PROGRESS ANALYSIS OF WEED IDENTIFICATION AND VARIABLE RATE HERBICIDE SPRAYING IN FARMLAND BASED ON BIBLIOMETRICS
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基于文献计量学的农田杂草识别及变量施药研究进展分析

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ABSTRACT
The identification of farmland weeds and variable rate herbicide spraying technology are core components of precision agriculture, playing a significant role in enhancing agricultural productivity, reducing pesticide usage, and protecting the ecological environment. Currently, global agriculture faces dual challenges of increasing resource constraints and rising environmental protection demands. This technology, by precisely locating weed distribution and adjusting pesticide application rates accordingly, has become a key approach to breaking the vicious cycle of "pesticide overuse-weed resistance-ecological pollution." Based on bibliometric methods and using the Web of Science database as the data source, this study retrieved literature related to farmland weed identification and variable rate herbicide spraying from 2005 to 2024. VOSviewer software was employed for visual analysis, systematically examining the temporal evolution characteristics, regional collaboration networks, institutional contributions, and keyword clustering patterns in this field. The results indicate that research in this area entered a rapid development phase after 2018, driven significantly by artificial intelligence technology. Research hotspots focus on image recognition algorithms, multi-source data fusion, variable rate herbicide spraying system design, and field application validation. Current studies face challenges in adaptability to complex environments and multi-scale data coordination. Future efforts should strengthen lightweight recognition model optimization, space-air-ground integrated data fusion, cost-effective smart equipment development, and interdisciplinary collaboration to provide technical support for the sustainable development of precision agriculture.

摘要
农田杂草识别与变量施药技术是精准农业的核心组成部分，对提升农业生产效率、降低农药使用量及保护生态环境具有重要意义。当前，全球农业面临资源约束加剧、生态环保需求提升的双重挑战，该技术通过精准定位杂草分布并按需调控施药量，已成为破解“农药滥用-杂草抗药性-生态污染”恶性循环的关键途径。本研究基于文献计量学方法，以 Web of Science 数据库为数据源，检索 2005-2024 年农田杂草识别及变量施药领域相关文献，运用 VOSviewer 软件进行可视化分析，系统梳理该领域研究的时间演化特征、地域合作网络、机构贡献及关键词聚类规律。结果表明：该领域研究在 2018 年后进入快速发展期，受人工智能技术驱动显著；研究热点集中于图像识别算法、多源数据融合、变量施药系统设计及田间应用验证等方面。当前研究在复杂环境适应性、多尺度数据协同等方面存在挑战，未来需加强轻量级识别模型优化、空天地一体化数据融合、低成本智能装备研发及跨学科协同，为精准农业可持续发展提供技术支撑。

INTRODUCTION

Weeds compete with crops in terms of nutrient uptake, water absorption, and light utilization, making them a significant factor in reduced crop yield and quality *(Wang et al., 2019)*. In the field, weeds exhibit irregular "patchy" and "pointed" distribution patterns. When herbicides are uniformly sprayed across the entire farmland without considering the presence or density of weeds, a substantial amount of herbicide is applied to

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areas without weeds or with sparse weed growth, thereby reducing pesticide efficiency. Additionally, prolonged uniform herbicide application leads to weed resistance, causing the entire weed population to gradually develop tolerance to multiple herbicides over time, diminishing the effectiveness of weed control *(Saini and Nagesh, 2025)*.

The identification of farmland weeds and variable rate herbicide spraying technology, which precisely targets weed distribution and applies pesticides on demand, serves as a crucial pathway to achieving green agricultural development. With the continuous advancement of artificial intelligence, computer vision technology has been widely applied in the agricultural sector for crop identification *(Hamuda et al., 2016; Wu et al., 2024)*. As a key method for revealing the developmental patterns of disciplines, bibliometrics has been extensively utilized in agricultural research across various fields *(Zha et al., 2023)*. It is an interdisciplinary field that explores the structure, characteristics, and laws of science and technology, and quantitatively analyzes knowledge carriers *(Xu et al., 2024)*. However, systematic bibliometric analysis in the field of farmland weed identification and variable rate herbicide spraying remains relatively scarce, particularly in areas such as technological evolution trajectories, interdisciplinary characteristics, and future trend forecasting. Therefore, this study examines global literature data from 2005 to 2024, employing bibliometric analysis, visual mapping, and topic modeling to systematically review the current research status, hotspots, and development trends in farmland weed identification and variable rate herbicide spraying. The purpose is to provide reference for researchers to grasp research trends, enterprise layout technology research and development, and policy makers to plan industrial development.

KNOWLEDGE GRAPH ANALYSIS BASED ON VOSVIEWER

Data source

A scientific literature database is a collection of disciplinary knowledge built by scholars in related fields, responsible for recording and disseminating disciplinary knowledge *(Bornmann., 2019)*. Conducting statistical analysis on literature data can showcase current research hotspots, quickly grasp the latest research trends, and efficiently predict future research trends *(Garg and Kumar, 2016)*.

Using the Web of Science literature search platform, Science Citation Index Expanded and Social Sciences Citation Index as citation indexes, and leveraging Boolean logic operation rules, based on TS = ("weed recognition" OR "weed identification" OR "weed detection" OR "management zone") AND ("variable rate application" OR "variable rate application of pesticides" OR "precision pesticide use" OR "prescription map" OR "weed zoning" OR "variable rate herbicide application") Search within the time range of January 1, 2005 to December 28, 2024, with a search date of December 28, 2024. Retaining Article and Review Article, excluding irrelevant data such as Proceedings Paper, Early Access, Book Chapters, Data Paper, Retracted, and Publication, after steps such as deduplication, completion, merging, and deletion of severely missing fields, a total of 751 valid literatures were screened.

The publication time of 751 articles collected by Web of Science from 2005 to 2024 is shown in Fig.1.

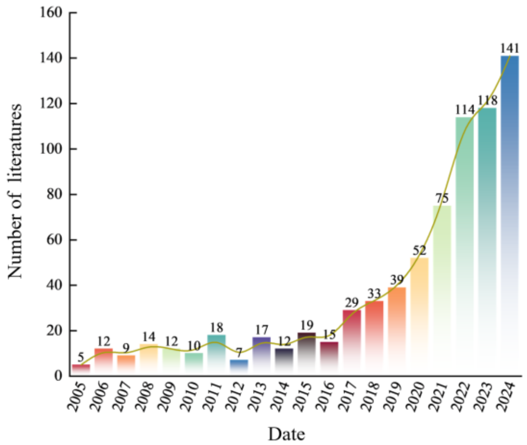


Fig. 1 - Number of publications of relevant literature over the years

The level of annual publication can serve as an important parameter for evaluating the level of research and development in a certain field, and can to some extent reflect the growth and changing patterns of knowledge in that field. According to the statistical data in Fig. 1, the number of published papers each year from 2005 to 2016 did not exceed 20, with fluctuations in the number of publications.

The cumulative number of publications in the past 12 years accounted for 19.97% of the total number of publications. Between 2017 and 2024, there was a significant annual increase in the number of published papers. In 2022, the annual growth rate of publications reached its highest point and exceeded 100 for the first time. In 2023, the growth rate continued but was relatively low, and it continued to show a rapid growth trend until 2024. This statistical data reflects that research in this field has entered a rapid development stage since 2018, which is highly consistent with the timing of the third wave of artificial intelligence development. It indicates that the rapid development of weed identification and variable rate herbicide spraying is driven by artificial intelligence technology.

VOSviewer Analysis Methodology

To ensure the reproducibility of bibliometric visualization results, the following parameter settings and analysis protocols were adopted in VOSviewer for multi-dimensional analysis. VOSviewer is a free open-source software for bibliometrics and scientific visualization. It can be used for multi-dimensional bibliometric analysis, including geographical, institutional, author, and keyword analysis. The 751 valid literatures screened were exported from Web of Science in "Full Record and Cited References" format, including metadata such as authors, affiliations, countries/regions, keywords, and citation information. Before importing VOSviewer, duplicate entries in keywords were manually standardized to ensure consistency across the dataset.

For the parameter settings of co-occurrence analysis, the minimum occurrence threshold was defined differently by entity type: for keyword co-occurrence analysis, the minimum number of occurrences of a keyword was set to 5 to exclude noise, while all countries/regions with published literature were retained (no minimum threshold) to fully reflect the global collaboration network, and the minimum number of publications by an institution was set to 10 to focus on core contributing institutions. The clustering resolution parameter was set to 0.7, the default optimal value for VOSviewer, which balances the granularity of keyword clusters (with values ranging from 0 to 1, where higher values result in more fragmented clusters). The "full counting" method was adopted for all co-occurrence analyses, counting each co-occurrence relationship between two entities (keywords, countries, institutions) as a complete connection to highlight strong collaborative relationships and core research themes.

The type of analysis was tailored to research objectives: regional collaboration was analyzed using "country/region co-occurrence" to visualize cross-national collaborative networks, institutional contribution was analyzed using "affiliation co-occurrence" to identify core research institutions and their partnerships, and keyword clustering was analyzed using "keyword co-occurrence" to explore research hotspots and thematic clusters, with cosine similarity used to measure the correlation between entities based on their co-occurrence frequency. For visualization settings, the size of nodes in the knowledge graph was proportional to the frequency of occurrence, the color of nodes represented different clusters, and the thickness of connecting lines corresponded to the strength of the co-occurrence relationship. The layout of the graph was generated using the VOS clustering algorithm, which minimizes the distance between closely related entities to intuitively display the structure of the network.

Regional co-occurrence knowledge graph and publication statistics

The regional co-occurrence knowledge graph is shown in Fig. 2.

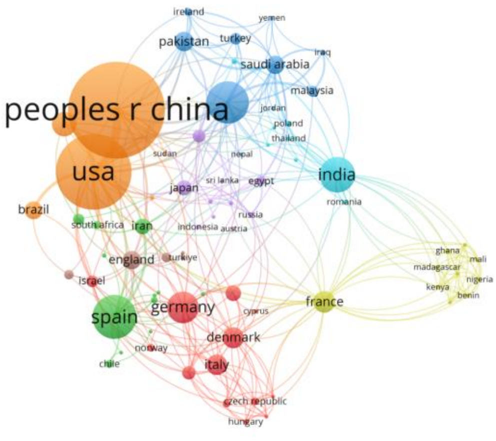


Fig. 2 - Regional co-occurrence knowledge graph

As shown in Fig. 2, China is a central node in the figure, ranking first in terms of the number of publications in this field, and has connections with many countries. Due to the frequent contact between countries, which often involves knowledge sharing, joint research projects, etc., a large number of academic literature is generated. Therefore, countries with more connections, such as the United States, India, and France, also have higher publication volumes in related fields. Some countries in the figure that only have connections with a few countries, such as Hungary and Kenya, have relatively low activity in related research and publication due to their low participation in international cooperation networks. Therefore, their publication volume in this field is relatively small.

The volume of publications in a specific region is calculated by accumulating the publications from research institutions in that country. To understand the publication status of institutions, statistics were collected on the publication status of research institutions in the field of weed identification and variable rate application, as shown in Table 1.

Table 1

Top 15 institutions in terms of the number of international publications

Institution name	Country of residence	Quantity	Percentage%
Consejo Superior de Investigaciones Científicas	Spain	32	4.26
University of Florida	the United States	25	3.33
Texas A&M University	the United States	18	2.40
China Agricultural University	China	18	2.40
South China Agricultural University	China	17	2.26
Peking University	China	16	2.13
University of Sydney	Australia	16	2.13
Nanjing Forestry University	China	15	2.00
Chinese Academy of Sciences	China	14	1.86
United States Department of Agriculture Agricultural Research Service	the United States	14	1.86
North Dakota State University	the United States	14	1.86
Jiangsu University	China	13	1.73
Jilin Agricultural University	China	12	1.60
University of Copenhagen	Denmark	12	1.60
Mississippi State University	the United States	11	1.46

From Table 1, it can be seen that among the top 15 institutions in terms of publication volume, 7 institutions are from China and 5 institutions are from the United States. Their total publication volume accounts for 13.98% and 10.91% of the top 15 institutions respectively, indicating to some extent that Chinese institutions have conducted a lot of research in this field and achieved fruitful results.

Keyword co-occurrence analysis

Keyword co-occurrence analysis refers to the situation where keywords with the same or different types of characteristics appear together in a document. In Fig. 3, a node represents a keyword, and the larger the node, the higher the frequency of its appearance. The nodes are connected by lines, and the thicker the line, the stronger the correlation between them.

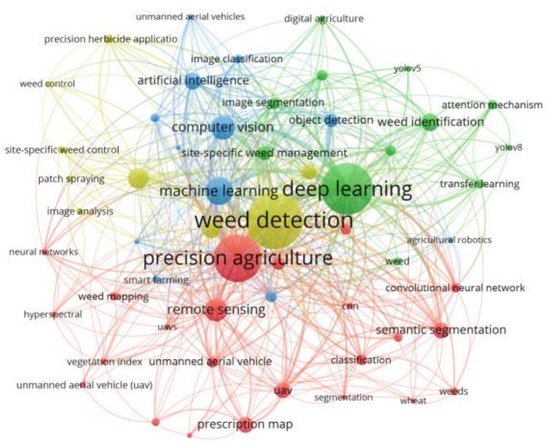


Fig. 3 - Keyword co-occurrence map

As shown in Fig. 3, the keywords are divided into four clusters, each representing a research topic. Table 2 lists the top four keywords that appear in different clusters.

Table 2

Keyword co-occurrence distribution

Clustering	Top 4 keywords by frequency	Total number of keywords
1	Classification (190), precision agriculture (160), remote sensing (51), segmentation (50)	23
2	deep learning (163), weed identification (64), site-specific weed management (27), image segmentation (22)	12
3	machine learning (68), computer vision (61), artificial intelligence (34), unmanned aerial vehicle (28)	12
4	weed detection (267), machine vision (61), image processing (40), weed recognition (290	9

Cluster 1 contains 23 keywords, with the core theme of building a precision agriculture technology system. It covers artificial intelligence technologies such as "convolutional neural networks" and "neural networks", which are applied in precision agriculture operations such as "precision agriculture", "prescription map", and "variable rate application". Data is obtained through devices such as "remote sensing", and then processed through "classification" and "segmentation". In addition, this cluster involves agricultural management content such as "weed management" and "weed mapping", as well as the use of "vegetation index" to assess crop growth.

Cluster 2 contains 12 keywords, with the core topic being weed identification technology driven by deep learning. This involves deep learning techniques such as "deep learning" and "transfer learning", which are applied to operations such as "weed classification" and "weed identification". The "image segmentation" technique can be used to assist weed identification and localization, especially for "site-specific weed management". In addition, the "attention mechanism" helps to improve the accuracy of related models. In terms of deep learning frameworks, "yolov5" and "yolov8" are mentioned, which are widely used in the field of object detection and recognition.

Cluster 3 contains 12 keywords, with the core theme of integrated application of agricultural intelligent technology, involving intelligent technologies such as "artificial intelligence", "machine learning", and "computer vision". These technologies are applied to complete operations such as "image classification" and "object detection", and are applied in fields such as "precision farming" and "smart agriculture", assisted by devices such as "unmanned aerial vehicle".

Cluster 4 contains 9 keywords, with the core theme of precision weed control driven by image technology. It covers image technologies such as "image analysis", "image processing", and "machine vision", which are used in operations such as "patch spraying", "precision herbicide application", and "site-specific weed control". These technologies enable functions such as "weed detection" and "weed recognition", which help to precisely manage weeds and reduce herbicide abuse.

Based on the cluster analysis of the aforementioned keywords, current research on crop field weed identification and variable rate herbicide spraying technology primarily focuses on data acquisition and processing, algorithms, weed-related management, and precision agriculture applications. In terms of data acquisition and processing, remote sensing, drones, and other equipment are used to obtain data. Image processing, deep learning, and machine learning are applied as typical artificial intelligence algorithms for key tasks such as weed classification and identification. The YOLO series of deep learning frameworks play an important role in object detection and recognition tasks, especially with the integration of attention mechanisms and other technologies. By enhancing the network's ability to capture key information, the accuracy of the model is effectively improved. By evaluating crop growth conditions using vegetation indices, combining weed distribution maps and prescription maps, variable rate herbicide spraying and other operations, targeted spraying, precise herbicide application, and other methods are used to achieve weed control in specific locations, thereby achieving precise weed management and reducing herbicide abuse.

Analysis of main research directions

Through bibliometric analysis, it can be seen that the research on crop field weed identification and variable rate herbicide spraying technology involves multiple key aspects, with a good development trend and much attention. However, to further promote research and application in this field, it is particularly important to deeply explore the specific research status of "crop field weed identification", "farmland precision management zoning", and "variable rate herbicide spraying technology".

(1) Crop field weed identification: With the help of artificial intelligence algorithms such as image processing, deep learning and machine learning, it is applied to key tasks such as weed classification and identification.

(2) Precision management zoning of farmland: Based on the spatial variability exhibited by the fields and actual needs, divide them into several sub-fields with different homogeneity, and adjust soil and crop management measures according to specific formulas, timing, location and quantity.

(3) Variable rate herbicide spraying technology: Utilize satellite positioning system to receive information, combine real-time feedback values of flow pressure in the pesticide supply system, generate pesticide application instructions with the help of flow, pressure and other sensors, and carry out variable rate herbicide spraying operations through a control system.

Although existing research has made significant progress in the above three directions, there are still deficiencies in the deep integration of technology integration and practical application: a complete technical system of "weed identification-zoning decision making-application execution" has not yet been formed, and there are problems such as incompatible data interfaces between different links, inconsistent spatial and temporal scales; in complex farmland environments, the accuracy and stability of multi-source data fusion are insufficient, and the adaptability of different algorithms in different crop types has not been fully verified. Therefore, an in-depth analysis of the current research status of the above core directions, clarifying advantages and disadvantages, can provide a clear direction for subsequent research and is of great significance for promoting the implementation of technology in this field.

PROGRESS ANALYSIS OF WEED IDENTIFICATION AND VARIABLE RATE HERBICIDE SPRAYING IN FARMLAND

Research progress on weed identification in crop fields

As a new generation of information technology deeply integrates with agriculture, the sector has entered a new era of digitalization and intelligence, with agricultural remote sensing and agricultural models playing a crucial supporting role as key core technologies *(Yun et al., 2024)*. Agricultural remote sensing utilizes remote sensors, drones, and satellite remote sensing to monitor and collect crop growth data in real-time within the farmland environment *(Olson and Anderson, 2021)*.

To implement variable-rate pesticide application technology, accurately detecting and identifying weeds is the primary step *(Liu and Bruch, 2020)*. With the development of data collection platforms, sensors, and data processing and analysis methods, high-throughput phenotyping technology has been widely applied *(Lobet, 2017)*. Crop field image acquisition devices with high-throughput, automation, and high-resolution characteristics play a key role in accelerating crop improvement and breeding processes, increasing crop yields, and enhancing resistance to pests and diseases. They are also important ways to construct crop growth models and collect high-dimensional and rich phenotypic datasets of crops *(Cheng et al., 2020)*. Integrating crop image acquisition devices based on optical imaging principles with crop models and accurately analyzing the acquired image data can lay the foundation for quantitative decision-making and management in the process of agricultural development *(Sun et al., 2020)*. By analyzing the current research status of crop field weed identification, this paper provides references for the selection of field weed image acquisition equipment and weed identification methods.

Research progress on weed identification methods based on image processing and machine learning

In the field of weed identification, image processing, machine learning, and deep learning are three core technologies. Image processing technology performs pre-processing tasks such as denoising, enhancement, and grayscale transformation on acquired images to improve image quality and clarity *(Zhang et al., 2024)*. Threshold segmentation, edge detection, and morphological operations are used to separate weeds from background, other plants, and other interference factors, providing accurate target areas for subsequent classification and identification *(Montalvo et al., 2012)*. Generally, image processing technology is combined with machine learning or deep learning to achieve more accurate weed identification.

Fig. 4 shows the general process of weed identification based on image processing.

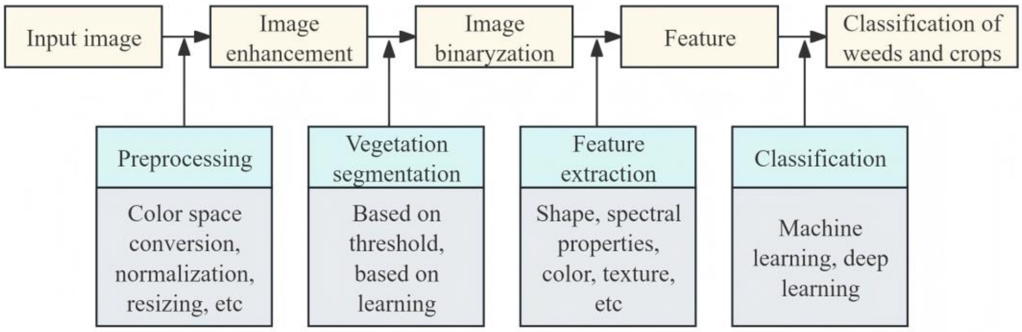


Fig. 4 - General process of weed identification based on image processing

Machine learning technology utilizes feature data extracted from images to build various classifiers, such as support vector machines, decision trees, and random forests. The focus of machine learning technology is to help computers learn the potential relationship between input and output from given data and make accurate predictions *(Samuel., 2000)*. Machine learning uses statistical methods to learn from data without requiring specific clear programming instructions *(Mitchell., 1999)*.

In the research on weed identification using machine learning, *Wu et al. (2009)* proposed a corn and weed identification scheme based on image processing and support vector machine (SVM) technology. Based on the characteristics of color images of corn, weed and soil, an image graying method was designed to denoise the grayscale image, thereby separating the target objects. The shape feature parameters of the target objects were further extracted and used as input feature vectors. The recognition rate of this method reached 98.3%. *Wu et al. (2010)* used shape features as inputs for SVM to identify corn and weed. The leaf shape parameters were input into SVM models using RBF, sigmoid, and polynomial kernel functions, respectively. The accuracy of RBF-SVM reached 96.50%, which was the best among these models in terms of recognition performance. *Ahmed et al. (2012)* proposed an SVM algorithm for weed identification in pepper field images. They used a binary segmentation technique based on global threshold to distinguish plants from the ground and extract features. The features in each image were divided into color features, shape features, and moment invariants. The experimental results showed that the overall accuracy of support vector machine reached 97% on 224 test images. *Bakhshipour et al. (2018)* proposed a weed detection method in sugar beet fields based on shape factors, moment invariants, and other shape features. They separated highly similar sugar beets from weeds and used KNN and SVM classifiers to distinguish weeds and sugar beets, with overall accuracies of 92.92% and 95%, respectively.

Machine learning, combined with image processing, boasts low computational resource requirements and cost-effectiveness, making it suitable for low-cost embedded devices or small datasets with distinct crop-weed morphological differences. However, it relies heavily on manual feature engineering, limiting stability and generalization.

Research progress on weed identification methods based on deep learning

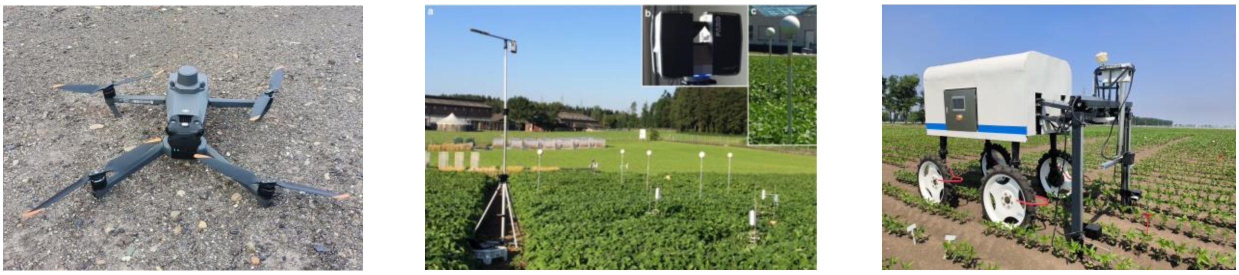
Deep learning is a key branch of machine learning. Compared to machine learning, deep learning can directly learn and extract high-dimensional features from raw image data without requiring manual feature selection and transformation *(Rakhmatulin et al., 2021)*. This not only simplifies the algorithm implementation process but also improves the algorithm's adaptability and generalization ability. Through deep neural networks, deep learning can capture subtle differences and complex features in images, which has significant advantages for weed identification tasks in real-time environments *(Rai et al., 2023)*. Existing object detection frameworks include two stage detectors (e.g., the R-CNN series) *(Islam et al., 2025; Zhang et al., 2024)* and single-stage detectors (e.g., SSD and YOLO series) *(Chen et al., 2022; Dang et al., 2023; Fan et al., 2024)*. Model enhancement and feature optimization have become key research focuses in UAV based weed detection *(Das et al., 2025; Zheng et al., 2024)*. Carrying out weed identification work in complex farmland environments faces many problems: due to fluctuations in light intensity, image quality is reduced, increasing the difficulty of image preprocessing and recognition; weed species are diverse, morphologically varied, and distributed in a chaotic manner in the field, placing higher demands on model accuracy and prone to misjudgment and missed judgments; the farmland environment is complex and variable, such as soil color, humidity, crop growth status, etc., which can cause some interference in weed identification.

Scholars at home and abroad have adopted many solutions to address the existing problems of weed identification in farmland environments. *Fan et al. (2021)* studied seven common weeds in cotton seedling stage in Xinjiang cotton fields under natural conditions, using optimized Faster R-CNN and data augmentation to effectively identify and locate weeds in different situations, such as weeds growing together with cotton seedlings, sparse weed distribution, or dense weed distribution with numerous targets. *Wang et al. (2022)* constructed a detection model YOLO-CBAM by fusing YOLOv5 and attention mechanism. The recognition accuracy in field experiments was 0.9465, and the recall rate was 0.9017. It can be applied to real-time detection of invasive weed Solanum nigrum seedlings. The model has been further improved through multi-scale training. *Zhang et al. (2022)* proposed a weed identification model based on YOLOv4-Tiny, which integrates multi-scale detection and attention mechanism for weed detection in peanut fields. This model improves the ability to identify small target weeds, avoids the problem of missed weed detection, and enables the model to reach convergence faster. Although this study achieved a mAP of 94.54% in the test dataset, the limited number of crops and weeds in the image and the limited recognition range restricted the application of the model in large fields.

Compared with machine learning, deep learning autonomously extracts high-dimensional features, achieving higher accuracy and stronger adaptability to complex environments. Its limitations lie in high demands for datasets and computing power, requiring lightweight optimization for edge deployment. Deep learning is preferred for large-scale farmlands and real-time detection, while machine learning is more applicable for small-scale, simple scenarios.

Research progress of field weed image acquisition equipment

When acquiring field image information, commonly used equipment or technologies include satellite remote sensing, Unmanned aerial vehicle (UAV) remote sensing, and ground image acquisition platforms *(Zhang and Zhao, 2023)*. As shown in Fig. 5, it is a part of the image acquisition platform.



（a）DJI Mavic 3M UAV platform *(Li et al., 2024)*　（b）Outdoor fixed platform *(Friedli et al., 2016)*　（c）Self-propelled collection device *(Yu et al., 2025)*

Fig. 5 - Image acquisition platform

Satellite remote sensing utilizes sensors on satellites to acquire information about the Earth's surface, with a wide coverage area but low spatial resolution and slow response to ground dynamic changes. The ground image acquisition platform refers to equipment that is typically placed relatively close to the ground and can be equipped with high-resolution cameras and sensors to better capture field image information.

Sun et al. (2019) used a Canon SX730 HS camera to collect crop images of broccoli seedlings during the weed control period. These image samples covered various conditions such as different light intensities, different soil moisture contents, and different weed densities, providing a reference for crop identification in agricultural intelligent weed control operations.

Jiang et al. (2020) used an Intel Real Sense Depth Camera D435 camera to capture images of weeds in a corn field at a distance of 1m from the ground under different light intensities and soil backgrounds. In the field variable spraying experiment, the accuracy rate of accurately spraying on identified weeds was 85%, meeting the control requirements of variable spraying of pesticides].

Zhang et al. (2023) developed a mobile robot platform that combines an improved YOLOv5 algorithm to achieve weed detection in vegetable seedling fields. It can accurately segment and label weeds, providing a reference for precise weed control operations.

UAV remote sensing involves equipping drones with various types of sensors to obtain crop images and other relevant information at low altitudes without direct contact with crops. This effectively extracts detailed information about crop morphology, nutritional status and other aspects, thereby completing an instant, non-destructive and reliable task of crop information collection *(Khaki et al., 2021)*. Currently, research teams have utilized UAV as high-throughput crop phenotype detection tools and conducted systematic testing work *(Feng et al., 2020)*, providing a new technological approach for achieving precise management in crop fields. The deep integration of deep learning and UAV technology has broken through the limitations of traditional weed identification in efficiency and scope, opening up a new path for field weed identification *(Rai et al., 2023)*. At present, the sensors used in plant phenotype analysis research using UAV remote sensing mainly include digital cameras, multispectral cameras, hyperspectral cameras, lidar and thermal imagers *(Liu et al., 2016)*. Through the use of advanced sensors with UAV, plant phenotype research can be improved in a more efficient and environmentally friendly way *(Mohidem et al., 2021)*, which is the technological focus for improving efficiency, sustainability, technological innovation and agricultural modernization.

Satellite offers wide coverage, ideal for regional-scale weed distribution trend analysis, but suffers from low resolution and is unsuitable for seedling-stage detection. UAV combines high resolution, wide coverage, and fast data acquisition, outperforming satellites in large-scale farmland weed mapping and dynamic monitoring. Ground platforms provide high-precision local data for small-scale test fields or precise surveys, yet face limitations like narrow coverage, lighting interference, or soil compaction. In summary: satellites for regional trends, UAVs for large-scale operations, and ground platforms for small-scale precision detection.

Current research status of precision management zoning in farmland

Precision management zoning is based on the spatial variability and actual demand conditions of the fields, dividing the fields into several sub-fields with different homogeneity. For these sub-fields, soil and crop management measures are adjusted according to specific formulas, timing, fixed points, and quantities. It is a key link in precision agriculture *(Ferguson et al., 2002)*. The goal of carrying out precision management zoning is to achieve precision variable operation, thereby reducing agricultural input, improving soil quality, and maximizing the potential of arable land resources. This measure is of great significance in improving land productivity and ensuring food security *(Bao et al., 2021)*, thus promoting the natural environmental system and ecosystem in the region to maintain a dynamic balance state *(Koch et al., 2004)*. In the research process of management zoning at the field scale, most studies focus on the differences in soil conditions (fertility, moisture content) and crop growth conditions (seedling growth, pest and disease conditions) within the field to set basic management units within the field *(Huang et al., 2020)*. By combining variable operation, precise application of fertilizer, water, and pesticides is promoted *(Ding, 2019)*.

Current research status of management zoning based on vegetation index

In recent years, the main source of input for precision management zoning has been data obtained from remote sensing technology. These remote sensing data contain rich information about land features, among which vegetation-related information is crucial for precision management zoning.

Liu et al. (2018) effectively improved the precision and accuracy of cotton field zoning by combining object-oriented hyperspectral image segmentation technology with vegetation indices such as NDVI and OSAVI, based on the characteristics and differences of different management areas. This approach enhanced crop yields and land use efficiency. The study found that the selection and weight allocation of different vegetation indices could affect zoning results, and the high cost of hyperspectral image acquisition and processing limited the widespread application of this technology.

Liu et al. (2021) obtained Sentinel-2 A satellite remote sensing image data of corn emergence over many years, from which they extracted the normalized difference vegetation index (NDVI). They used object-oriented segmentation to implement precise management zoning operations. After completing the zoning, the coefficient of variation of NDVI decreased within the range of 70.690%-76.420%. This research provides a reference for the effective connection between precise management zoning and field variable management measures such as precise fertilization and precise pesticide application. NDVI plays a key role in regional detection work, providing strong support for precise management zoning operations based on NDVI. However, some related research has pointed out that single-period NDVI spatial data contains limited information and considers insufficient factors, resulting in a decrease in the accuracy of precise zoning. In contrast, the zoning results obtained from integrating multi-period image information are significantly better than those from single-period zoning *(Li et al., 2012)*. Therefore, in another study by *Liu et al. (2019)*, they integrated soil organic matter spatial data, topographic data, and spatial data such as NDVI extracted from SPOT-6 remote sensing images, which are closely related to zoning, and used object-oriented segmentation to carry out zoning work for typical black soil areas.

The results showed that the accuracy reached its highest when using comprehensive four-period NDVI spatial information for zoning. This achievement provides a reference for data selection in the process of precise management zoning.

Guo et al. (2023) proposed a method for obtaining the influence weight of environmental variables using the normalized vegetation index NDVI. By screening out 15 key environmental variables closely related to NDVI and their weights, they used the K-means clustering method to divide the rubber plantation into six zones, effectively distinguishing the levels of soil nutrient abundance and deficiency. The differences in environmental variables between each zone showed a significant state ($P<0.05$), providing a practical and reliable approach for soil management zoning work. In addition, this study looked forward to the potential of other vegetation indices in indicating vegetation conditions, proposing to carry out zoning research using other vegetation indices in the future and verifying their feasibility. *Chen et al. (2022)* obtained NDVI data for soybeans and corn by using a built-up platform for collecting spectral information from crop canopies. They applied a model-based fuzzy C-means clustering algorithm to divide the fertilization management zones for soybeans and corn. When analyzing the NDVI data for soybeans and corn, they found that when the number of soybean zones was greater than 2 and the number of corn zones was greater than 3, the decrease in the sum of squared errors was no longer significant, and the subsequent curve tended to be smooth. At this point, the number of zones was considered reasonable. Taking into account the specific conditions of the crop fertilization site and past fertilization experience on the farm, it was ultimately determined to set the number of fertilization management zones for soybeans and corn to 4. *Breunig et al. (2020)* used remote sensing data from the Planet Scope satellite to predict crop biomass using surface reflectance and vegetation index as predictors. Based on the prediction results, they implemented precise management zoning using fuzzy C-means clustering and verified it using yield data.

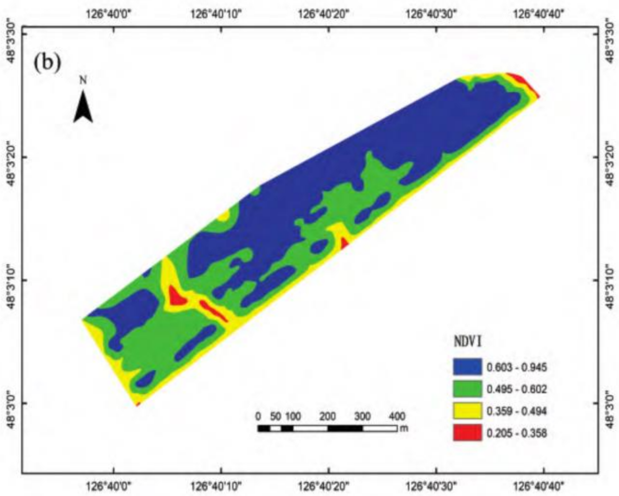


Fig. 6 - Soybean fertilization management zoning map based on NDVI *(Chen et al., 2022)*

Vegetation indices are generally calculated based on spectral characteristics and are mainly used to assess the growth status, coverage and health of vegetation. Given the high similarity in morphological and physiological characteristics between seedling crops and weeds, their spectral characteristics are not significantly different, resulting in a high degree of overlap or difficulty in distinguishing between the calculated vegetation indices. Therefore, using vegetation indices as input features for clustering algorithms may increase the complexity and uncertainty of the algorithm during the recognition process.

Current research status of management zoning based on clustering algorithms

By using only clustering algorithms and focusing on non-spectral feature extraction and analysis, it is possible to deeply explore and utilize differences in non-spectral features such as morphology, texture, and growth patterns between seedling crops and weeds, thereby providing a more reliable and effective basis for clustering algorithms. *Davatgar et al. (2012)* used fuzzy clustering methods to define different fertility level areas based on soil fertility characteristics and proposed targeted nutrient management strategies for rice planting areas, which can effectively improve nutrient utilization efficiency and crop yield, providing a scientific basis and technical path for sustainable nutrient management in rice fields.

Chen et al. (2008) used Fuzzy C-Means clustering to divide 176 soil data points in the oasis cotton region of Xinjiang into four zones, with significant differences in soil properties between each zone. The zoning results can be used as individual operation units for variable fertilization to carry out farming management work. However, the current zoning results do not yet cover the specific field management measures formulation issues between zones.

An et al. (2011) used real-time data on cotton yield as the data source and used K-Means clustering algorithm to divide the management zones of oasis farmland in Xinjiang, evaluating the effectiveness of management zone division using variance reduction rate change. When the number of management zones is four, the variation degree of cotton yield within each zone is relatively small, while the variation degree of cotton yield between zones is relatively large. Therefore, it is suitable to carry out variable operations at this zoning scale.

Zhu et al. (2018) proposed a density map method, which combines dimensionality reduction with qualitative analysis to form a gradual subdivision method. Using this method, 315 administrative village units in Xinzheng City were divided into six types of farmland consolidation areas. There are significant differences in grain yield and its influencing factors among different types of areas, and the focus of farmland consolidation project construction also varies among different types of areas. The proposed method is suitable for farmland consolidation type area division work in multi-factor and large sample situations, and can provide key reference for farmland consolidation planning and design.

Zhang et al. (2022) established a zoning evaluation index system from three dimensions: ecological sensitivity, land suitability, and consolidation urgency. They applied a two-level selective clustering integration method to carry out spatiotemporal allocation of agricultural land consolidation in Huaihua City, Hunan Province, dividing 300 clustering units in Huaihua City into five consolidation area types. This indicates that the two-level selective clustering integration method can balance cluster quality recognition and geographical spatial advantages, and is suitable for situations with many clustering units and complex attribute spaces.

Chen et al. (2019) used the Fuzzy C-Means clustering algorithm to divide the corn field into three management zones. During the crop growth period, crop height, leaf area index, and soil moisture content showed significant differences in different zones. Based on the different soil properties and nutrient conditions within the zones, scientific guidance can be provided for formulating different irrigation and fertilization systems.

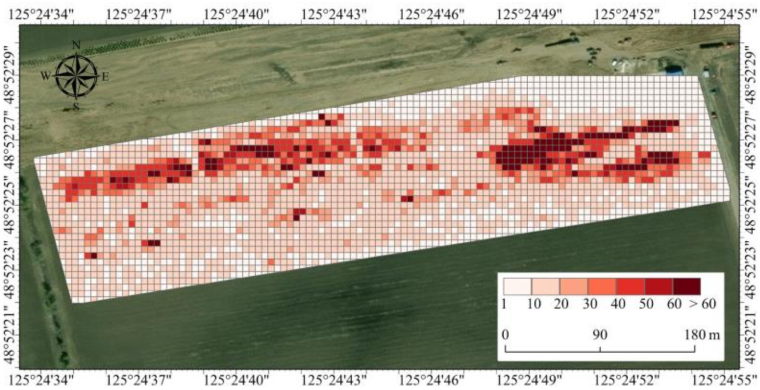


Fig. 7 - Weed distribution map *(Yue et al., 2025)*

In summary, vegetation indices are computationally simple and timely, suitable for rapid large-scale zoning or mature-stage crops with obvious spectral differences. However, their accuracy declines in seedling stages due to overlapping crop-weed spectral features. Clustering algorithms utilize non-spectral features, improving zoning precision in complex scenarios. Compared with vegetation indices, clustering algorithms require more comprehensive data and parameter tuning but adapt better to seedling-stage farmlands. Vegetation indices excel in automated large-scale zoning, while clustering algorithms are preferred for medium-to-small-scale fine management.

Research progress on variable rate herbicide spraying technology

Variable rate herbicide spraying technology aims to improve pesticide utilization and moderately reduce pesticide use *(Smedbol et al., 2020; Swarnkar and Verma, 2014)*. It is a key topic in the field of precision agriculture and a development trend in pesticide application technology *(Feng et al., 2021)*.

Variable rate herbicide spraying technology relies on the decision-making and execution process *(Zhao et al., 2025)*. Based on the satellite positioning system and the information received by the system, combined with the real-time feedback values of flow pressure obtained from the pesticide supply system, various sensors such as flow and pressure sensors generate specific pesticide application instructions. The control system then carries out variable rate herbicide spraying operations. This technology is mainly divided into machine vision-based variable rate herbicide spraying technology and prescription map-based variable rate herbicide spraying technology *(Wei et al., 2011)*.

Research progress on variable rate herbicide spraying technology based on machine vision

Variable rate herbicide spraying technology based on machine vision is the core technology for achieving precise, efficient, and environmentally friendly crop pest and weed control. This technology utilizes a machine vision system to analyze crop growth conditions, pest and disease conditions, and environmental factors in real time, automatically adjusting the amount and method of pesticide application. During operation, visual sensors, ultrasonic sensors, infrared sensors, laser sensors, and other devices are used to obtain information such as the spray target contour, position, and density. The control system analyzes and processes the acquired information to determine the specific amount of pesticide to be applied, further forming a pesticide application decision-making plan, thus achieving precise pesticide application, improving control effectiveness while reducing pesticide use.

Guo (2023) developed a set of real-time target-oriented spraying equipment based on machine vision, deeply integrating deep learning object detection technology, electronic control technology, and agricultural spraying machinery. By improving and optimizing the YOLOv5 model, precise identification of field weeds was achieved. A precise control algorithm for target-oriented spraying with real-time delay compensation was designed, which corrects the matching grid position by predicting weed position information and system execution time, thus achieving precise spray control.

Liu et al. (2013) developed an infrared target-oriented detection system based on simulated sine modulation. This system uses infrared light to illuminate target objects, and receives the reflected infrared light through a receiver to determine the target position. By combining automation technology with spray technology, the pesticide application method for crops is transformed from continuous application to intermittent target-oriented spraying, greatly improving pesticide utilization efficiency.

Lei (2002) developed an intelligent spraying system based on visual sensors by combining a single nozzle controller with a real-time visual sensing system. The controller of this system can independently control each individual nozzle, and combined with a GPS system, it can achieve precise positioning of field weeds. Based on visual sensors, it can estimate the density and position of field weeds in real time, and decide whether to turn on or turn off the nozzles based on this information, thus achieving precise pesticide application and improving spray accuracy and pesticide effective utilization efficiency.

Variable rate herbicide spraying technology based on machine vision has been widely used in the field of variable rate herbicide spraying due to its high accuracy and strong real-time performance. However, this technology is still constrained by some factors. For example, the variable spraying weed control equipment based on machine vision designed by *R.D. Lamm et al. (2002)* and *T. Bakker et al. (2010)* has low weed recognition rate and long processing time. The probability of misjudgment is high during the recognition process, especially in complex environments, and there is still room for improvement in recognition accuracy. In addition, the resolution of sensors, image processing effect, speed sensor measurement time, and computer processing time all have a direct impact on the control accuracy of the system nozzle application amount.

Research progress on variable rate herbicide spraying technology based on prescription maps

The variable rate herbicide spraying technology based on prescription maps is a personalized spraying method that is field-wide and based on the diagnosis and control of plant pests and diseases *(Liu et al., 2024)*. Through professional technical means, pests and diseases are diagnosed, and targeted control measures are formulated based on the actual distribution of weeds, pests, and diseases in the field. Using precision spraying devices, spraying operations are carried out according to pre-set prescriptions, achieving efficient and precise control of pests and diseases *(Romero and Heenkenda, 2024)*.

As shown in Fig. 8, a variable rate herbicide spraying prescription map is constructed to implement this technology.

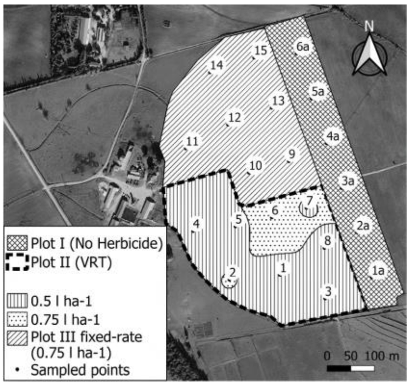


Fig. 8 - Variable rate herbicide spraying prescription map *(Conceição et al., 2025)*

In the application of variable rate herbicide spraying technology, UAV remote sensing as an emerging technology demonstrates numerous advantages. It can conduct multiple monitoring of farmland at different growth stages and dynamically update prescription map information. Not only can it grasp weed growth dynamics in real time, but it can also adjust pesticide application strategies in a timely manner based on weed growth conditions. By obtaining high-resolution images of farmland through UAV and using deep learning technology to deeply mine and analyze the images, precise weed information can be identified, providing more targeted decision-making basis for variable rate herbicide spraying *(Munir et al., 2024)*.

Bento et al. (2023) obtained multispectral images of coffee plantations using drones and, based on crop spectral characteristics, employed the random forest algorithm to classify and identify coffee, weeds, and soil. They mapped the weed distribution in the study area and, according to the weed distribution map, applied pesticides only in weed-covered areas, resulting in a 92.68% savings in pesticide use compared to applying pesticides across the entire study area.

Guo et al. (2024) constructed a rice paddy weed recognition model based on YOLOv8n DT, generated an actual weed distribution map of the rice paddy based on the recognition results, determined the specific dosage of pesticides by counting the number of weeds in each experimental plot, and generated a prescription map accordingly, achieving variable spraying operations. The accuracy of YOLOv8n-DT in recognizing weeds in rice paddies reached 0.82, saving about 15.28% of herbicides. However, despite the excellent performance in saving herbicides in the above two studies, there is still much room for improvement in the effectiveness of weed recognition models, which requires further refinement.

Sapkota et al. (2023) proposed a threshold segmentation method that can remove corn rows from drone images while classifying the remaining vegetation as weeds, thereby generating spatial distribution information of field weeds. Based on this, a grid-based prescription map for pesticide application was created, and variable pesticide application operations were carried out using commercial sprayers. Although this study achieved a 26.2% savings in the area of herbicides sprayed, the relatively fixed threshold used may increase the risk of misidentifying corn and weeds to some extent.

Machine vision-based technology enables real-time response, suitable for dynamic weed distribution with high spraying accuracy. However, it has higher requirements for sensor resolution and processing speed, with potential misjudgment in complex environments. Prescription map-based technology is efficient for large-scale commercial farms, utilizing UAV remote sensing for weed mapping, but lacks real-time adaptability and requires timely updates. Machine vision suits small-to-medium-scale dynamic scenarios, while prescription maps are optimal for large-scale, stable weed distribution.

CONCLUSIONS AND PROSPECTS

Characteristics and breakthroughs of technological evolution

The development of farmland weed identification and variable rate herbicide spraying technology has shown a clear path of technological iteration. In terms of weed identification, early machine learning methods relying on manual feature extraction required the design of proprietary feature engineering for different crop and weed combinations, limiting their generalization ability. Deep learning, which learns high-dimensional features autonomously, performs well in detecting small target weeds and in occluded scenes. Among them, the combination of attention mechanism and multi-scale training enhances the model's ability to capture key regional features and reduces the missed detection rate.

Variable rate herbicide spraying technology has formed two parallel paths: "real-time response" and "global planning". Real-time target-specific technology based on machine vision achieves dynamic response by spraying as soon as weeds appear through the closed-loop linkage of sensor-controller-actuator. Prescription-based application technology utilizes drone remote sensing to map weed distribution over a large area, suitable for large-scale farmland. In recent years, the two paths have shown a trend of integration, such as using real-time identification data to update prescription maps and dynamically adjust application strategies to further improve application accuracy. In addition, the combination of lightweight hardware and algorithms has promoted the miniaturization and low cost of variable rate herbicide spraying systems.

Current issues and challenges

Despite significant progress in farmland weed identification and variable rate application technology, there are still three core challenges in practical applications that restrict the large-scale promotion of the technology:

(1) Inadequate adaptability to complex environments. Models constructed under laboratory conditions often exhibit performance degradation in field environments, primarily due to the following reasons: drastic changes in illumination (such as strong sunlight at noon on a clear day and weak light on a cloudy day) cause fluctuations in image brightness and contrast, leading to a decrease in recognition accuracy; crops and weeds have similar morphology (such as rice and barnyard grass, wheat and red fescue), especially during the seedling stage, where the spectral and morphological characteristics of the two overlap significantly, resulting in a high rate of misidentification; soil background interference (such as different colored soils, soil water reflection) can lead to an increase in the rate of missed weed detection in areas with low vegetation coverage.

(2) The technical cost and promotion threshold are excessively high. A complete variable spraying system (including drones, high-resolution cameras, embedded controllers, and high-precision nozzles) costs approximately 3-5 times that of traditional sprayers, which exceeds the affordability of small farmers. Furthermore, technical operation requires professional knowledge (such as remote sensing data processing, model training, and equipment debugging), and small farmers lack relevant skills, necessitating reliance on professional service teams, which further increases the application cost.

(3) The system integration level is relatively low. There is often a "technical gap" in the three links of weed identification, decision-making generation, and pesticide application execution, which leads to a decline in overall performance: data interfaces are incompatible, the output format of the identification model does not match the input format of the pesticide application controller, and additional development of conversion modules is required, which increases the complexity of the system; the spatial and temporal scales are not unified, and the spatial resolution of drone remote sensing data and the resolution of ground sensor data differ greatly, which can easily lead to errors during data fusion, resulting in deviations in pesticide application locations; execution delays, the total time consumed from weed identification to nozzle opening (image acquisition, processing, decision-making, execution), when the equipment moves at a faster speed, can lead to deviations between the pesticide application location and the actual weed location, affecting the weed control effect.

(4) Inadequate interdisciplinary collaboration: This field involves multiple disciplines such as computer science (algorithm development), agricultural engineering (equipment design), agricultural ecology (weed distribution patterns), and environmental science (ecological risks of pesticides), but there is currently little collaborative research between these disciplines. Research in the field of computer science focuses mostly on optimizing algorithm accuracy, ignoring practical needs in the field (such as model real-time performance and equipment costs); equipment research and development in the field of agricultural engineering lacks deep integration with algorithms, resulting in hardware performance that cannot be fully utilized (such as mismatch between nozzle flow adjustment range and algorithm-recommended application rate); weed resistance research in the field of agricultural ecology is insufficiently combined with variable application technology, making it difficult to develop application strategies based on resistance evolution.

Prospects of interdisciplinary integration

Breakthroughs in the field of farmland weed identification and variable rate herbicide spraying rely on deep interdisciplinary integration. In the future, the following directions can be focused on to provide new ideas for solving existing challenges:

(1) Integration of agricultural ecology and artificial intelligence: Agricultural ecology provides theoretical support for the distribution patterns and evolution of herbicide resistance in weeds, while artificial intelligence

offers efficient data analysis tools. For instance, by combining weed niche models (predicting the distribution probability of weeds in different environments) with machine learning, a predictive pesticide application decision-making system based on population dynamics can be developed. By long-term monitoring of weed growth cycles and diffusion paths, a weed distribution prediction model can be constructed; combined with meteorological data (such as temperature and precipitation), weed density changes in the next 1-2 weeks can be predicted; based on the prediction results, a dynamic prescription map can be generated to adjust pesticide application strategies in advance, reducing the risk of weed resistance. Furthermore, optimizing the timing of image acquisition using agricultural ecology knowledge (such as selecting the growth stage with the greatest morphological differences between weeds and crops) can make weed identification features more prominent and improve identification accuracy.

(2) Integration of computer vision and mechanical engineering: Computer vision drives the iteration of recognition algorithms, while mechanical engineering enables precise control of pesticide application equipment. In the future, emphasis can be placed on developing an integrated "algorithm-hardware" system. Develop lightweight deep learning models to reduce the number of model parameters, adapt to embedded devices, and reduce hardware costs; design high-precision, low-power actuators, such as piezoelectric ceramic sprayers, to improve pesticide application accuracy and real-time performance; develop multi-sensor fusion modules (such as vision + infrared + lidar) to improve recognition and positioning accuracy in complex environments through complementary data. For example, lidar can obtain three-dimensional spatial information and effectively distinguish the height differences between crops and weeds.

(3) The integration of environmental science and precision agriculture: Environmental science provides methods for pesticide reduction and ecological risk assessment, while precision agriculture provides technical means. In the future, a closed-loop system of "application-monitoring-assessment" can be established. Based on variable application technology, pesticide usage can be reduced, and combined with environmental science risk assessment models (such as pesticide migration and transformation models in soil and water), the impact of pesticides on the ecological environment can be predicted. Rapid detection equipment for pesticide residues (such as portable Raman spectrometers) can be developed to monitor pesticide residues in real time after application and optimize application parameters. Combined with biological control techniques (such as natural enemy insects, microbial herbicides), a comprehensive weed management system of "chemical control + biological control" can be established to further reduce the usage of chemical pesticides and achieve sustainable agricultural ecological development.

(4) Integration of agricultural IoT and big data: With the development of digital agriculture, the integration of agricultural IoT and big data platforms will provide richer data support for weed identification and variable rate application. By collecting real-time data such as soil moisture, crop growth, and weed density through agricultural IoT, the parameter weights of weed identification models can be dynamically adjusted (for example, increasing the attention to weed leaf texture when soil moisture is high), making the application decision more in line with the actual needs of the field. A regional-level weed big data platform can be built to integrate weed identification data and application effect data from different regions and crops. A general weed identification model can be trained through federated learning technology (to protect data privacy) to improve the generalization ability of the model. Big data can be used to analyze the evolutionary trend of weed resistance, providing reference for the formulation of regional application strategies. For example, for resistant weeds in a certain region, it is recommended to use herbicides with different mechanisms of action alternately.

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