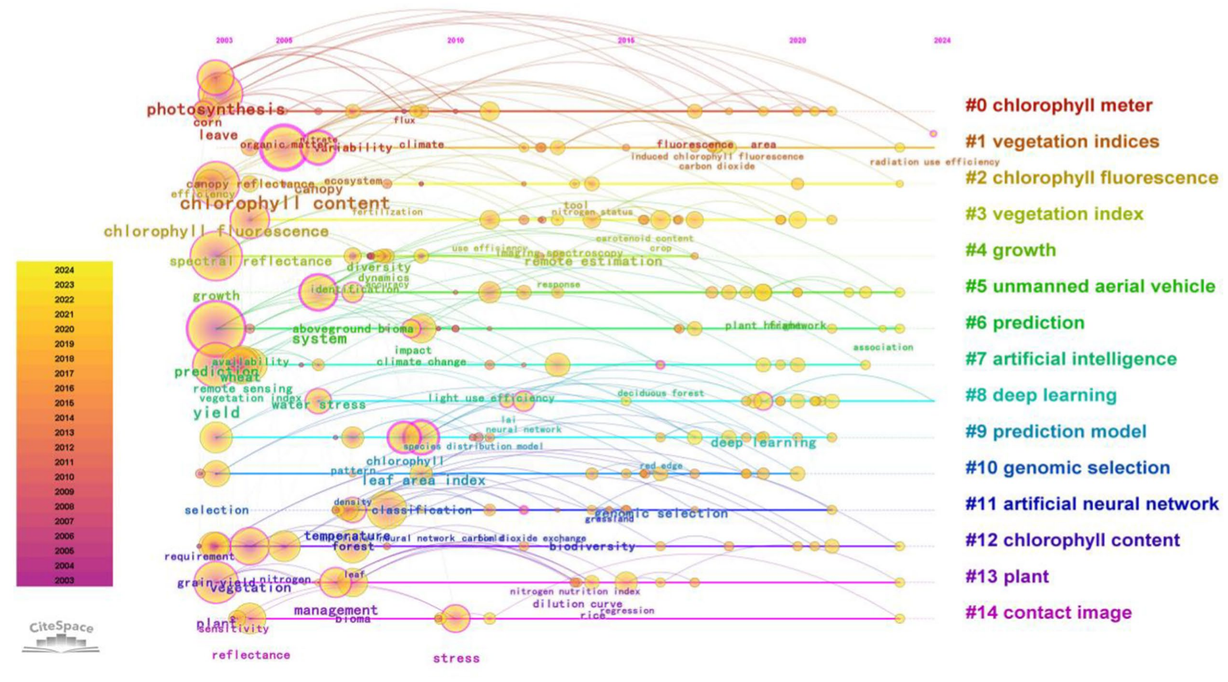

FIGURE 7
Illustration of keyword co-citation time.

monitoring. A visualized analysis of 700 relevant paper in China was carried out using CiteSpace software (Lim et al., 2022).

3.7.2 Statistical analysis of target literature

Through a focused literature review, the selected data were used for statistical analysis to track field development. Using keywords "multispectral" and "yield prediction" to retrieve the literature in the last 20 years in China. Analyzing the annual number of published papers is crucial for understanding research activity and trends in a specific field or topic over time. The number of Chinese publications from 2005 to 2024 is shown in Figure 8.

Through an intuitive analysis of the image data, we observed an increasing trend in multispectral technology for predicting agricultural yields, reaching its peak in 2019 but significantly declining in 2020. We analyzed four possible reasons based on the historical context and scientific research environment.

1. Research project delays and cancelations: The sudden outbreak of the pandemic has caused delays and cancelations in many research projects due to funding shortages and personnel inability to work on-site. *2. Closure of laboratories and equipment:* Due to quarantine measures, many laboratories have closed or limited access, leading researchers to pause or switch to remote work, affecting data collection and analysis. *3. Reduction in international collaboration:* Travel restrictions and quarantine measures have reduced international scientific collaboration, thereby affecting joint research efforts and publication. *4. Redistribution of resources:* During the pandemic, global research resources and attention shifted significantly toward addressing COVID-19, resulting in a slowdown in research progress and a decrease in the number of research papers published, affecting both domestic and international output.

However, by 2021, research momentum has rapidly recovered and reached new heights. The compilation of publication volumes from the past two decades into a single chart allows for a clear observation of China's research development trends, aligning closely with overall global trends. The data segments indicate that China is among the leading nations in terms of worldwide publication output. Based on this, it can be inferred that China has a significant influence and leadership in the global arena of research using multispectral technology for crop yield prediction.

Based on recent publication trends, it is reasonable to predict the research development trajectory for 2024 as follows. In the field of agricultural technology, advancements and widespread application of multispectral technology are projected to sustain the growth trend in research output. China is likely to maintain its global leadership in this research direction, continuing to drive the development of precision agriculture. This trend will contribute to further advancements and innovations in the application of multispectral technology for crop yield prediction and overall agricultural efficiency.

3.7.3 National distribution

Regional analysis of publication trends in a specific field. It is essential to investigate collaborative networks among various publishing institutions and their developmental status. These connections provide insights into the progress and activity levels of multispectral technology for estimating agricultural yields across various regions. Utilizing scientific visualization tools such as CiteSpace, representative diagrams can be generated, as shown in Figure 9, in which each node represents a publishing institution and the edges between nodes indicate their collaborative associations. A higher number of connections between nodes generally signifies increased collaboration among research institutions in a region, potentially leading to more extensive research outcomes. This trend also indicates that there are more and more institutions involved in crop yield prediction research using multispectral technology, and the research is becoming more and more extensive.

Through an examination of associated research institutions, a systematic assessment of the widespread implementation of multispectral technology in agriculture can be conducted across various geographical areas. These assessments provide crucial insights for macro-level policy formulation, resource allocation, and decisions regarding research directions. When examining the collaborative networks within publishing institutions in a particular region,

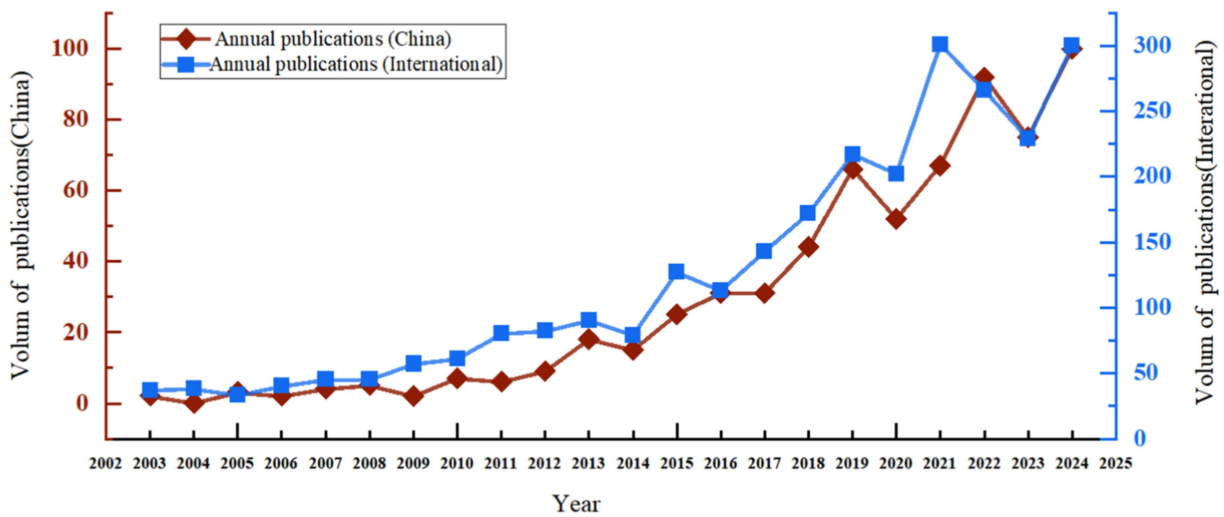

FIGURE 8
Number of publications in China from 2005 to 2024.

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FIGURE 9
Visualization of China's output forecasting agency based on multiple spectra.

characterized by numerous interconnections between nodes, it can be inferred that the region is leading in the research and utilization of multispectral technologies for estimating agricultural yields. This suggests a significant research and innovation capacity within the region.

The Chinese Academy of Sciences emerged as a leading institution in the analysis of spectral image data, with 98 articles, showing its prominence and expertise in scientific research, particularly in the field of crop yield prediction based on multispectral technology. As pioneers of scientific research in China, the Chinese Academy of Sciences has played a key role in promoting the development and practical application of this technology. Moreover, China Agricultural University, Nanjing Agricultural University, Chinese Academy of Agricultural Sciences, and Northwest A&F University have exhibited significant potential for research on multispectral agricultural yield measurement technology. These institutions not only contribute to academic achievement but also have an important influence on the promotion and practical application of technology. Their research progress is full of encouragement, indicating that the future agricultural science and technology field will become more advanced and intelligent because of the innovation and results of these research centers. These academic establishments not only contribute to scholarly accomplishments but also have a substantial effect on the dissemination and practical utilization of technology.

3.7.4 Cooperation and co-citation analyses

By utilizing the co-authorship network of Chinese researchers (Figure 10), it is possible to conduct a thorough analysis of the level of collaboration intensity among experts in a particular field and their interactions through shared citations. In this process, each node in this network corresponds to an author of a published work, with the width and number of connections between nodes indicating the frequency of collaboration and the number of published papers. Through dense node connections, leading experts in the field and their closely collaborating teams can be identified easily.

In the field of multispectral agricultural yield estimation, prominent researchers, such as Zhang Zhitao, Han Wenting, Cao Weixing, and He Yong are recognized as key figures. Their academic achievements and remarkable publication outputs within their research groups are noteworthy. This analysis highlights the close collaborative relationships between these experts and other researchers, indicating high productivity within their teams and their significant influence within the research community. Using this information, we can identify key researchers and research teams in the industry. This identification facilitates the exploration of collaboration opportunities, resource sharing, and policy support for leading experts and their teams, to advance the development of the entire field. Moreover, the collaborative framework established among these experts and teams can serve as a model to encourage greater cross-institutional cooperation and knowledge exchange within the research community (Wang et al., 2019).

3.7.5 Keyword analysis

Through the utilization of VOSviewer software, a visual analysis of keyword co-citations in Chinese literature was conducted (Figure 11). The identified key terms included machine learning, vegetation index, drones, wheat, and corn. Notably, a strong co-citation relationship was observed between machine learning and drones, indicating a keen interest among Chinese researchers in integrating deep-learning algorithms into drone technology. Research in China has emphasized the use of drones equipped with spectral devices for plant data collection, particularly in the context of yield prediction using multispectral technologies. The substitution of traditional remote sensing methods with drones

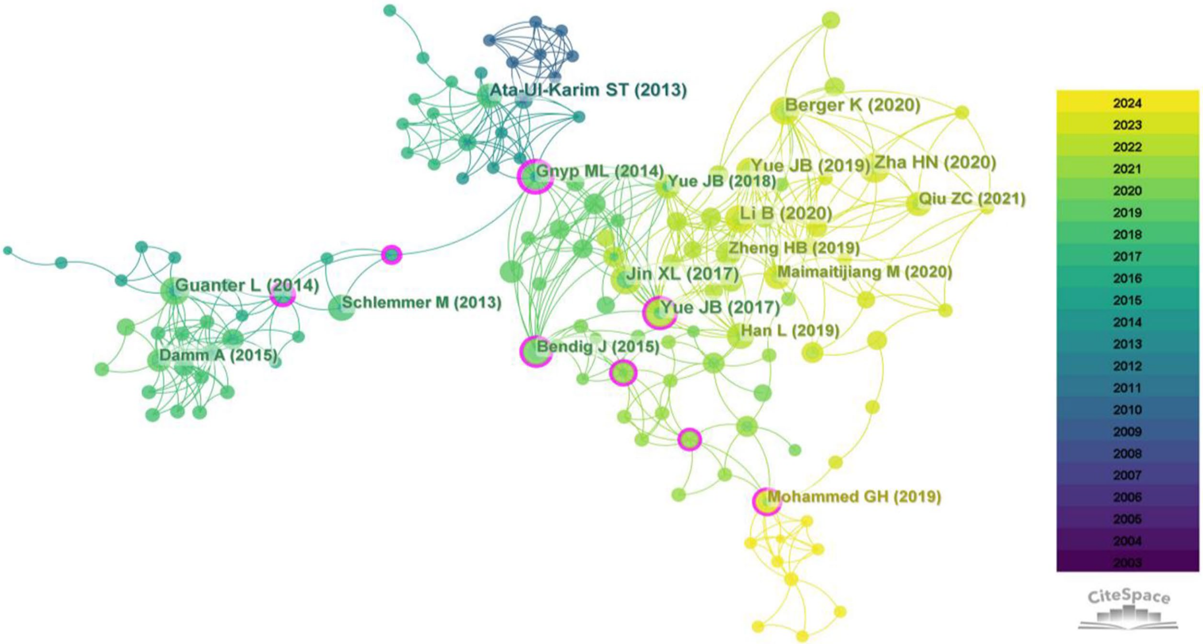

FIGURE 10
Illustration of author cooperation network (China).

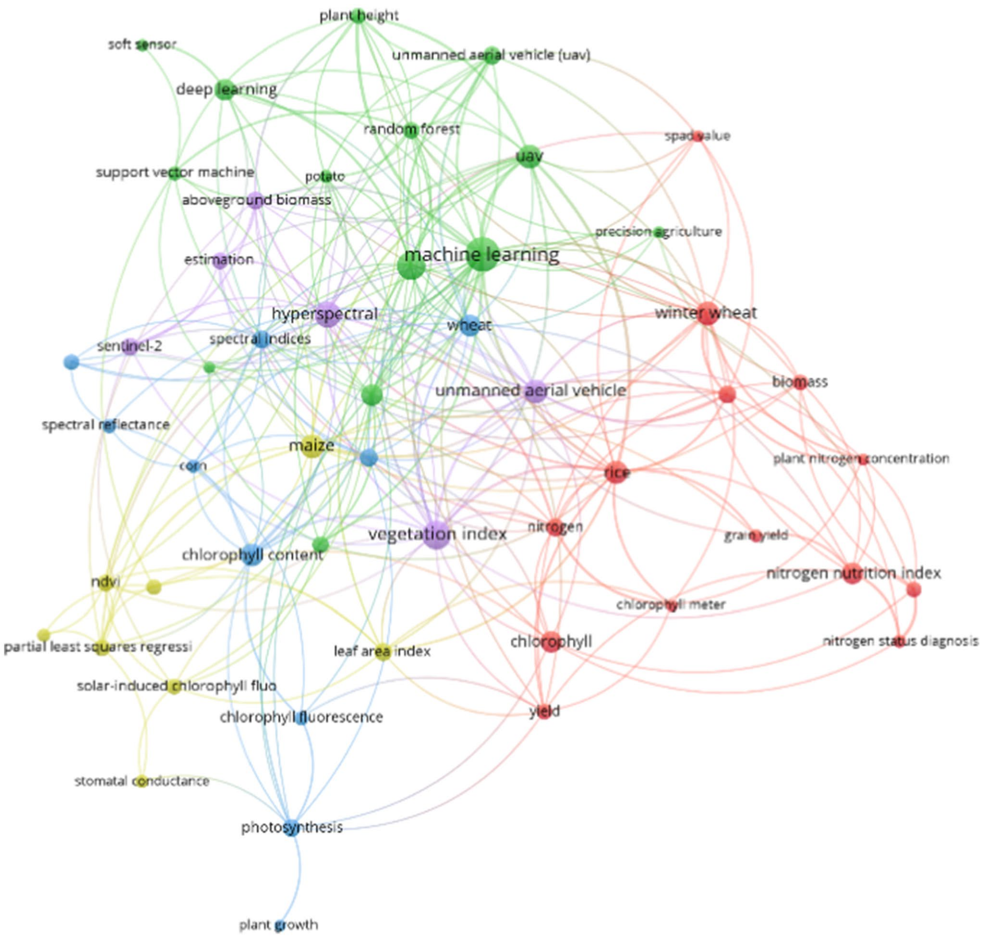

FIGURE 11
Illustration of keyword co-citation analysis (China).

represents a significant technological advancement that facilitates rapid and precise vegetation data acquisition (Puri et al., 2017; King, 2017). Furthermore, the term 'precision agriculture' has emerged, indicating a growing area of research. Multispectral-based yield prediction is a critical technological pillar in precision agriculture, and its rapid progress in China has the potential to propel the field forward significantly. Lastly, the presence of keywords such as rice and corn, staple crops crucial for China's food security and feed production, underscores the practical agricultural concerns prioritized in Chinese research. This highlights the emphasis of Chinese agricultural researchers on yield prediction based on multispectral techniques (Ribeiro et al., 2022).

4 Discussion

4.1 Visual analysis and summary of plant yield prediction based on multi-spectrum

4.1.1 Visual analysis and summary of plant yield predictions based on multi spectra worldwide

This study used various data mining methods, including cluster analysis, and utilized software for data visualization to overcome the limitations of using a single analytical approach, thereby providing comprehensive and in-depth data analysis (Wong and Monaco, 1995; Wong and Selvi, 1998). Trend analysis of annual publication volumes predicts a new research peak in this field by 2024. Geographic analysis indicates that research is predominantly concentrated in Asia, North America, and Central Europe, with China and the United States leading in publication volume, reflecting their prominent positions in agricultural and multispectral technology development. Keyword analysis identified "remote sensing," "machine learning," and "deep learning" as current research hotspots, indicating a trend toward more intelligent research approaches. Furthermore, cluster analysis revealed that keywords such as chlorophyll content, artificial neural networks, remote sensing, and models formed the main clusters, highlighting the central role of chlorophyll content monitoring and machine-learning models in this field. Current research hotspots primarily focus on three main areas.

1. *Data acquisition methods:* This area of focus investigated the effective use of multispectral cameras or remote sensing imagery to collect accurate crop and field data. It also explores the best practices for data collection at different time points and under various environmental conditions (Magney et al., 2017). Research continues to extract useful information from multispectral images and convert it into actionable data, involving complex image processing and analysis techniques, such as classification algorithms, calculation of vegetation indices, and algorithm refinements to enhance image quality and accuracy (Rinaldi et al., 2010; Magney et al., 2017).
2. *Identifying key performance indicators:* Chlorophyll content and LAI are critical indicators that reflect crop health and growth conditions. Multispectral technology can effectively measure these indicators and provide researchers with precise data. Developing more intelligent data-processing workflows to automatically detect and calibrate errors caused by environmental factors ensures the validity of the key indicators, thereby ensuring the stability and reliability of the results.
3. *Predictive model development:* This research area focuses on developing and validating models that use data extracted from multispectral images to predict agricultural yield (Riihimäki et al., 2019). This involves the use of machine-learning algorithms, statistical methods, and other computational techniques to build accurate models that describe crop productivity (Nguyen et al., 2014). This study emphasizes the construction and optimization of prediction models as central to multispectral technology applications. These models, based on regression analysis, decision trees, random forests, support vector machines, neural networks, and other methods, analyze multispectral data to provide estimates of crop growth status, health, and eventual yield.

Research on plant yield prediction based on multispectral technology involves several key indicators and methodologies. Chlorophyll content, LAI, NDVI, EVI, moisture index, and temperature are the primary indicators. Data acquisition methods include the use of drones and satellites for multispectral imaging, and image processing algorithms to extract and handle crucial data. Prediction models have been developed and optimized using machine-learning and deep-learning techniques. The integrated application of these methods enhances the accuracy and efficiency of plant yield predictions, thereby providing robust technical support for precision agriculture. These research hotspots provide valuable insights into the practical value and potential challenges of multispectral imaging technology in agricultural yield prediction and plant monitoring. As technology advances, these focal points are expected to evolve, paving the way for further research and applications. The evolution of crop yield prediction research has transitioned from traditional methods to modern artificial intelligence and machine learning technologies, and continues to advance toward intelligent applications based on remote sensing technology and machine learning models. These developments are poised to guide applications in crop monitoring, precision agriculture, and resource management, thereby demonstrating a broad practical potential and future research opportunities.

4.1.2 Visual analysis and summary of plant yield predictions based on multi-spectra in China

In China, multispectral imaging is widely used for agricultural yield prediction and plant monitoring. Using authoritative Web of Science, Scopus, and CNKI databases as primary literature sources, our team searched literature containing keywords such as "multispectral imaging," "agricultural yield," and "plant monitoring." In the past 20 years, multispectral technology has shown a growing trend in agricultural yield forecasting research, demonstrating the strong resilience and resilience of scientific research activities in China. China's research trends in this field are highly consistent with the world, ranking among the top in the number of global publications, highlighting China's influence and leadership in the global agricultural science and technology field, and research results are expected to continue to grow in 2024 and beyond, further promoting the development of precision agriculture.

The analysis of domestic institutional collaboration networks using scientific visualization tools, such as CiteSpace, reveals

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cooperative patterns among various research institutions. The Chinese Academy of Sciences stands out as a leader in this technology, with other institutions such as China Agricultural University, Nanjing Agricultural University, the Chinese Academy of Agricultural Sciences, and Northwest A&F University also showing significant research potential and practical impact. Researchers such as Zhang Zhitao, Han Wenthing, Cao Weixing, and He Yong are noted for their frequent collaborations and substantial publication output, highlighting their important influence on the research community. This establishes a solid basis for future cross-institutional collaboration and resource sharing, which can drive the entire field forward. Keyword analysis revealed that machine learning, vegetation indices, drones, wheat, and corn are the core topics. The close co-citation relationship between machine learning and drones suggests significant domestic interest in using artificial intelligence technologies for drone-based monitoring. Progress in these technologies provides crucial support for precision agriculture, demonstrating China's dedication to addressing practical production challenges and enhancing yield prediction research through multispectral technology.

4.1.3 Influence of key technology development on yield prediction

With the progress of science and technology, especially breakthroughs in remote sensing technology, machine learning, convolutional neural networks and other fields, the methods and accuracy of crop yield prediction have been significantly improved. The integrated use of these technologies not only improves the efficiency of data processing, but also enhances the ability of models to understand the relationships between complex variables, thus playing an important role in ensuring food security and optimizing agricultural resource management. In the bibliographic analysis of this study, we pay special attention to the specific application and impact of multispectral techniques, remote sensing, convolutional neural networks (CNN), and machine learning in crop yield prediction. Through CiteSpace's keyword co-citation analysis, we found that 'predictive model', 'machine learning' and 'deep learning' are hot keywords in the research, which not only improve the accuracy of crop yield prediction, but also show their importance in promoting the development of precision agriculture technology. Visual analysis via VOSviewer reveals how remote sensing and machine learning techniques can be combined with traditional agricultural practices to enable more efficient data processing and analysis, which is critical to optimizing crop yield prediction models. For example, remote sensing technology enables timely monitoring of crop growth, while machine learning methods can learn and predict crop growth trends from complex data, which significantly improves the accuracy and practicality of forecasting.

Remote sensing technology allows researchers to monitor crop growth across vast fields in real time through high-resolution satellite imagery. These image data, combined with geographic information systems (GIS), can provide a detailed picture of crop growth dynamics, which is crucial for predicting crop yields. For example, the use of remote sensing technology to monitor the chlorophyll content, water status and biomass of crops can predict the potential yield of crops in time. The application of machine learning techniques enables yield prediction models to process large-scale data sets and learn from them the complex relationships between crop growth and environmental factors. These models can be trained to identify which factors are the key variables affecting yield and thus predict crop yields under different environmental conditions. For example, by analyzing historical weather data and crop growth records, machine learning models can predict the likely impact of future weather changes on yields. The application of Convolutional neural network (CNN) in image recognition, especially in processing multi-spectral image data, can effectively distinguish crop pests and diseases and their growth. This advanced image analysis technology enables accurate assessment of crop health and is essential to accurately predict the final yield of a crop.

Assessing these key technologies, documenting their adoption and adaptation, also provides a quantitative basis for understanding their impact on crop yield projections. This approach highlights the significant benefits of integrating advanced imaging and analytics into modern agricultural practices, pointing to a future in which agricultural decisions are increasingly data-driven and precise.

The application of multispectral techniques and related intelligent technologies in academic research also underscores their potential value in practical agricultural production. Future research should further explore the application effects of these technologies in different crops and different growing environments, and how to better integrate these advanced technologies into daily agricultural production to maximize crop yield forecasts.

4.2 Similarities and differences between the world and China

The similarities and differences in multi-spectral yield forecasting research between China and the world are as follows:

1. The early start of global research shows that literature combining multispectral techniques with agricultural yield prediction has been published since 2003.
2. China has the highest number of publications in the Asian region and is on par with the United States in North America, the two countries that are leaders in this field.
3. Keyword analysis showed that "prediction," "model," "leaf area content" and "LAI" were important keywords in plant yield prediction based on multi-spectral technology.
4. China's research involves a huge network of international cooperation, particularly the extensive cooperation of the Chinese Academy of Sciences with other institutions.
5. Machine learning and drone technology have become research hotspots in China, indicating that China has shown special enthusiasm and development potential for integrating high-tech means with agricultural production.

4.3 China is forecasting the future direction of its production based on multiple spectra

China maintains its leading position in the application of multispectral technology in precision agriculture, particularly in crop growth monitoring and yield prediction. This study demonstrates the significant contributions of institutions such as the Chinese Academy of Sciences and various agricultural universities, emphasizing their accomplishments in both academic research and practical applications.

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Current research focuses on key areas, including the rapid and precise collection of vegetation data using drones and the integration of machine learning algorithms, reflecting a transition toward the adoption of advanced technology in traditional agricultural practices. Precision agriculture is emerging as a significant research area in China, with special emphasis on staple crops such as rice and maize.

In light of recent advances, it is anticipated that China will persist in its growth trajectory in this domain, strengthening international cooperation to promote both domestic and global food security and sustainable agriculture. Through ongoing advancements in data acquisition and processing procedures, development of more precise analytical models, and enhancement of interdisciplinary research collaborations, the potential application of multispectral imaging technology in precision agriculture continues to show promise. With technological advancements, it is expected that these will be gradually overcome, thereby propelling the development and progress of agricultural science and technology.

Simultaneously, there has been rapid advancement in domestic algorithmic technologies, which integrate novel algorithms, such as Improved Particle Swarm Optimization-Extreme Learning Machine (IPSO-ELM), with traditional regression analysis, decision trees, and random forest models. We believe that China will make significant advancements in this area in coming years. Chinese research not only follows global trends but also demonstrates distinctive practical application orientations and technological innovation capabilities, providing a robust foundation and offering extensive opportunities for the future progress of agricultural technology.

4.4 Challenges and limitations of multi-spectrum yield prediction

Although multispectral imaging technology offers valuable tools for precision agriculture, its applications encounter several challenges. Environmental factors, such as cloud cover, atmospheric conditions, and lighting, can affect imaging quality and consequently affect prediction accuracy. Furthermore, the choice of algorithms and models is crucial; different crop types and growth stages require tailored-modeling strategies, and the generalization ability of models is a key factor in evaluating their potential applications.

These challenges highlight the ongoing need for advancements in data processing techniques, model refinement, and development of robust strategies that can accommodate diverse environmental and agricultural conditions.

Environmental factors play a crucial role in influencing multispectral imaging. For instance, cloud cover can impact the quality of images obtained by satellites and aerial platforms, whereas atmospheric conditions such as fog and haze can disrupt spectral signals. Moreover, variations in illumination conditions, including fluctuations in solar radiation intensity and changes in the solar angle, can introduce biases in the acquired image data, affecting crop growth analysis and yield predictions. To address these challenges, robust atmospheric correction algorithms are essential to mitigate the effects of atmospheric conditions on the imaging data. Furthermore, researchers must develop advanced data-processing workflows capable of automatically detecting and correcting errors caused by environmental factors, thus ensuring the stability and reliability of the results. The selection of appropriate algorithms and models is critical to achieve accurate yield predictions. Customized modeling strategies are required to accommodate disparities between different crops and growth stages. Some crops may require high-precision models to capture subtle growth changes in the data, whereas others may require models that prioritize the responsiveness to environmental stressors. Additionally, the generalization capacity of the models play a crucial role in determining their potential applications. An exemplary model should demonstrate the capability to produce effective predictions across a wide range of regions, climatic conditions, and crop varieties. The enhanced generalization ability of the model indicates a higher level of credibility in its predictive results and broader applicability across various scenarios. To enhance both the accuracy and generalization capacity of models, researchers may consider incorporating machine-learning and deep-learning methodologies in the development of predictive models. These approaches can identify complex patterns and regularities from extensive training datasets, thereby enhancing predictive precision. Additionally, it is crucial to strengthen interdisciplinary collaboration, particularly by integrating agronomy, ecology, and computer science, to ensure that the models comprehensively capture the complexity of agricultural systems. The evolution of research focus over the past two decades not only reflects the impact of technological advancements on agriculture and ecology but also demonstrates the response of researchers to global challenges. With the progress of research, we anticipate the development of increasingly innovative technologies and strategies to address global issues, such as climate change, resource scarcity, and biodiversity loss.

In conclusion, the utilization of multispectral imaging technology in precision agriculture shows significant promise for the future, despite facing various challenges. These challenges are expected to be addressed by improving the data acquisition and processing methods, developing more accurate analytical models, and enhancing cross-disciplinary research collaboration. The iterative improvement of these methodologies and the synergistic integration of diverse scientific domains will likely catalyze substantial progress in addressing the current limitations, thereby realizing the full potential of multispectral imaging in agricultural applications. This developmental trajectory not only demonstrates the resilience and adaptability of the field but also emphasizes the transformative impact that sustained research and innovation can have on addressing complex agricultural challenges in the context of global environmental change.

Author contributions

JXu: Conceptualization, Investigation, Methodology, Writing – original draft. YS: Writing – review & editing. ZR: Supervision, Writing – review & editing. ZZ: Supervision, Writing – review & editing. CH: Writing – review & editing. LW: Supervision, Writing – review & editing. WL: Writing – review & editing. JXi: Funding acquisition, Supervision, Writing – review & editing. XW: Funding acquisition, Project administration, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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