

Review

Global Trends and Future Directions in Agricultural Remote Sensing for Wheat Scab Detection: Insights from a Bibliometric Analysis

Sarfraz Hussain ^{1,†}, Ghulam Mustafa ^{1,2,3,†} , Imran Haider Khan ^{2,3}, Jiayuan Liu ¹, Cheng Chen ¹, Bingtao Hu ¹, Min Chen ¹, Iftikhar Ali ³ and Yuhong Liu ^{1,*} 

- ¹ Key Laboratory of Integrated Regulation and Resource Development on Shallow Lakes, Ministry of Education, College of Environment, Hohai University, Nanjing 210098, China; 20210936@hhu.edu.cn (S.H.); 20220939@hhu.edu.cn or gmawan197@outlook.com (G.M.); lly17695687200@hhu.edu.cn (J.L.); chencheng93@hhu.edu.cn (C.C.); 200205020006@hhu.edu.cn (B.H.); minchen@hhu.edu.cn (M.C.)
- ² National Engineering and Technology Center for Information Agriculture, Key Laboratory for Crop System Analysis and Decision Making, Ministry of Agriculture, Jiangsu Key Laboratory for Information Agriculture, Jiangsu Collaborative Innovation Center for Modern Crop Production, Nanjing Agricultural University, Nanjing 210095, China; 2018201104@njau.edu.cn or imranhaiderkhan110@hotmail.com
- ³ Department of Agronomy, University of Agriculture Faisalabad, Faisalabad 38000, Pakistan; dr.iftikharali@uaf.edu.pk
- * Correspondence: yhliu@hhu.edu.cn
- † These authors contributed equally to this work.

Abstract: The study provides a comprehensive bibliometric analysis of imaging and non-imaging spectroscopy for wheat scab (INISWS) using CiteSpace. Therefore, we underpinned the developments of global INISWS detection at kernel, spike, and canopy scales, considering sensors, sensitive wavelengths, and algorithmic approaches. The study retrieved original articles from the Web of Science core collection (WOSCC) using a combination of advanced keyword searches related to INISWS. Afterward, visualization networks of author co-authorship, institution co-authorship, and country co-authorship were created to categorize the productive authors, countries, and institutions. Furthermore, the most significant authors and the core journals were identified by visualizing the journal co-citation, top research articles, document co-citation, and author co-citation networks. The investigation examined the major contributions of INISWS research at the micro, meso, and macro levels and highlighted the degree of collaboration between them and INISWS knowledge sources. Furthermore, it identifies the main research areas of INISWS and the current state of knowledge and provides future research directions. Moreover, an examination of grants and cooperating countries shows that the policy support from the People's Republic of China, the United States of America, Germany, and Italy significantly benefits the progress of INISWS research. The co-occurrence analysis of keywords was carried out to highlight the new research frontiers and current hotspots. Lastly, the findings of kernel, spike, and canopy scales are presented regarding the best algorithmic, sensitive feature, and instrument techniques.

Keywords: wheat scab; agricultural remote sensing; knowledge map; CiteSpace; co-authorship; institution co-authorship



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1. Introduction

Investigating a research field's comprehensive academic background and knowledge structure is a prolific method to determine the hotspots, research themes, knowledge foundations, and research frontiers in that particular research domain at a global scale. The comprehensive background of scientific studies can be classified by a series of different specialties, such as collaborating authors, institutions, countries, journals, co-occurring keywords, hot research topics, knowledge clusters, and cited references. Additionally, the

clustering of the literature can determine the knowledge structure and domains based on co-occurring keywords and research themes from the research papers downloaded from the databases [1,2]. These analyses, also referred to as bibliometric or scientometric analyses, can be conducted, and the networks can be visualized to extract knowledge maps [3,4]. This new method for analyzing scientific literature includes thorough and comprehensive interpretations of the intellectual background of almost any research field. Additionally, it aids in understanding cutting-edge research frontiers, author or institutional collaborations, knowledge structures, and novel developments that are important to engineers, business investors, and researchers. In this article, we emphasized the scab disease of the wheat crop in the context of agricultural remote sensing (ARS).

For the first time, scab was identified as a new wheat, barley, and ryegrass disease in England caused by *Fusisporium culmorum*, *hordei*, and *Lolii* W. Sm, respectively [5]. At the end of the 19th century, it was noted as a significant disease in the United States of America (USA). At the start of the 20th century, scab was well-known worldwide in wheat-producing regions [6]. McMullen et al. (2012) characterized it as a re-emerging disease due to the frequent epidemics of wheat in the USA and Canada from 1991 to 1996 [7]. China has experienced 30 fusarium head blight (FHB) epidemics since 1950, each affecting more than 10% of the country's land area. In 2012, a massive outbreak of wheat disease affected about 10 mha land of wheat production and resulted in a yield loss of more than 2 million tons [8]. Lower Yangtze River Valley and Heilongjiang Province are two of China's most frequently hit regions in the east. Also noteworthy is that damage has spread north and west, devouring the Huang-Huai River Valley, China's largest wheat-growing region. Approximately 17 percent of world wheat is produced in China, where scab has the most significant impact, causing yield losses of 10 to 20% in moderate epidemics and up to 50% in severe epidemics [9]. In addition, Japan, Korea, and the far east of Russia adjacent to Heilongjiang Province, China, were also severely affected by scab. The outbreak of 1963 in Japan affected 71.5% of the wheat acreage and resulted in a yield loss of 53.5% [10].

The involvement of two species from the genus *Microdochium* and multiple species from the genus *Fusarium* is referred to as a scab disease complex. The primary distinction between these two is that *Microdochium* species do not produce mycotoxins, while *Fusarium* species do [11]. In contrast, *Fusarium graminearum* is the most common pathogen of scab worldwide [7,12,13]. However, various studies revealed that other *Fusarium* species may significantly contribute to this disease in various parts of the world with various climatic conditions. For example, *F. graminearum*, *F. avenaceum*, *F. culmorum*, *F. tricinctum*, *F. poae*, and *M. majus* were Europe's dominant species [14,15]. While in Canada, *F. avenaceum*, *F. graminearum*, *F. poae*, *F. equiseti*, and *F. sporotrichioides* were the most frequent species during the last two decades [16]. FHB is a monocyclic disease; ascospores, macroconidia, and microconidia are all forms of the pathogen that can survive in the debris (Figure 1) of a previous crop within sexual structures called perithecia. These spores are regarded as the disease's primary inoculum. These spores are considered the main inoculum of the disease. Besides serving as hosts, both gramineous and non-gramineous weeds are known sources of the inoculum for scab. When weather conditions are favorable and in the anthesis stage, the inoculum is spread by wind or splashed by rain and lands on the open wheat kernels. The spores germinate on the spikelet tissue and form germ tubes [13,17].

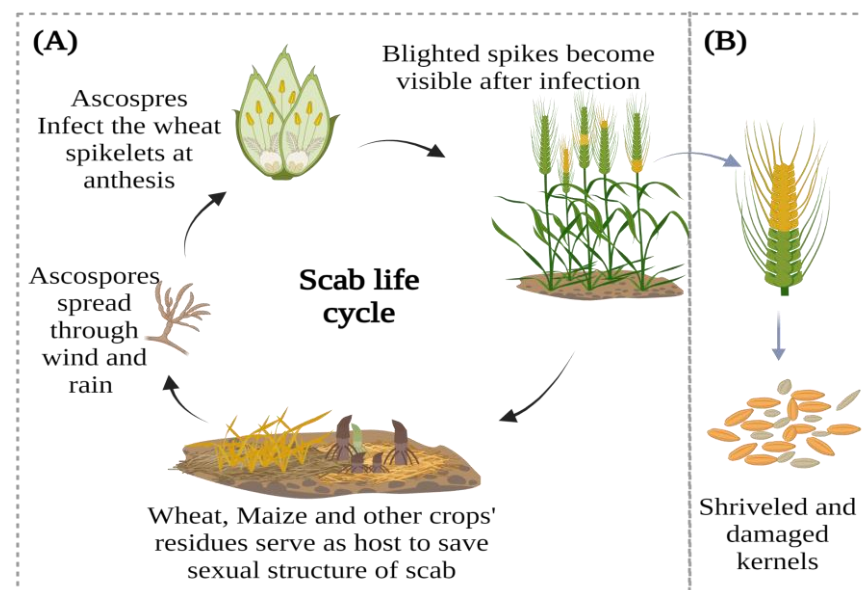


Figure 1. Illustration of the life cycle of scab (A) and damaged or shriveled grains (B), modified from [18].

Scab is critical as it causes colossal damage to crops—often causing damage or crop failure [19,20]. However, inappropriate fungicide application, control, and disease quantification employing inadequate measures are the leading factors causing substantial yield losses annually [21]. To this end, different optical sensor technologies have been introduced for several precision agriculture measures in phenotyping, phytopathology, and pedology [22–24]. The frontiers and hotspots of the study can explain the current scab study development under ARS advancements. This study conducted a bibliometric investigation of the advanced research conducted in ARS for wheat scab detection. The relevant scientific data published between 2000 and 2022 in high-quality journals were retrieved from the Web of Science core collection (WOSCC). The co-citation, co-occurrence, co-authorship, and cluster analyses were performed in CiteSpace. The objectives of the current study are as follows:

- Highlight the major research efforts in the domain of ARS for wheat scab detection at the level of contributing authors, institutions, and countries.
- Evaluate the contribution of key journals in the same area.
- Classify and interpret the obtained literature and knowledge into brief knowledge clusters using co-occurring keywords.
- Determine the research frontiers, knowledge foundation, and hot topics in the field of ARS for wheat scab detection for future studies.
- Review the conducted studies for scab detection at different scales (grains, spike, and canopy) of wheat crops.

2. Data Collection and Bibliometric Methodology

2.1. Retrieval of Data from Web of Science

The most precise literature-indexing resource is the Web of Science (WOS), which covers scientific and social, health, and economic knowledge. Therefore, worldwide WOS is frequently acknowledged as the best source of data collection for bibliometric analyses [2]. The WOS core collection (WOSCC) databases retrieved the relevant data. A large number of iterations were used to obtain an optimal searching keyword code to download the most relevant articles related to ARS for wheat scab detection. Table 1 shows a development series of iterative-searching keyword codes for probing WOS database data. The most effective searching keywords were as follows: (“wheat spike”) (Topic) or (“fusarium head blight” OR “Scab”) (Topic) and (“remote sensing”) OR (“hyperspectral

imaging" OR "fluorescence" OR "reflectance" OR "hyperspectral reflectance") (Topic) and ("detection") OR ("classification") (Topic). It implies that the published documents were searched for contained words in the titles, abstracts, or keywords. Only peer-reviewed, original research articles published in English were extracted; review articles, books, and conference proceedings were omitted. The time frame of the data collection was from 1 January 2000 to 31 December 2022, inclusive. While downloading the pertinent literature, the research domains were limited to the sciences and technologies.

Table 1. Optimization of search keywords for finding WOS publications relevant to agricultural remote sensing for wheat scab detection.

No.	Searching Code	Results	Quality
1	("Wheat spike") (Topic) or ("Fusarium head blight")	3560	Very rough, very generic, highly irrelevant
2	("Wheat spike") (Topic) or ("Fusarium head blight" OR "Scab")	6825	Improved, yet irrelevant
3	("Wheat spike") (Topic) or ("Fusarium head blight" OR "Scab") (Topic) and ("remote sensing")	163	Very generic and highly irrelevant
4	("Wheat spike") (Topic) or ("Fusarium head blight" OR "Scab") (Topic) and ("remote sensing") OR ("hyperspectral imaging")	198	Improved, yet irrelevant
5	("Wheat spike") (Topic) or ("Fusarium head blight" OR "Scab") (Topic) and ("remote sensing") OR ("hyperspectral imaging" OR "Fluorescence")	307	A little improved, yet irrelevant
6	("Wheat spike") (Topic) or ("Fusarium head blight" OR "Scab") (Topic) and ("remote sensing") OR ("hyperspectral imaging" OR "Fluorescence" OR "hyperspectral reflectance")	338	More improved, yet irrelevant
7	("Wheat spike") (Topic) or ("Fusarium head blight" OR "Scab") (Topic) and ("remote sensing") OR ("hyperspectral imaging" OR "Fluorescence" OR "reflectance" OR "hyperspectral reflectance") (Topic) and ("detection") OR ("classification") OR ("monitoring") OR ("identification") (Topic)	238	Much improved, highly relevant.

2.2. Schematic of the Study

Based on the methodology given above, a total of 238 original research articles were retrieved. The whole record and cited references were saved as "other file formats" results, and plain text was chosen as the file format. The schematic reveals the steps taken to continue the study in Figure 2.

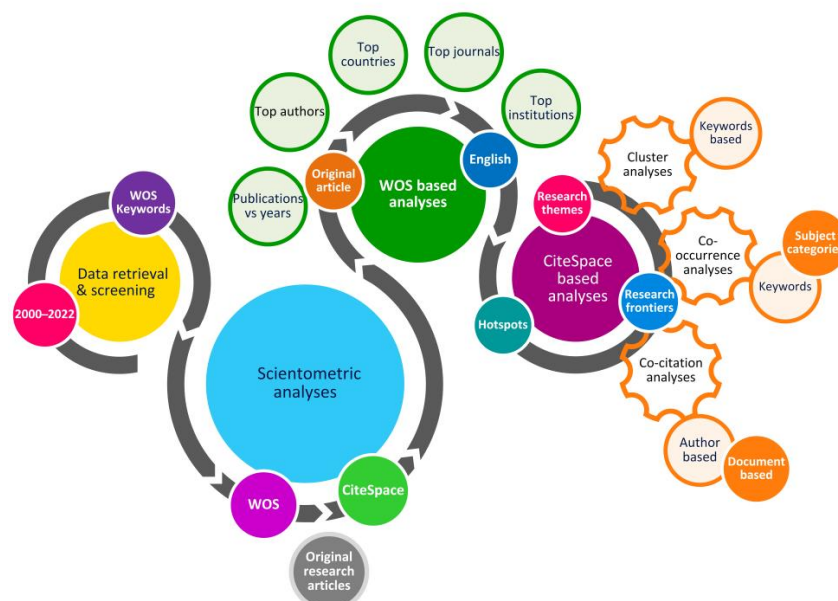


Figure 2. Step-by-step layout and schematic of the current study.

2.3. CiteSpace-Based Bibliometric Analyses

The more advanced capabilities for bibliometric analyses include a map or network analyses and the visualization of the scientific literature. CiteSpace is a Java-based program that maps and visualizes scientific domains for bibliometric analysis. Dr. Chen Chaomei developed this at Drexel University of United States [25], and it is freely available online. CiteSpace's advanced features and wide range of applications allowed for the visualization analyses of the literature maps in the field of ARS to detect wheat scab. The following steps were used to visualize the obtained data in CiteSpace. First, a project was created with the input of publications that were downloaded, complete with full records and cited references in plain text. Then, as shown in Table 2, subsequent parameters were established.

Table 2. CiteSpace parameters and values for bibliometric analysis of advanced research in agricultural remote sensing for wheat scab detection.

No.	Parameters	Definition
1	Time slicing	Year span from 2005 to 2022; years per slice of 1 year for all
2	Term source	Title, author, abstract, keywords, and keywords plus
3	Node type	Author, cited author, cited reference, institution, country, cited journal, and keywords
4	Selection criteria	Top 15%
5	Pruning	Pathfinder and pruning sliced networks
6	Links	Default
7	Visualization	Show merged network and cluster view-static

After defining the parameters, the co-citation analysis and keywords co-occurrence analysis were run in CiteSpace to obtain the networks showing the co-citations among the authors, documents, and journals (co-citation analysis) and keywords, hot research topics, and research frontiers (keywords co-occurrence analysis), respectively. Finally, the relevant data and mapping networks were investigated, and the corresponding results of the current research study's visualization investigation were presented and discussed.

3. Examination and Interpretation of Scientometrics Analysis

3.1. Bibliometric Analyses Based on Web of Science

The distribution of corresponding citations and publications in the research area of ARS for wheat scab detection is plotted for a period from 1 January 2005 to 1 February 2022, as shown in Figure 3. It can be observed that a considerably slow rise was observed in the number of significant publications over the initial decade (years ranging from 2005 to 2010). A total of 13 studies were published in 2010, with a fall in the subsequent couple of years. From 2014, the concerns were significantly increased for the research. Compared to the statistics in 2020, the number increased in 2021, when a maximum of 34 studies were published. Relatively few numbers of publications in the area show that the ARS for wheat scab detection is still in its infancy, and significant efforts are required in the future to achieve further advancements in the field. The trends are almost similar for the citations, with a maximum of 724 in 2021.

The top 15 journals in which most articles related to ARS for wheat scab detection are published are enlisted against the number of publications and their percentage contribution, as shown in Table 3. Table 4 shows the top 15 institutions in the research domain of ARS for wheat scab detection. Tables 5 and 6 show the 15 most important countries and the most prolific authors, respectively, with the highest number of studies in the given research domain. The distribution of the top 7 funding agencies involved in the relevant articles extracted from the WOS in ARS research is exhibited in Table 7. Similarly, the top 15 WOS subject categories in the research domain of ARS for wheat scab detection are shown in Table 8.

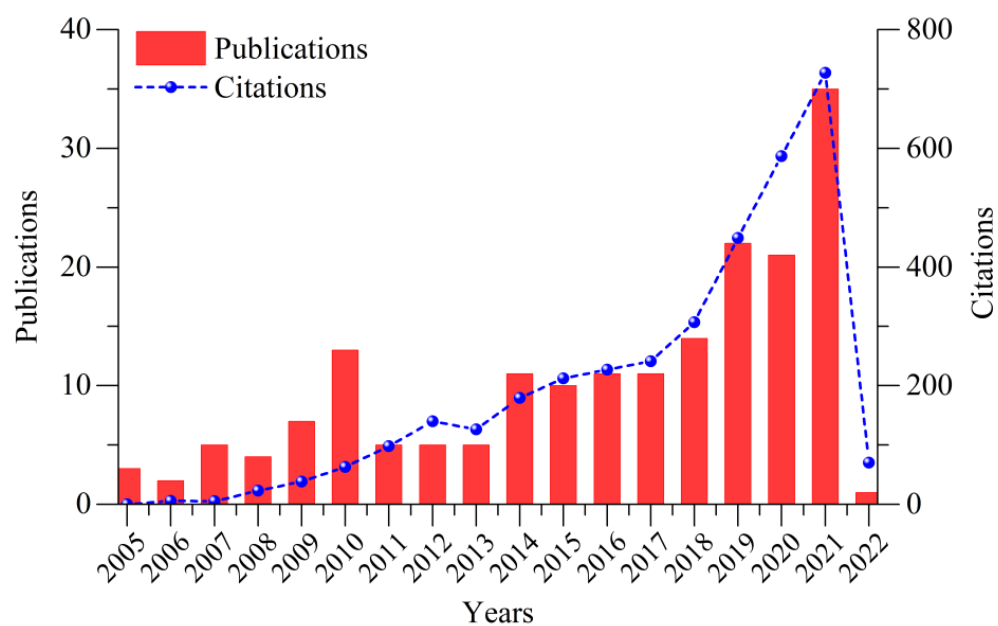


Figure 3. Publications and citations of total articles in agricultural remote sensing for wheat scab detection from 2005 to 2022.

Table 3. Top 15 journals in the research domain of agricultural remote sensing for wheat scab detection.

No.	Journals	Records	% of Total
1	REMOTE SENSING	14	7.568
2	COMPUTERS AND ELECTRONICS IN AGRICULTURE	7	3.784
3	FRONTIERS IN PLANT SCIENCE	7	3.784
4	BIOSYSTEMS ENGINEERING	6	3.243
5	MOLECULAR BIOLOGY REPORTS	4	2.162
6	PHYTOPATHOLOGY	4	2.162
7	PLANT PATHOLOGY	4	2.162
8	SENSORS	4	2.162
9	BMC GENOMICS	3	1.622
10	CROP PASTURE SCIENCE	3	1.622
11	EUROPEAN JOURNAL OF PLANT PATHOLOGY	3	1.622
12	PLANT BIOTECHNOLOGY JOURNAL	3	1.622
13	PLANT DISEASE	3	1.622
14	PLANT PHYSIOLOGY	3	1.622
15	PLANTA	3	1.622

Table 4. Top 15 institutions in the research domain of agricultural remote sensing for wheat scab detection.

No.	Affiliations	Records	% of Total
1	CHINESE ACADEMY OF SCIENCES	22	11.892
2	ANHUI UNIVERSITY	13	7.027
3	UNITED STATES DEPARTMENT OF AGRICULTURE USDA	12	6.486
4	UNIVERSITY OF CHINESE ACADEMY OF SCIENCES CAS	11	5.946
5	CHINESE ACADEMY OF AGRICULTURAL SCIENCES	8	4.324
6	NORTHWEST A F UNIVERSITY CHINA	8	4.324
7	CHINA AGRICULTURAL UNIVERSITY	7	3.784
8	INSTITUTE OF CROP SCIENCES CAAS	7	3.784
9	INSTITUTE OF GENETICS DEVELOPMENTAL BIOLOGY CAS	7	3.784
10	INRAE	6	3.243
11	NANJING AGRICULTURAL UNIVERSITY	6	3.243
12	AGRICULTURE AGRI FOOD CANADA	5	2.703
13	BIOTECHNOLOGY AND BIOLOGICAL SCIENCES RESEARCH COUNCIL BBSRC	5	2.703
14	CONSEJO NACIONAL DE INVESTIGACIONES CIENTIFICAS Y TECNICAS CONICET	5	2.703
15	TUSCIA UNIVERSITY	5	2.703

Table 5. Top 15 countries in the research domain of agricultural remote sensing for wheat scab detection.

No.	Countries	Records	% of Total
1	CHINA	73	39.459
2	USA	37	20.0
3	GERMANY	18	9.730
4	ITALY	12	6.486
5	CANADA	11	5.946
6	FRANCE	9	4.865
7	ENGLAND	7	3.784
8	SOUTH KOREA	7	3.784
9	BELGIUM	6	3.243
10	ARGENTINA	5	2.703
11	AUSTRALIA	5	2.703
12	JAPAN	4	2.162
13	RUSSIA	4	2.162
14	BRAZIL	3	1.622
15	CZECH REPUBLIC	3	1.622

Table 6. Top 15 authors in the research domain of agricultural remote sensing for wheat scab detection.

No.	Authors	Records	% of Total
1	Huang WJ	10	5.405
2	Ma HQ	9	4.865
3	Dong YY	8	4.324
4	Liu LY	7	3.784
5	Huang LS	6	3.243
6	Cruz CD	5	2.703
7	Chen G	4	2.162
8	Chibbar RN	4	2.162
9	Favaron F	4	2.162
10	Gu CY	4	2.162
11	Hong MJ	4	2.162
12	Li LH	4	2.162
13	Schafer W	4	2.162
14	Sella L	4	2.162
15	Seo YW	4	2.162

Table 7. Top 15 funding agencies in the research domain of agricultural remote sensing for wheat scab detection.

No.	Funding Agencies	Records	% of Total
1	National Natural Science Foundation of China NSFC	53	22.269
2	National Key Research and Development Program of China	21	8.824
3	National Key R D Program of China	9	3.782
4	UK Research Innovation	9	3.782
5	Biotechnology and Biological Sciences Research Council	7	2.941
6	China Postdoctoral Science Foundation	7	2.941
7	National Basic Research Program of China	7	2.941
8	Youth Innovation Promotion Association Cas	6	2.521
9	Beijing Nova Program of Science and Technology	5	2.101
10	Chinese Academy of Sciences	5	2.101
11	Natural Sciences and Engineering Research Council of Canada	5	2.101
12	United States Department of Agriculture	5	2.101
13	Canada Research Chairs	4	1.681
14	Deutscher Akademischer Austausch Dienst Daad	4	1.681
15	French National Research Agency	4	1.681

Table 8. Top 15 WOS subject categories in the research domain of agricultural remote sensing for wheat scab detection.

No.	WOS Subject Categories	Records	% of Total
1	Plant Sciences	64	34.595
2	Agriculture Multidisciplinary	29	15.676
3	Agronomy	29	15.676
4	Food Science Technology	19	10.27
5	Geosciences Multidisciplinary	15	8.108
6	Remote Sensing	15	8.108
7	Environmental Sciences	14	7.568
8	Imaging Science Photographic Technology	14	7.568
9	Biochemistry Molecular Biology	12	6.486
10	Biotechnology Applied Microbiology	12	6.486
11	Genetics Heredity	12	6.486
12	Horticulture	10	5.405
13	Agricultural Engineering	9	4.865
14	Chemistry Applied	9	4.865
15	Computer Science Interdisciplinary Applications	7	3.784

3.2. Co-Citation Analysis

A co-citation relationship exists among two or more authors or documents if they are cited simultaneously by a third author or document [26]. CiteSpace performed three basic types of co-citation analyses to identify documents' relationship and mapping structures, co-citing authors and journals. The co-citation analysis is a powerful tool for determining the degree of inter-relationship between journals, authors, and articles by creating a mapping structure and tracking the progress of scientific research fields [27].

3.2.1. Document Co-Citation Analysis

The articles or documents are the major constituents of the repository or databases of knowledge in ARS for wheat scab detection. The reference co-citation analysis or document is an effective method to assess the mapping and evolution of any research area [28]. A visualization network for cited documents was developed after the scientometric analysis in CiteSpace was run, as shown in Figure 4. The connections between the nodes serve as indicators of the co-citation relationships between the references or cited articles, whereas the nodes represent the cited documents. A larger node represents a more important document, and documents frequently cited by other documents are closely linked. Figure 4

shows that Alisaac et al. (2018) and Jin et al. (2018) are the most important studies conducted in the domain. The modularity Q and weighted mean silhouette S were 0.6262 and 0.8854, respectively, for the document co-citation analysis.

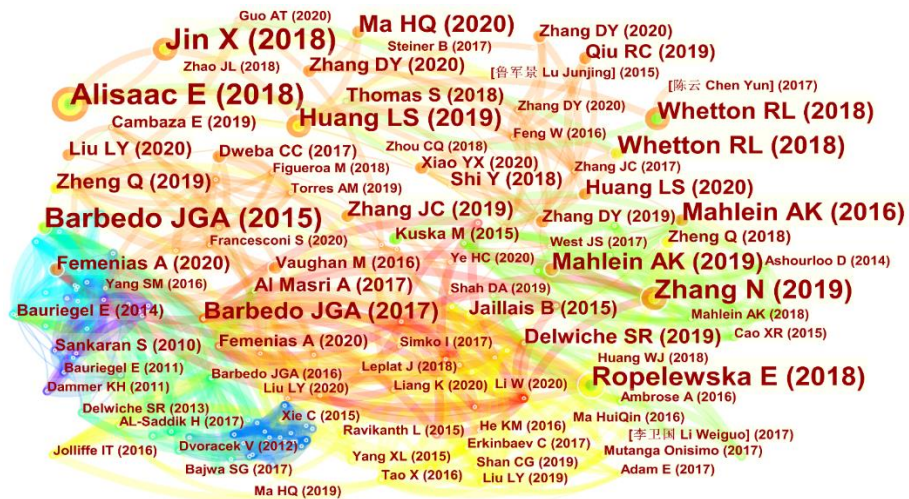


Figure 4. The visualization map for the document co-citation network of literature related to agricultural remote sensing for wheat scab detection.

The topmost fifteen cited articles are presented in Table 9, along with order and position (considering citation counts), citation counts, first author, publication year, journal name, volume number, pages, and DOIs. It can be observed that Jin et al. (2018) and Alisaac et al. (2018) were the leading authors with the highest co-citations, 12 and 11, respectively. Some other distinguished authors (and their co-citations) were Barbedo (10), Ropelewska (8), Zhang (8), etc. The knowledge structure of ARS for wheat scab detection can be gradually reshaped with the help of document co-citation analysis, as it facilitates the determination of the highly cited documents and significant research articles, which comprise the knowledge databases or domains of the field under consideration.

Table 9. Top 15 effective co-cited documents on agricultural remote sensing for wheat scab detection.

Sr. No.	Count	Year	Cited References
1	12	2018	[29]
2	11	2018	[23]
3	10	2015	[30]
4	8	2018	[31]
5	8	2019	[32]
6	7	2020	[9]
7	7	2018	[33]
8	7	2019	[34]
9	7	2016	[35]
10	7	2018	[36]
11	6	2019	[37]
12	6	2017	[38]
13	6	2019	[39]
14	6	2020	[40]
15	6	2019	[41]

3.2.2. Author Co-Citation Analysis

The distribution of authors with a greater number of citations in that specific field of study was also examined using the author co-citation analysis, which is used to identify the most productive authors in a field. Additionally, the co-citation analysis allows for visualizing similar authors' research areas and subject areas. The author's co-citation analysis for the study on ARS for scab detection in wheat was completed, and the resulting visualization network is shown in Figure 5. The connecting lines between two nodes demonstrate their co-citation relationship, whereas the nodes represent the authors. The number of citations for a given author in the network increases as a node's size increases, making that author more important.

Similarly, the distance between two consecutive nodes or authors is inversely correlated with how frequently each author is cited by the other. The research interests of these authors are more closely correlated with the size of the gap between the nodes. Detailed analysis of the visualization network reveals that the degree of collaboration among most authors is very good, as justified by author co-authorship analysis. The modularity Q and weighted mean silhouette S were 0.6262 and 0.8854, respectively, for the author's co-citation analysis.

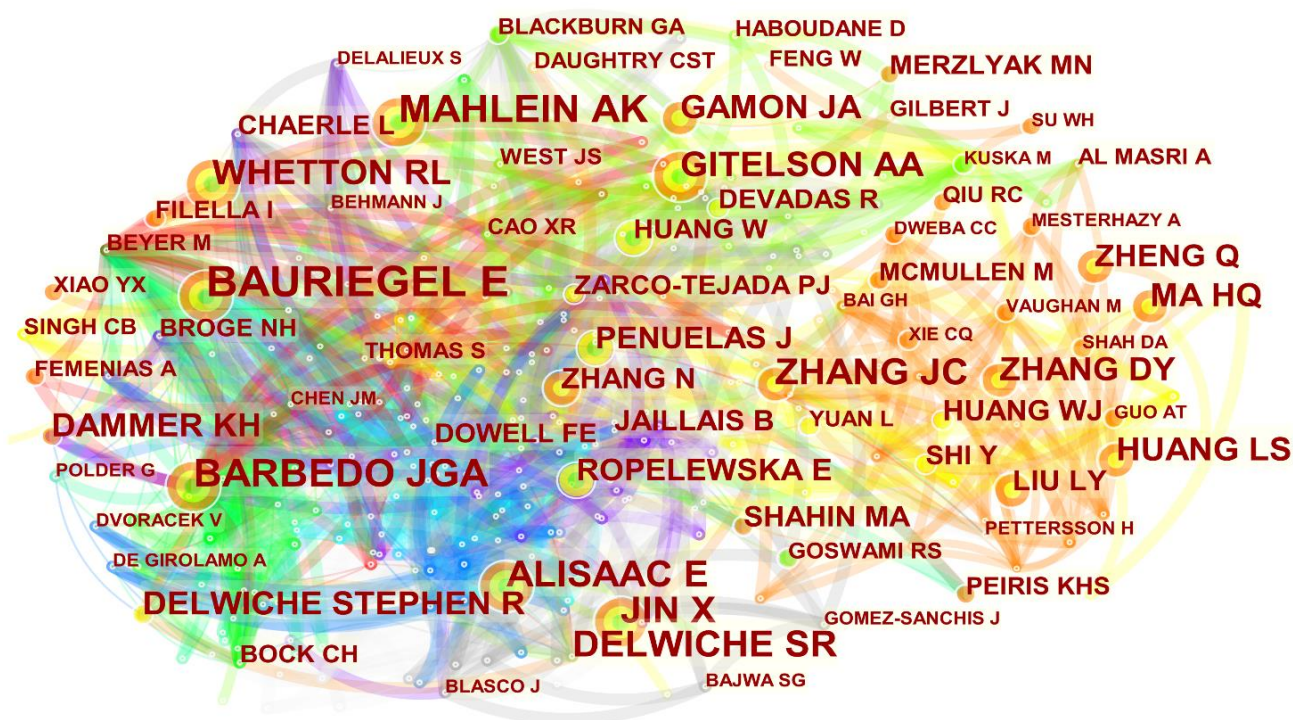


Figure 5. The visualization map for the author co-citation network of literature related to agricultural remote sensing for wheat scab detection.

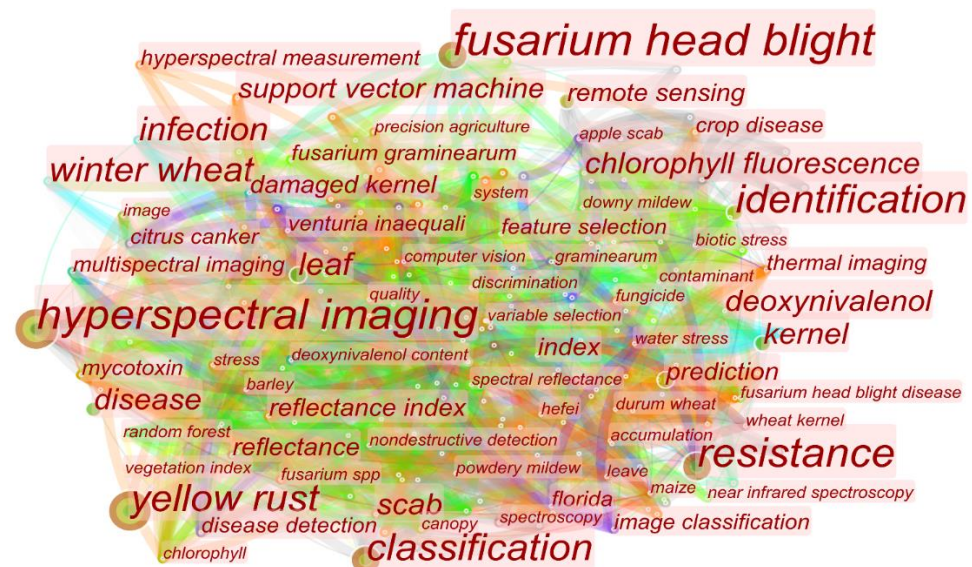
The top fifteen highly co-cited authors are ranked concerning the citation counts of their publications and are listed along with counts of citations, year of citation counts, and the respective authors in Table 10. The statistics reveal that the mentioned authors' work contributed critically to the field of ARS for wheat scab detection, making them highly influential contributors to the upcoming development of agricultural disease detection research. From the results, the authors, including BAURIEGEL, MAHLEIN, and BARBEDO, were the most prolific in the research domain.

Table 10. Top 15 most effective co-cited authors of the agricultural remote sensing for wheat scab detection.

Sr. No.	Count	Year	Cited Authors
1	21	2010	BAURIEGEL E
2	16	2019	MAHLEIN AK
3	16	2017	BARBEDO JGA
4	14	2019	ZHANG JC
5	13	2006	DELWICHE SR
6	13	2019	ALISAAC E
7	13	2019	JIN X
8	11	2019	GITELSON AA
9	11	2019	WHETTON RL
10	10	2020	HUANG LS
11	9	2013	DAMMER KH
12	9	2020	ZHANG DY
13	9	2015	DELWICHE STEPHEN R
14	9	2020	MA HQ
15	9	2009	GAMON JA

3.3. Co-Occurrence Keywords Analysis

In an article, keywords give details about the subject or broad category to which it specifically belongs. It also represents the primary information in the research papers. Overall, the hotspots and research frontiers can be identified with the aid of keyword co-occurrence analysis. The keywords with the highest citation bursts represent the hotspots frequently cited over time or will be considered in future research. Figure 6 displays the outcomes of the CiteSpace keyword co-occurrence analysis in the form of a visualization network. The nodes represent the keywords, and the size of each node corresponds to the frequency of co-occurrence of each keyword.

**Figure 6.** The visualization map for the keywords co-occurrence network of agricultural remote sensing for wheat scab detection.

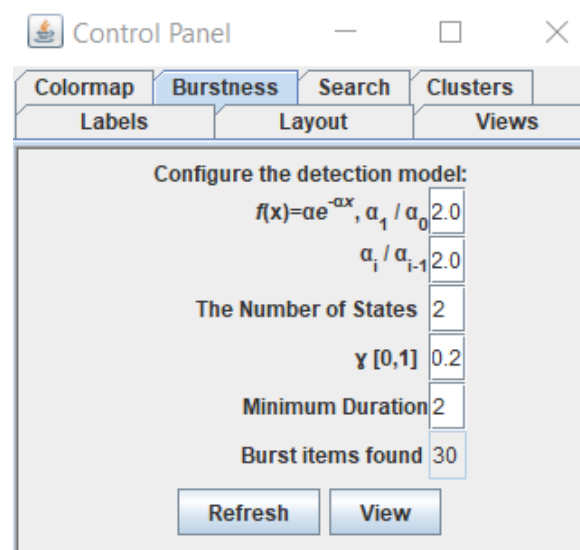
The topmost twenty keywords graded by the number of counts in the field of ARS for wheat scab detection are listed in Table 11. The keywords with the highest co-occurring frequencies (and their counts) were Fusarium head blight (20), hyperspectral imaging (16), resistance (15), and identification (13).

Table 11. Top 20 effective keywords of agricultural remote sensing for wheat scab detection ranked by usage frequency.

Ranking	Counts	Year	Keywords
1	20	2006	Fusarium head blight
2	16	2009	Hyperspectral imaging
3	15	2009	Resistance
4	13	2009	Identification
5	11	2019	Yellow rust
6	11	2011	Classification
7	9	2006	Winter wheat
8	8	2006	Infection
9	7	2019	Leaf
10	6	2006	Deoxynivalenol
11	6	2009	Chlorophyll fluorescence
12	6	2010	Scab
13	6	2006	Kernel
14	6	2016	Disease
15	5	2019	Support vector machine
16	4	2010	Reflectance
17	4	2019	Reflectance index
18	4	2015	Damaged kernel
19	4	2009	Index
20	4	2020	Prediction


























3.4. Hotspots and Research Frontiers

The citation frequency analysis provides a brief overview of the use of the most frequently used keywords in a given time period and can be used to plot these keywords on a time scale for the time period in which these keywords were most frequently used and cited. In the current scenario, citation burst analysis based on co-occurring keywords was performed to determine the hotspots and research frontiers in ARS for wheat scab detection. Hotspots can be recognized as the subfields that are studied most frequently during the development stage of a research area. On the other hand, the keywords that can probably be the most interesting and demanded research fields in the future can be regarded as research frontiers. The conditions, including the number of states, minimum duration, and detection model configuration, used to determine the research limits are shown in Figure 7.

**Figure 7.** Conditions used to evaluate the burst keywords.

In Table 12, from the blue-red-colored timeline analysis, it can be noticed that all 26 keywords with the highest citation bursts were considered by the researchers for small time periods between 2009 and 2022. The studies are being conducted in the research areas related to these keywords. The first nine burst keywords can be regarded as hotspots that were significantly studied before 2022. The last seven burst keywords are the research frontiers that are still in their infancy or need further efforts for their research enhancements.

Table 12. Top 26 keywords with the most robust citation bursts in the field of agricultural remote sensing for scab detection.

Keywords	Strength	Begin	End	2009–2022
¹ Citrus canker	1.47	2009	2013	
⁵ Florida	1.47	2009	2013	
¹ Biotic stress	1.07	2009	2011	
¹ Venturia inaequali	0.97	2009	2013	
¹ Scab	1.31	2010	2015	
² Reflectance	1.19	2010	2011	
¹ Apple scab	1.17	2011	2013	
² Image classification	1.13	2011	2018	
² Multispectral imaging	1.08	2011	2015	
¹ Disease detection	1.06	2011	2013	
¹ Deoxynivalenol content	0.98	2015	2018	
¹ Damaged kernel	0.9	2015	2017	
¹ Graminearum	0.7	2015	2019	
¹ Infection	0.75	2016	2017	
¹ Identification	0.82	2017	2018	
³ Kernel	1.49	2018	2019	
¹ Fusarium head blight disease	0.95	2018	2019	
¹ <i>Fusarium graminearum</i>	0.74	2018	2019	
¹ Yellow rust	1.93	2019	2022	
² Support vector machine	1.38	2019	2020	
³ Spike	1.21	2019	2022	
⁴ Feature selection	1.03	2019	2020	
¹ Fusarium head blight	1.41	2020	2022	
² Classification	1.37	2020	2022	
¹ Crop disease	0.94	2020	2022	

¹ The disease; ² application of remote sensing; ³ scale or organ for disease detection; ⁴ sensitive feature selection; ⁵ region.

3.5. Description of Cluster Analysis

The research papers published in a given journal describe the cutting edge of the fields covered by that journal. In contrast, the references cited in those papers represent the body of knowledge on which those papers are based. Using CiteSpace, the most frequently employed keywords or references can be clustered through cluster analysis and could be helpful in determining the foundation of basic knowledge in the ARS for wheat scab detection research. The cluster analysis was performed based on co-occurring keywords. The results from cluster analysis are comprehensively discussed in Figure 8. The modularity Q and weighted mean silhouette S were 0.6262 and 0.8854, respectively, for the knowledge cluster analysis.

Furthermore, the details, including cluster ID, cluster size, silhouette, years, and the respective LLR labels, are enlisted in Table 13. A total of 9 knowledge clusters were obtained based on co-occurring keywords' information and ranked in inverse chronological order. The fact that each of the nine major clusters has a silhouette greater than 0.8 indicates that the knowledge has been expertly clustered for the purpose of detecting wheat scab using ARS. The latest (in 2018) cluster ranked (#3) was remote sensing, with 27 articles and a silhouette of 0.827, followed by (#1) random forest, with 31 articles and a silhouette of 0.849 in around 2017.

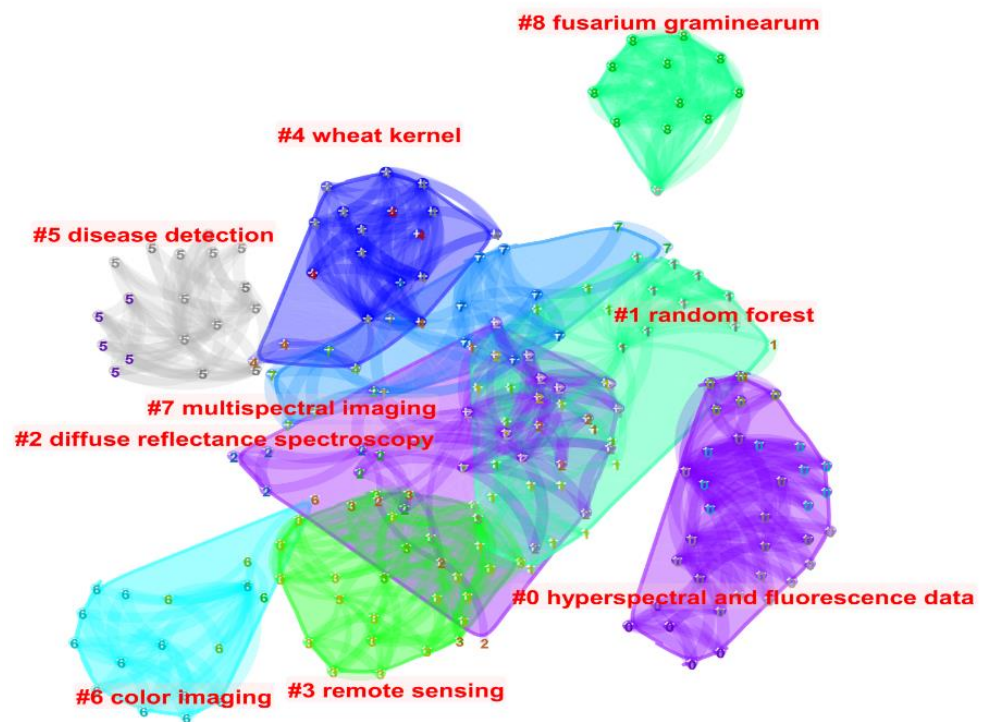


Figure 8. Co-occurring keywords-based knowledge clusters of agricultural remote sensing for wheat scab detection based on keywords.

Table 13. Details of co-occurring keywords-based knowledge clusters of agricultural remote sensing for wheat scab detection based on keywords.

Cluster-ID	Size	Silhouette	Year	LLR * Based Keywords
3	27	0.827	2018	Remote sensing (9.82, 0.005); hyperspectral (6.5, 0.05); precision agriculture (6.5, 0.05); continuous wavelet analysis (6.5, 0.05); feature selection (3.23, 0.1)
1	31	0.849	2017	Random forest (8.3, 0.005); support vector machine (4.74, 0.05); correlation analysis (4.11, 0.05); fusarium damage (4.11, 0.05); fusion of spectral and image (4.11, 0.05)
8	12	0.987	2017	<i>Fusarium graminearum</i> (7.02, 0.01); fungicide resistance (7.02, 0.01); benzimidazole fungicides (7.02, 0.01); fusarium asiaticum (7.02, 0.01); loop-mediated isothermal amplification-fluorescent loop primer (7.02, 0.01)
6	17	0.909	2016	Color imaging (6.14, 0.05); potato (6.14, 0.05); fluorescence resonance energy transfer (6.14, 0.05); hybprobes (6.14, 0.05); common scab pathogens (6.14, 0.05)
7	15	0.833	2015	Multispectral imaging (4.58, 0.05); optical wavelength selection (4.03, 0.05); visualization map (4.03, 0.05); band selection (4.03, 0.05); plant disease (4.03, 0.05)
4	19	0.886	2014	Wheat kernel (4.03, 0.05); early detection (4.03, 0.05); toxigenic fungi (4.03, 0.05); near-infrared spectroscopy (4.03, 0.05); food commodities (4.03, 0.05)
0	35	0.966	2013	Hyperspectral and fluorescence data (6.39, 0.05); oculimacula spp (6.39, 0.05); ojip (6.39, 0.05); chlorophyll fluorescence (6.39, 0.05); scab detection (6.39, 0.05)
2	30	0.826	2013	Diffuse reflectance spectroscopy (3.17, 0.1); hyperspectral image (3.17, 0.1); early disease detection (3.17, 0.1); photosynthesis (3.17, 0.1); flour (3.17, 0.1)
5	18	0.931	2010	Disease detection (7.55, 0.01); citrus canker (7.55, 0.01); hyperspectral reflectance imaging (5.54, 0.05); lesion size (5.54, 0.05); spectral similarity (5.54, 0.05)

* LLR abbreviation of log-likelihood ratio used to achieve the optimal results with maximum coverage and uniqueness.

Although disease effects can vary yearly, they are always present and can be a significant challenge even if they only infect certain plant parts. All parts of a plant are susceptible to disease, and multiple diseases can infect the same plant simultaneously; as long as host cultivars and environmental conditions are favorable, they can appear in any field. Scab and three types of rust fungi have historically caused significant crop losses. They remain economically important despite the widespread use of fungicides and host resistance cultivars. However, many pests and diseases are known to reduce grain quality and yield potential [21]. Therefore, scab attracts attention because of its widespread distribution and severe impact on grain quality. However, the bibliometric review and analyses of scab under ARS demand the significant attention of the scientific community. Although the recent focus has been devoted to scab [40,42–45] and other plant diseases, a conclusive methodology at a large scale is still highly needed.

3.6. New Trends and Recent Research Status in the Field of INISWS

The following are some of the study's most important findings:

- Regarding INISWS research, the most productive authors at the micro level are Jin X, Alisaac E., Barbedo J.G.A., Ropelewska, Zhang N., Ma H.Q., and others. Researchers who have been cited frequently in INISWS include Bauriegel E., Mahlein A.K., Barbedo J.G.A., Zhang J.C., and others.
- At the meso level, the Chinese Academy of Sciences, Anhui University, and the United States Department of Agriculture are the most active and effective contributors to INISWS research.
- At the macro level, China, the United States, Germany, Italy, Canada, France, and England are the most active and effective contributors to INISWS research. China and the United States have a much higher number of publications than the rest of the countries on the list, and the most likely explanation for this is the more robust funding support policy from both governments. The National Natural Science Foundation of China (NSFC), National Key Research and Development Program of China, National Key R D Program of China, UK Research Innovation, and others have provided the most funding for INISWS research.
- In terms of core journals, the most valuable publications that contributed were: *Remote Sensing*, *Computers and Electronics in Agriculture*, *Frontiers in Plant Science*, and *Biosystems Engineering*.
- The essential knowledge clusters under CiteSpace analysis were hyperspectral and fluorescence data, random forest, diffuse reflectance spectroscopy, and remote sensing.
- The hot research topics were crop disease, identification, feature selection, fusarium head blight, and classification.
- Recent advancements in scab monitoring or detection still need to produce conclusive findings, which are essentially needed.

Conclusively for INISWS researchers, the above results provide important information on new trends and the most recent research status in the field.

3.7. Scab Examination in Wheat Using ARS

Scab is a devastating spike disease that has appealed the researchers to devise a remedy for the quality and quantity concerns. Thus, several worldwide scientists worked on this, using different ARS approaches. In this section, we reviewed the summary of conducted investigations for scab detection in wheat kernels (Figure 9A), spikes (Figure 9B), and canopy scale (Figure 9C,D). The below-mentioned studies were conducted using imaging (hyperspectral imaging, fluorescence imaging) and non-imaging (hyperspectral reflectance) instruments. This section highlights the conclusive findings about Scab disease in ARS considering the wavelength range, sensors, sensitive band selection algorithms, classification algorithms, and sensitive bands for different studies conducted in different countries.

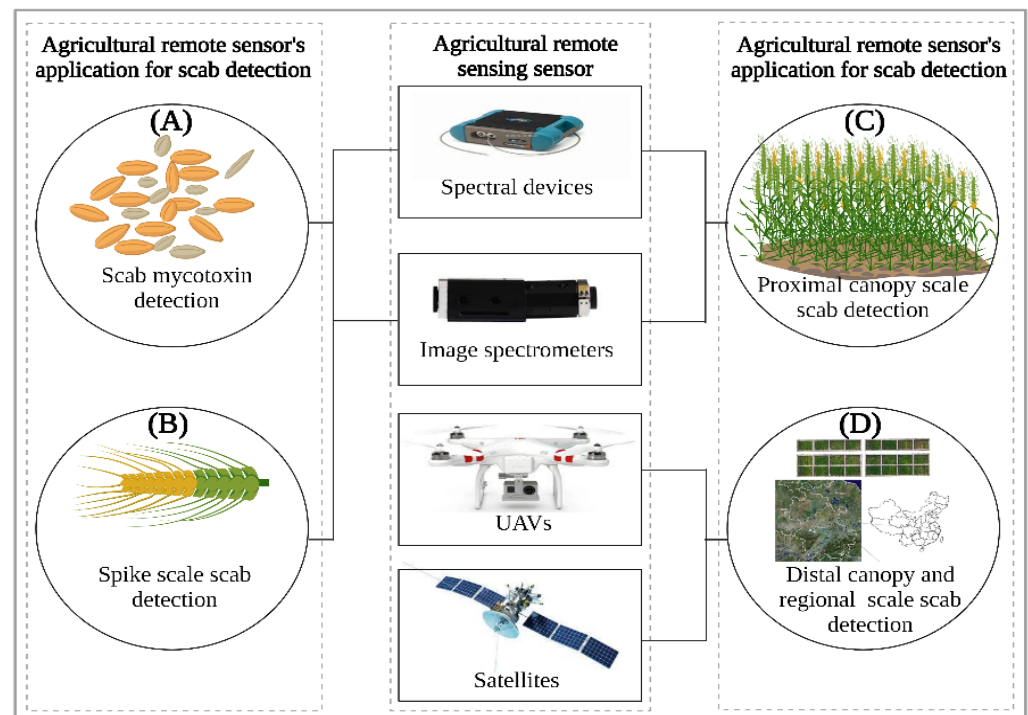


Figure 9. Agricultural remote sensors and their application for scab detection (A) to quantify the mycotoxin quantity in wheat seeds, (B) detect the wheat scab through examination of wheat spike, (C) detect and monitor the scab at proximal canopy scale, and (D) monitor the scab at canopy and regional scale.

3.7.1. ARS for Scab Detection in Wheat Kernels

Table 14 enlists the studies conducted for INISWS detection in wheat kernels. Numerous studies have been conducted for scab detection because grain is the most useful part of human and livestock consumption, directly affecting food and feed quality. Considering INISWS, different algorithmic and sensors are employed for the non-destructive monitoring of plants. Hyperspectral image (HSI) analysis with ratio analysis (RA) selected sensitive bands 568 and 715 nm and manifested high classification accuracy with linear discriminant analysis (LDA) [46]. In another study, texture features classified the healthy and infected grains with PCA and support vector machine (SVM) [47]. In recent studies [48–51], HSI and multispectral images were employed to discriminate between the scab-infected and healthy grains through sensitive feature selection and machine learning classifiers. The application of machine learning classifiers for discrimination among healthy and treated plants has become the top-notch approach for the ARS community [35].

Table 14. Summary of the investigations for scab detection in wheat kernels using ARS technology.

Wavelength Range (nm)	Spectrometer (Sensor)	Sensitive Band Selection Approach	Discriminant and Estimation Algorithms	Sensitive Bands (nm)	Location	References
425–860	HSI	RA	LDA	568, 715	USA	[46]
900–1700	HSI	PCA	SVM	Texture features	Canada	[47]
1000–1600	NIR-HSI	PCA	LDA, QDA, MD	1284, 1316, 1347	Canada	[52]
1000–1700	NIR-HSI	LMM	LDA	1002, 1127, 1199, 1315, 1474	USA	[53]
400–1000	NIR-HSI	PCA	LDA, PCA	484, 567, 684, 818, 900, 950	Canada	[54]
400–1700	NIR-HSI	RA	LDA	502, 678, 1198, 1496	USA	[55]

Table 14. Cont.

Wavelength Range (nm)	Spectrometer (Sensor)	Sensitive Band Selection Approach	Discriminant and Estimation Algorithms	Sensitive Bands (nm)	Location	References
400–1700	HSI	PCA	LDA, QDA, MD	870	Canada	[56]
400–1000	HSI	PLSR	PLS-DA	450, 494, 578, 639, 678, 717, 819, 853, 883, 903, 917, 942, 950	Canada	[57]
1000–1700	HSI	PCA, PLS-DA, iPLS-DA	PLS-DA	1209–1230, 1489–1510, 1601–1622	Italy	[58]
360–950	HSI	PCA	URA	875, 950	France	[59]
528–1785	HSI	PCA	LDA	672, 1361, 1411, 1509, 1657	Brazil	[30]
1000–1600	NIR-HSI	PCA	MD, LDA, QDA	1280, 1300, 1350	Canada	[60]
820–1666	NIR-HSI	GA	ICA		Canada	[61]
405–970	MS	PCA,	Knn	590–890	Denmark	[62]
528–1785	HSI		PC	623, 672, 1361, 1411, 1509, 1657	Brazil	[38]
866.4–1701.0	HSI	PCA	PLS-DA, SVM, Knn	1105.3, 1199.2, 1305.3, 1321.7, 1439.3, 1458.7, 1478.1	China	[63]
400–2500	HSI	COR		538–572, 828–1000, 1350–2500	Germany	[64]
400–1000	HSI	PCA, SPA, RF	SVM, RF, NB	513, 754, 836, 849, 860, 880	China	[65]
900–1700	HSI	PCA	PLS and LDA	955, 1278, 1403, 1455, 1528, 1671, 1714	Spain	[66]
400–2500	HSI	GA	SVM, SAE	570–710, 1050–1089, 1128–1313, 1666–1744, 1005, 1403, 1843, 1879, 1912, 1980	China	[67]
350–2500	HR	SPA	PLS-DA, SVM	1878, 1887	China	[68]
374–1030	HSI	R-Frog	Knn, CNNs	940, 678, 728, 798, 1009	China	[69]
900–1700	HSI-NIR	PLS, LDA	PLS, LDA	1220, 1380	Spain	[70]
960–1700	HSI		Knn	Whole spectra	Canada	[71]
900–1700	HSI-NIR	PCA	LDA, NB, PLSR	1325, 1396, 1406, 1421	Canada	[72]
940–1600	HSI	PCA,	LDA	986, 1000, 1111, 1197, 1394, 1200, 1260, 1460	USA	[73]
900–1700	HSI-NIR	PCA	PLS, SVM, local PLS	970, 1200, 1365, 1430, 1623	China	[50]
374–1030	HSI	Relief F, R-Frog, shuffled frog	KNN, SVM, CNN, LeNet, VGG-16	732, 876, 941, 988	China	[51]
866–1701	HSI-NIR	DCGAN	CNN, SVM, DT	1150–1300, 1400–1650	China	[48]
405–970	MS	PCA, GA	SVM, PLS, BPNN	910, 910–970	China	[49]

HSI: hyperspectral images; RA: ratio analysis; LDA: linear discriminant analysis; USA: united states of America; PCA: principal component analysis; SVM: support vector machine; NIR-HSI: near-infrared hyperspectral images; QDA: quadratic discriminant analysis; MD: Mahalanobis discriminant; LMM: local minima or maxima; PLSR: partial least square regression; PLS-DA: partial least squares discriminant analysis; iPLS-DA: interval partial least squares discriminant analysis; URA: univariate regression analysis; GA: genetic algorithm; ICA: independent component analysis; MS: multispectral; Knn: k-nearest neighbor; PC: probabilities calculation algorithm; SPA: successive projection algorithm; RF: random forest; COR: correlation; NB: Naive Bayes; SAE: sparse autoencoder; R-Frog: random frog; CNN: convolution neural networks; HR: hyperspectral reflectance; DCGAN: deep convolutional generative adversarial network; DT: decision tree; PLS: partial least square; BPNN: back propagation neural network.

3.7.2. ARS for Scab Detection in Wheat Spikes

Table 15 shows the application of imaging and non-imaging spectrometers for scab detection at spike scale in different studies and highlights the sensitive bands of different sensors and best algorithmic approaches for scab detection at spike scale. Principal component analysis (PCA) and spectral angle mapper (SAM) for the feature selection and classification were used by [74], employing HSI of scab disease in wheat crops. In addition, they also compared HSI with chlorophyll fluorescence using SAM for the classification-wavelength range 400–1000 nm [75]. In other findings, the PLS-DA model was used with a Euclidean distance matrix cladogram to classify the diseased and healthy spikes at different severity levels. The VIS-NIR spectral analysis could facilitate the detection of scab [76]. SVM for classification with non-metric multidimensional scaling (NMDS) to analyze different vegetation indices is a good approach for scab disease detection [23]. In HSI, a hybrid two-dimensional convolutional bidirectional gated recurrent unit neural network (2D-CNN-BidGRU) has an accuracy of 0.75 and 0.743 for classifying the diseased pixels compared to healthy ones [29]. Moreover, [39] compared infrared thermography (IRT), chlorophyll fluorescence imaging (CFI), and HSI techniques to relate the temperature, stress and spectral response of diseased spikes against healthy spikes with an accuracy of 78, 56, and 78%, respectively. Combining the IRT-HSI or CFI-HSI parameters improved the accuracy to 89% three days after inoculation. All the scientists acquired good results in scab detection and classification, but there was a lack of early detection approaches. Nevertheless, a reliable method of scab detection has yet to be developed.

Table 15. Summary of the investigations for scab detection in wheat spikes using ARS technology.

Wavelength Range (nm)	Spectrometer	Sensitive Band Selection Approach	Discriminant and Estimation Algorithms	Sensitive Bands (nm)	Location	References
620	FluorCam 700 MF		URA		Czech Republic	[77]
400–1000	HSI		PCA, SAM	560–560, 665–675	Germany	[74]
400–1000	HSI	PCA	DCNN, DCRNN, DRNN	670, 665–675	China	[29]
400–2500	HSI	MDS	SVM	430–525, 560–710, 1115–2500	Germany	[23]
400–1000	HR	FLDA	SVM, LDA	First order derivatives (490–530, 510–530)	China	[34]
400–2400	IRT, CFI, HSI	COR	SVM	500, 675, 760, 1440, 1880, 2000	Germany	[39]
400–1000	HSI	ISI	SAM	539, 417, 468	China	[32]
	RGB		DCNN	KMC, Otsu's method	China	[78]
400–1000	HR		URA	450–488, 500–540	China	[43]
400–900	HSI	COR, Relief F, RF, SFS-FS, SVM-RFE, LASSO-LR	QDA	540, 591, 696, 766, 868	USA	[79]
	RGB		PCNN, KMC		China	[80]
374–1050	HSI	RF	URA	560, 565, 570, 661, 663, 678	China	[81]
400–1000	HR	CWT, COR	SVM, GA-SVM	MSR, SIPI, NDVI	China	[82]

Table 15. Cont.

Wavelength Range (nm)	Spectrometer	Sensitive Band Selection Approach	Discriminant and Estimation Algorithms	Sensitive Bands (nm)	Location	References
400–1000	HSI	SPA, COR	PSO-SVM	442, 491, 552, 675, 685, 693, 698, 706, 757, 767, 924, 935	China	[40]
400–2500	HR	CWA	FLDA	471, 696, 841, 963, 1069, 2272	China	[9]
400–1000	HSI	PCA, GB, DT	DCNN, RF, PLSR, SVR	480, 560, 660	China	[83]
	RGB		Mask-RCNN	IS	China	[84]
	RGB		Mask-RCNN	IS	China	[85]
400–1000	HR	CWT	PSO-SVM, RF, BPNN	474, 495, 528, 582, 615, 691, 738	China	[86]
	RGB		DCNN	IS	United States	[87]
	RGB	Relief-F	RF		China	[88]
400–1000	HR	COR	SVM	561, 562, 563, 581, 582, 585, 590, 597, 598, 599	China	[44]
400–1000	HR and CFI	Boruta	KNN, SVM, RF	Chlorophyll indices	China	[89]

SAM: spectral angle mapper; DCNN: deep convolutional neural network; DCRNN: deep convolutional recurrent neural network; DRNN: deep recurrent neural network; MDS: multidimensional scaling; FLDA: Fisher's linear discriminant analysis; IRT: infrared thermography; CFI: chlorophyll fluorescence imaging; ISI: instability index; SFS-FS: sequential feature selection—forward selection; SVM-RFE: support vector machine recursive feature elimination; LASSO-LR: LASSO logistic regression; PCNN: pulse-coupled neural network, KMC: K-means clustering; GA-SVM: genetic algorithm-SVM; CWT: continuous wavelet transform; MSR: modified simple ratio; SIPI: structure intensive pigment index; NDVI: normalized difference vegetation index; PSO-SVM: particle swarm optimization-SVM; GB: gradient boost; DT: decision tree; SVR: support vector regression; Mark-RCCN: Mask region convolutional neural network; IS: image segmentation.

3.7.3. ARS for Scab Detection in the Wheat Canopy

Table 16 demonstrates the ARS community's focus on employing imaging and non-imaging spectrometers to detect wheat scab at the canopy scale, which is unfortunately very limited in a number of studies. Given the devastating threat to food quality and quantity posed by scab, the proxy approach to scab monitoring, classification, detection, and quantification has yet to be studied and finalized. A recent study [45] examined the canopy scale infection of the scab through the development of scab-specific indices using continuous wavelet transform (CWT) and robustified their relevance using different machine learning algorithms (RF, Knn, SVM, NN, Xgboost). Another study used the whole spectral (400–2400 nm) analysis to quantify the scab disease at the canopy scale using SVM algorithmic approach [90]. Likewise, partial least squares regression (PLSR) with PCA at canopy level disease detection of scab and yellow rust diseases by HSI showed satisfactory results [36].

Table 16. Summary of the investigations for scab detection in wheat canopy using ARS technology.

Wavelength Range (nm)	Sensor	Sensitive Band Selection Approach	Discriminant and/or Estimation Algorithms	Sensitive Bands (nm)	Location	References
400–700		MANOVA, PCA	PLSDA	SA	Italy	[76]
400–730		PCA	PLSR	500–650, 650, 700	United Kingdom	[36]

Table 16. Cont.

Wavelength Range (nm)	Sensor	Sensitive Band Selection Approach	Discriminant and/or Estimation Algorithms	Sensitive Bands (nm)	Location	References
400–730	RGB		PLSR	On field	United Kingdom	[33]
	RGB		KMS			[91]
	MS		URA	NDVI, RVI, DVI	China	[92]
(400–100)	MS, HR		URA, OLS	665, 783, 842	China	[93]
	MODIS		DTM, RVM		China	[94]
450–950	HSI	backward feature selection,	URA, PLSR, FLDA, LR, RF, SVM, BPNN	650, 670, 690, 730, 770	China	[95]
400–2400	HR		SVM	Spectral analysis	Czech Republic	[90]
450–950	HSI		Logistic model	550, 670, 702, 740	China	[96]
400–2400	HR	CWT	RF, Knn, SVM, NN, Xgboost	401, 460, 789, 840	China	[45]
450–950		RF	RF, BPNN, SVM	518, 666, 706, 742, 846	China	[97]

MANOVA: multivariate analysis of variance; SA: spectral analysis; NN: neural net; Xgboost: extreme GB; RVI: ratio vegetation index; DVI: difference vegetation index; OLS: ordinary least square; DTM: decision tree model; RVM: relevance vector machine.

3.7.4. Quantitative Models for Scab Disease

Numerous studies have used univariate and multivariate quantitative models for disease estimation in ARS for diverse plant diseases [98]. Different studies estimated the scab disease at spike [89] and canopy scale [45] using KNN predictive model. The studies also used SVM and RF models, but KNN outperformed the competing models. Moreover, the studies have also concluded that the comparative performance of disease-specific or newly developed indices for model fitting is highly improved against conventional indices [45,89] that support different other studies [99]; based on these results, a precise FHB monitoring program can be developed. Moreover, the better disease estimation performance of models through disease-specific indices or bands has also been proved by previous findings [42,99]. Another study also estimated the canopy scale scab disease considering the optimal window size of texture features [96]. Hence, a separate detailed study can be conducted using raw data and the application of different predictive models for deep exploration of the features.

4. Limitations and Future Prospective

Although several sensors have been used for scab detection under ARS, a conclusive methodology or technical instrumental setup pertinent to scab-specific detection or monitoring is still lacking. Tables 14–16 show the suitability as well as the chaotic behavior of different algorithms because selected or extracted scab-specific features (wavelengths) vary under different machine learning algorithms. However, the spectral regions (green, blue, red, NIR) are the same among different studies. Hence, the core future perspective is to focus on specific features that can be generalized for real-time detection, monitoring, and quantifying scab disease from spike to canopy scale. Supportively, the burst keywords' analysis (Table 12—last seven burst keywords) highlights the research frontiers that are in need of further research enhancements.

Regarding reviewing the different scab studies, the future suggestion could be that further research and data analysis is required to extract quantitative information on disease levels. Integration of hyperspectral sensor-based information, such as sensitive bands and vegetation indices, into pesticide application maps is very likely. Even more technological advancement is required for online systems. It is needed to be simplified with automated calibration and processing to compensate for different plant parameters, suitable for specialists and non-specialists, and for practical applications of sensor systems and algorithms to analyze hyperspectral data.

5. Conclusions

This study conducted a scientometric analysis of the scientific literature on imaging and non-imaging spectroscopy for wheat scab (INISWS). INISWS research published between 2005 and 2022 was extracted from the Web of Science (WOS) using co-citation, co-authorship, and co-occurrence analysis of keywords. The new knowledge structures, developments, authors or institutional collaborations, hot topics, and research frontiers in INISWS-related research were all taken into consideration. However, despite the significant findings from the visualization analysis of INISWS-related articles, the current study has a number of shortcomings. Only English-language publications are included in the WOS core collection databases, so there is a small amount of residue in terms of citations.

In comprehensive conclusion, while remote sensing as a technique provides the potential for high-accuracy diagnosis, monitoring, and management of scab diseases in wheat, there exists a need for further research with a focus on identifying scab-specific features applicable across sensors and algorithms. This would enable more accurate and reliable detection, monitoring, and quantification of scab, thereby improving crop management practices, mitigating economic losses, and ensuring food security. Integration of hyperspectral sensor-based information into pesticide application maps, accompanied by technological advancement for simplified and automated processing and calibration, is envisaged as an essential step to enable practical applications of sensor systems and algorithms to analyze hyperspectral data in wheat crops. However, to develop comprehensive decision support systems, research needs to focus on extracting quantitative information on disease levels using hyperspectral data. To achieve reliable and accurate data results, researchers must use appropriate sensors, concentrate on green, blue, red, NIR spectral regions, and develop machine learning algorithms tailored explicitly for scab disease detection. With these developments, remote sensing and analysis of scab disease will greatly help improve agricultural productivity worldwide.

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References

1. Qian, J.; Law, R.; Wei, J. Knowledge Mapping in Travel Website Studies: A Scientometric Review. *Scand. J. Hosp. Tour.* **2019**, *19*, 192–209. [\[CrossRef\]](#)
2. Chen, X.; Liu, Y. Visualization Analysis of High-Speed Railway Research Based on CiteSpace. *Transp. Policy* **2020**, *85*, 1–17. [\[CrossRef\]](#)
3. Azam, A.; Ahmed, A.; Wang, H.; Wang, Y.; Zhang, Z. Knowledge Structure and Research Progress in Wind Power Generation (WPG) from 2005 to 2020 Using CiteSpace Based Scientometric Analysis. *J. Clean. Prod.* **2021**, *295*, 126496. [\[CrossRef\]](#)
4. Ahmed, A.; Azam, A.; Bhutta, M.M.A.; Khan, F.A.; Aslam, R.; Tahir, Z. Discovering the Technology Evolution Pathways for 3D Printing (3DP) Using Bibliometric Investigation and Emerging Applications of 3DP during COVID-19. *Clean. Environ. Syst.* **2021**, *3*, 100042. [\[CrossRef\]](#)
5. Smith, W.G. *Diseases of Field and Garden Crops: Chiefly Such as Are Caused by Fungi*; Macmillan and Company: New York, NY, USA, 1884.
6. Parry, D.W.; Jenkinson, P.; McLeod, L. Fusarium Ear Blight (Scab) in Small Grain Cereals—A Review. *Plant Pathol.* **1995**, *44*, 207–238. [\[CrossRef\]](#)
7. McMullen, M.; Bergstrom, G.; De Wolf, E.; Dill-Macky, R.; Hershman, D.; Shaner, G.; Van Sanford, D. A Unified Effort to Fight an Enemy of Wheat and Barley: Fusarium Head Blight. *Plant Dis.* **2012**, *96*, 1712–1728. [\[CrossRef\]](#)
8. Liu, W.C.; Liu, Z.D.; Huang, C.; Lu, M.H.; Liu, J.; Yang, Q.P. Statistics and Analysis of Crop Yield Losses Caused by Main Diseases and Insect Pests in Recent 10 Years. *Plant Prot.* **2016**, *42*, 1–9.
9. Ma, H.; Huang, W.; Jing, Y.; Pignatti, S.; Laneve, G.; Dong, Y.; Ye, H.; Liu, L.; Guo, A.; Jiang, J. Identification of Fusarium Head Blight in Winter Wheat Ears Using Continuous Wavelet Analysis. *Sensors* **2020**, *20*, 20. [\[CrossRef\]](#)
10. Ban, T.; Kawad, N.; Yanagisawag, A.; Takezaki, A. Progress and Future Prospects of Resistance Breeding to Fusarium Head Blight in Japan. *Cereal Res. Commun.* **2008**, *36*, 23–29. [\[CrossRef\]](#)
11. Xu, X.M.; Nicholson, P.; Thomsett, M.A.; Simpson, D.; Cooke, B.M.; Doohan, F.M.; Brennan, J.; Monaghan, S.; Moretti, A.; Mule, G. Relationship between the Fungal Complex Causing Fusarium Head Blight of Wheat and Environmental Conditions. *Phytopathology* **2008**, *98*, 69–78. [\[CrossRef\]](#)
12. Haile, J.K.; N'Diaye, A.; Walkowiak, S.; Nilsen, K.T.; Clarke, J.M.; Kutcher, H.R.; Steiner, B.; Buerstmayr, H.; Pozniak, C.J. Fusarium Head Blight in Durum Wheat: Recent Status, Breeding Directions, and Future Research Prospects. *Phytopathology* **2019**, *109*, 1664–1675. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Torres, A.M.; Palacios, S.A.; Yerkovich, N.; Palazzini, J.M.; Battilani, P.; Leslie, J.F.; Logrieco, A.F.; Chulze, S.N. Fusarium Head Blight and Mycotoxins in Wheat: Prevention and Control Strategies across the Food Chain. *World Mycotoxin J.* **2019**, *12*, 333–355. [\[CrossRef\]](#)
14. Spanic, V.; Lemmens, M.; Drezner, G. Morphological and Molecular Identification of Fusarium Species Associated with Head Blight on Wheat in East Croatia. *Eur. J. Plant Pathol.* **2010**, *128*, 511–516. [\[CrossRef\]](#)
15. Nielsen, L.K.; Cook, D.J.; Edwards, S.G.; Ray, R.V. The Prevalence and Impact of Fusarium Head Blight Pathogens and Mycotoxins on Malting Barley Quality in UK. *Int. J. Food Microbiol.* **2014**, *179*, 38–49. [\[CrossRef\]](#)
16. Xue, A.G.; Chen, Y.; Seifert, K.; Guo, W.; Blackwell, B.A.; Harris, L.J.; Overby, D.P. Prevalence of Fusarium Species Causing Head Blight of Spring Wheat, Barley and Oat in Ontario during 2001–2017. *Can. J. Plant Pathol.* **2019**, *41*, 392–402. [\[CrossRef\]](#)
17. Dong, F.; Xu, J.; Zhang, X.; Wang, S.; Xing, Y.; Mokoena, M.P.; Olaniran, A.O.; Shi, J. Gramineous Weeds near Paddy Fields Are Alternative Hosts for the *Fusarium graminearum* Species Complex That Causes Fusarium Head Blight in Rice. *Plant Pathol.* **2020**, *69*, 433–441. [\[CrossRef\]](#)
18. Karasi, M.; Jorge, D.S.; Pierce, A.L. *Fusarium Head Blight or Head Scab of Wheat, Barley and Other Small Grain Crops*. Agriculture and Natural Resources; Ohio State University, Ohio: Columbus, OH, USA, 2016.
19. Stack, R.W. History of Fusarium Head Blight with Emphasis on North America. In *Fusarium Head Blight Wheat Barley*; APS Press: St. Paul, MN, USA, 2003; pp. 1–34.
20. Shah, D.A.; De Wolf, E.D.; Paul, P.A.; Madden, L.V. Functional Data Analysis of Weather Variables Linked to Fusarium Head Blight Epidemics in the United States. *Phytopathology* **2019**, *109*, 96–110. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Ma, Z.; Xie, Q.; Li, G.; Jia, H.; Zhou, J.; Kong, Z.; Li, N.; Yuan, Y. Germplasms, Genetics and Genomics for Better Control of Disastrous Wheat Fusarium Head Blight. *Theor. Appl. Genet.* **2020**, *133*, 1541–1568. [\[CrossRef\]](#)
22. Mahlein, A.K.; Steiner, U.; Hillnhütter, C.; Dehne, H.W.; Oerke, E.C. Hyperspectral Imaging for Small-Scale Analysis of Symptoms Caused by Different Sugar Beet Diseases. *Plant Methods* **2012**, *8*, 3. [\[CrossRef\]](#)
23. Alisaac, E.; Behmann, J.; Kuska, M.T.; Dehne, H.; Mahlein, A. Hyperspectral Quantification of Wheat Resistance to Fusarium Head Blight: Comparison of Two Fusarium Species. *Eur. J. Plant Pathol.* **2018**, *152*, 869–884. [\[CrossRef\]](#)
24. Alisaac, E. *Phenotyping of Wheat Resistance to Fusarium Head Blight Using Hyperspectral Imaging*; Universität Bonn: Bonn, Germany, 2021.
25. Liu, Z.; Yin, Y.; Liu, W.; Dunford, M. Visualizing the Intellectual Structure and Evolution of Innovation Systems Research: A Bibliometric Analysis. *Scientometrics* **2015**, *103*, 135–158. [\[CrossRef\]](#)
26. Chang, Y.W.; Huang, M.H.; Lin, C.W. Evolution of Research Subjects in Library and Information Science Based on Keyword, Bibliographical Coupling, and Co-Citation Analyses. *Scientometrics* **2015**, *105*, 2071–2087. [\[CrossRef\]](#)

27. Behrend, J.; Eulerich, M. The Evolution of Internal Audit Research: A Bibliometric Analysis of Published Documents (1926–2016). *Account. Hist. Rev.* **2019**, *29*, 103–139. [\[CrossRef\]](#)
28. Liao, H.; Tang, M.; Luo, L.; Li, C.; Chiclana, F.; Zeng, X.J. A Bibliometric Analysis and Visualization of Medical Big Data Research. *Sustainability* **2018**, *10*, 166. [\[CrossRef\]](#)
29. Jin, X.; Jie, L.; Wang, S.; Qi, H.J.; Li, S.W. Classifying Wheat Hyperspectral Pixels of Healthy Heads and Fusarium Head Blight Disease Using a Deep Neural Network in the Wild Field. *Remote Sens.* **2018**, *10*, 395. [\[CrossRef\]](#)
30. Barbedo, J.G.A.; Tibola, C.S.; Fernandes, J.M.C. Detecting Fusarium Head Blight in Wheat Kernels Using Hyperspectral Imaging. *Biosyst. Eng.* **2015**, *131*, 65–76. [\[CrossRef\]](#)
31. Ropelewska, E.; Zapotoczny, P. Classification of Fusarium-Infected and Healthy Wheat Kernels Based on Features from Hyperspectral Images and Flatbed Scanner Images: A Comparative Analysis. *Eur. Food Res. Technol.* **2018**, *244*, 1453–1462. [\[CrossRef\]](#)
32. Zhang, N.; Pan, Y.; Feng, H.; Zhao, X.; Yang, X.; Ding, C.; Yang, G. Development of Fusarium Head Blight Classification Index Using Hyperspectral Microscopy Images of Winter Wheat Spikelets. *Biosyst. Eng.* **2019**, *186*, 83–99. [\[CrossRef\]](#)
33. Whetton, R.L.; Waine, T.W.; Mouazen, A.M. Hyperspectral Measurements of Yellow Rust and Fusarium Head Blight in Cereal Crops: Part 2: On-Line Field Measurement. *Biosyst. Eng.* **2018**, *167*, 144–158. [\[CrossRef\]](#)
34. Huang, L.; Wu, Z.; Huang, W.; Ma, H.; Zhao, J. Identification of Fusarium Head Blight in Winter Wheat Ears Based on Fisher's Linear Discriminant Analysis and a Support Vector Machine. *Appl. Sci.* **2019**, *9*, 3894. [\[CrossRef\]](#)
35. Mahlein, A.K. Present and Future Trends in Plant Disease Detection. *Plant Dis.* **2016**, *100*, 1–11.
36. Whetton, R.L.; Hassall, K.L.; Waine, T.W.; Mouazen, A.M. ScienceDirect Hyperspectral Measurements of Yellow Rust and Fusarium Head Blight in Cereal Crops: Part 1: Laboratory Study. *Biosyst. Eng.* **2017**, *166*, 101–115. [\[CrossRef\]](#)
37. Zheng, Q.; Huang, W.; Cui, X.; Dong, Y.; Shi, Y.; Ma, H.; Liu, L. Identification of Wheat Yellow Rust Using Optimal Three-Band Spectral Indices in Different Growth Stages. *Sensors* **2018**, *19*, 35. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Barbedo, J.G.A.; Tibola, C.S.; Lima, M.I.P. Deoxynivalenol Screening in Wheat Kernels Using Hyperspectral Imaging. *Biosyst. Eng.* **2017**, *155*, 24–32. [\[CrossRef\]](#)
39. Mahlein, A.K.; Alisaac, E.; Al Masri, A.; Behmann, J.; Dehne, H.W.; Oerke, E.C. Comparison and Combination of Thermal, Fluorescence, and Hyperspectral Imaging for Monitoring Fusarium Head Blight of Wheat on Spikelet Scale. *Sensors* **2019**, *19*, 2281. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Huang, L.; Li, T.; Ding, C.; Zhao, J.; Zhang, D.; Yang, G. Diagnosis of the Severity of Fusarium Head Blight of Wheat Ears on the Basis of Image and Spectral Feature Fusion. *Sensors* **2020**, *20*, 2887. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Delwiche, S.R.; Rodriguez, I.T.; Rausch, S.R.; Graybosch, R.A. Estimating Percentages of Fusarium-Damaged Kernels in Hard Wheat by near-Infrared Hyperspectral Imaging. *J. Cereal Sci.* **2019**, *87*, 18–24. [\[CrossRef\]](#)
42. Ma, H.; Huang, W.; Dong, Y.; Liu, L.; Guo, A. Using UAV-Based Hyperspectral Imagery to Detect Winter Wheat Fusarium Head Blight. *Remote Sens.* **2021**, *13*, 3024. [\[CrossRef\]](#)
43. Huang, L.; Zhang, H.; Ding, W.; Huang, W.; Hu, T.; Zhao, J. Monitoring of Wheat Scab Using the Specific Spectral Index from ASD Hyperspectral Dataset. *J. Spectrosc.* **2019**, *2019*, 9153195. [\[CrossRef\]](#)
44. Huang, L.; Zhang, H.; Huang, W.; Dong, Y.; Ye, H.; Ma, H.; Zhao, J. Identification of Fusarium Head Blight in Wheat Ears Using Vertical Angle-Based Reflectance Spectroscopy. *Arab. J. Geosci.* **2021**, *14*, 423. [\[CrossRef\]](#)
45. Mustafa, G.; Zheng, H.; Khan, I.H.; Tian, L.; Jia, H.; Li, G. Hyperspectral Reflectance Proxies to Diagnose In-Field Fusarium Head Blight in Wheat with Machine Learning. *Remote Sens.* **2022**, *14*, 2784. [\[CrossRef\]](#)
46. Delwiche, S.R.; Kim, M.S. *Hyperspectral Imaging for Detection of Scab in Wheat*; SPIE: Bellingham, WA, USA, 2000; Volume 4203, pp. 13–20.
47. Zhang, H.; Paliwal, J.; Jayas, D.S.; White, N. Classification of Fungal Infected Wheat Kernels Using Near-Infrared Reflectance Hyperspectral Imaging and Support Vector Machine. *Trans. ASABE* **2007**, *50*, 1779–1785. [\[CrossRef\]](#)
48. Li, H.; Zhang, L.; Sun, H.; Rao, Z.; Ji, H. Discrimination of Unsound Wheat Kernels Based on Deep Convolutional Generative Adversarial Network and Near-Infrared Hyperspectral Imaging Technology. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2022**, *268*, 120722. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Liu, W.; He, L.; Xia, Y.; Ren, L.; Liu, C.; Zheng, L. Monitoring the Growth of *Fusarium graminearum* in Wheat Kernels Using Multispectral Imaging with Chemometric Methods. *Anal. Methods* **2022**, *14*, 106–113. [\[CrossRef\]](#)
50. Shen, G.; Cao, Y.; Yin, X.; Dong, F.; Xu, J.; Shi, J.; Lee, Y.-W. Rapid and Nondestructive Quantification of Deoxynivalenol in Individual Wheat Kernels Using Near-Infrared Hyperspectral Imaging and Chemometrics. *Food Control* **2022**, *131*, 108420. [\[CrossRef\]](#)
51. Yipeng, L.; Wenbing, L.; Kaixuan, H.; Wentao, T.; Ling, Z.; Shizhuang, W.; Linsheng, H. Determination of Wheat Kernels Damaged by Fusarium Head Blight Using Monochromatic Images of Effective Wavelengths from Hyperspectral Imaging Coupled with an Architecture Self-Search Deep Network. *Food Control* **2022**, *135*, 108819. [\[CrossRef\]](#)
52. Singh, C.; Jayas, D.; Paliwal, J.; White, N. Fungal Detection in Wheat Using Near-Infrared Hyperspectral Imaging. *Trans. ASABE* **2007**, *50*, 2171–2176. [\[CrossRef\]](#)
53. Delwiche, S.R.; Kim, M.S.; Dong, Y. *Damage and Quality Assessment in Wheat by NIR Hyperspectral Imaging*; SPIE: Bellingham, WA, USA, 2010; Volume 7676, pp. 45–52.

54. Shahin, M.A.; Symons, S.J. Detection of Fusarium Damaged Kernels in Canada Western Red Spring Wheat Using Visible/near-Infrared Hyperspectral Imaging and Principal Component Analysis. *Comput. Electron. Agric.* **2011**, *75*, 107–112. [\[CrossRef\]](#)
55. Delwiche, S.R.; Kim, M.S.; Dong, Y. Fusarium Damage Assessment in Wheat Kernels by Vis/NIR Hyperspectral Imaging. *Sens. Instrum. Food Qual. Saf.* **2011**, *5*, 63–71. [\[CrossRef\]](#)
56. Singh, C.; Jayas, D.; Paliwal, J.; White, N. Fungal Damage Detection in Wheat Using Short-Wave near-Infrared Hyperspectral and Digital Colour Imaging. *Int. J. Food Prop.* **2012**, *15*, 11–24. [\[CrossRef\]](#)
57. Shahin, M.A.; Symons, S.J. Detection of Fusarium Damage in Canadian Wheat Using Visible/near-Infrared Hyperspectral Imaging. *J. Food Meas. Charact.* **2012**, *6*, 3–11. [\[CrossRef\]](#)
58. Serranti, S.; Cesare, D.; Bonifazi, G. The Development of a Hyperspectral Imaging Method for the Detection of Fusarium-Damaged, Yellow Berry and Vitreous Italian Durum Wheat Kernels. *Biosyst. Eng.* **2013**, *115*, 20–30. [\[CrossRef\]](#)
59. Jaillais, B.; Roumet, P.; Pinson-Gadais, L.; Bertrand, D. Detection of Fusarium Head Blight Contamination in Wheat Kernels by Multivariate Imaging. *Food Control* **2015**, *54*, 250–258. [\[CrossRef\]](#)
60. Senthilkumar, T.; Jayas, D.; White, N.; Fields, P.; Gräfenhan, T. Detection of Fungal Infection and Ochratoxin A Contamination in Stored Wheat Using Near-Infrared Hyperspectral Imaging. *J. Stored Prod. Res.* **2016**, *65*, 30–39. [\[CrossRef\]](#)
61. Saccon, F.A.; Elrewainy, A.; Parcey, D.; Paliwal, J.; Sherif, S.S. *Detection of Fusarium on Wheat Using Near Infrared Hyperspectral Imaging*; IEEE: Piscataway, NJ, USA, 2016; p. 1.
62. Vrešak, M.; Halkjaer Olesen, M.; Gislum, R.; Bavec, F.; Ravn Jørgensen, J. The Use of Image-Spectroscopy Technology as a Diagnostic Method for Seed Health Testing and Variety Identification. *PLoS ONE* **2016**, *11*, e0152011. [\[CrossRef\]](#)
63. Zhang, L.; Ji, H. Identification of Wheat Grain in Different States Based on Hyperspectral Imaging Technology. *Spectrosc. Lett.* **2019**, *52*, 356–366. [\[CrossRef\]](#)
64. Alisaac, E.; Behmann, J.; Rathgeb, A.; Karlovsky, P.; Dehne, H.W.; Mahlein, A.K. Assessment of Fusarium Infection and Mycotoxin Contamination of Wheat Kernels and Flour Using Hyperspectral Imaging. *Toxins* **2019**, *11*, 556. [\[CrossRef\]](#) [\[PubMed\]](#)
65. Zhang, D.; Chen, G.; Zhang, H.; Jin, N.; Gu, C.; Weng, S.; Wang, Q.; Chen, Y. Integration of Spectroscopy and Image for Identifying Fusarium Damage in Wheat Kernels. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2020**, *236*, 118344. [\[CrossRef\]](#)
66. Femenias, A.; Gatiús, F.; Ramos, A.J.; Sanchis, V.; Marín, S. Standardisation of near Infrared Hyperspectral Imaging for Quantification and Classification of DON Contaminated Wheat Samples. *Food Control* **2020**, *111*, 107074. [\[CrossRef\]](#)
67. Liang, K.; Huang, J.; He, R.; Wang, Q.; Chai, Y.; Shen, M. Comparison of Vis-NIR and SWIR Hyperspectral Imaging for the Non-Destructive Detection of DON Levels in Fusarium Head Blight Wheat Kernels and Wheat Flour. *Infrared Phys. Technol.* **2020**, *106*, 103281. [\[CrossRef\]](#)
68. Zhang, D.; Wang, Q.; Lin, F.; Weng, S.; Lei, Y.; Chen, G.; Gu, C.; Zheng, L. New Spectral Classification Index for Rapid Identification of Fusarium Infection in Wheat Kernel. *Food Anal. Methods* **2020**, *13*, 2165–2175. [\[CrossRef\]](#)
69. Weng, S.; Han, K.; Chu, Z.; Zhu, G.; Liu, C.; Zhu, Z.; Zhang, Z.; Zheng, L.; Huang, L. Reflectance Images of Effective Wavelengths from Hyperspectral Imaging for Identification of Fusarium Head Blight-Infected Wheat Kernels Combined with a Residual Attention Convolution Neural Network. *Comput. Electron. Agric.* **2021**, *190*, 106483. [\[CrossRef\]](#)
70. Femenias, A.; Gatiús, F.; Ramos, A.J.; Sanchis, V.; Marín, S. Near-Infrared Hyperspectral Imaging for Deoxynivalenol and Ergosterol Estimation in Wheat Samples. *Food Chem.* **2021**, *341*, 128206. [\[CrossRef\]](#) [\[PubMed\]](#)
71. Nadimi, M.; Brown, J.; Morrison, J.; Paliwal, J. Examination of Wheat Kernels for the Presence of Fusarium Damage and Mycotoxins Using Near-Infrared Hyperspectral Imaging. *Meas. Food* **2021**, *4*, 100011. [\[CrossRef\]](#)
72. Femenias, A.; Bainotti, M.B.; Gatiús, F.; Ramos, A.J.; Marín, S. Standardization of near Infrared Hyperspectral Imaging for Wheat Single Kernel Sorting According to Deoxynivalenol Level. *Food Res. Int.* **2021**, *139*, 109925. [\[CrossRef\]](#)
73. Delwiche, S.R.; Baek, I.; Kim, M.S. Does Spatial Region of Interest (ROI) Matter in Multispectral and Hyperspectral Imaging of Segmented Wheat Kernels? *Biosyst. Eng.* **2021**, *212*, 106–114. [\[CrossRef\]](#)
74. Bauriegel, E.; Giebel, A.; Geyer, M.; Schmidt, U.; Herppich, W.B. Early Detection of Fusarium Infection in Wheat Using Hyperspectral Imaging. *Comput. Electron. Agric.* **2011**, *75*, 304–312. [\[CrossRef\]](#)
75. Bauriegel, E.; Herppich, W.B. Hyperspectral and Chlorophyll Fluorescence Imaging for Early Detection of Plant Diseases, with Special Reference to Fusarium Spec. Infections on Wheat. *Agriculture* **2014**, *4*, 32–57. [\[CrossRef\]](#)
76. Menesatti, P.; Antonucci, F.; Pallottino, F.; Giorgi, S.; Matere, A.; Nocente, F.; Pasquini, M.; D'Egidio, M.G.; Costa, C. Laboratory vs. in-Field Spectral Proximal Sensing for Early Detection of Fusarium Head Blight Infection in Durum Wheat. *Biosyst. Eng.* **2013**, *114*, 289–293. [\[CrossRef\]](#)
77. Bauriegel, E.; Giebel, A.; Herppich, W. Rapid Fusarium Head Blight Detection on Winter Wheat Ears Using Chlorophyll Fluorescence Imaging. *J. Appl. Bot. Food Qual.* **2010**, *83*, 196–203.
78. Qiu, R.; Yang, C.; Moghimi, A.; Zhang, M.; Steffenson, B. Detection of Fusarium Head Blight in Wheat Using a Deep Neural Network and Color Imaging. *Remote Sens.* **2019**, *11*, 2658. [\[CrossRef\]](#)
79. Moghimi, A.; Yang, C.; Anderson, J.A.; Reynolds, S.K. *Selecting Informative Spectral Bands Using Machine Learning Techniques to Detect Fusarium Head Blight in Wheat*; American Society of Agricultural and Biological Engineers: St. Joseph, MI, USA, 2019; p. 1.
80. Zhang, D.; Wang, D.; Gu, C.; Jin, N.; Zhao, H.; Chen, G.; Liang, H.; Liang, D. Using Neural Network to Identify the Severity of Wheat Fusarium Head Blight in the Field Environment. *Remote Sens.* **2019**, *11*, 2375. [\[CrossRef\]](#)
81. Zhang, D.; Wang, Q.; Lin, F.; Yin, X.; Gu, C.; Qiao, H. Development and Evaluation of a New Spectral Disease Index to Detect Wheat Fusarium Head Blight Using Hyperspectral Imaging. *Sensors* **2020**, *20*, 2260. [\[CrossRef\]](#) [\[PubMed\]](#)

82. Huang, L.; Zhang, H.; Ruan, C.; Huang, W.; Hu, T.; Zhao, J. Detection of Scab in Wheat Ears Using in Situ Hyperspectral Data and Support Vector Machine Optimized by Genetic Algorithm. *Int. J. Agric. Biol. Eng.* **2020**, *13*, 182–188. [\[CrossRef\]](#)
83. Zhang, D.Y.; Chen, G.; Yin, X.; Hu, R.J.; Gu, C.Y.; Pan, Z.G.; Zhou, X.G.; Chen, Y. Integrating Spectral and Image Data to Detect Fusarium Head Blight of Wheat. *Comput. Electron. Agric.* **2020**, *175*, 105588. [\[CrossRef\]](#)
84. Su, W.H.; Zhang, J.; Yang, C.; Page, R.; Szinyei, T.; Hirsch, C.D.; Steffenson, B.J. *Evaluation of Mask RCNN for Learning to Detect Fusarium Head Blight in Wheat Images*; American Society of Agricultural and Biological Engineers: St. Joseph, MI, USA, 2020; p. 1.
85. Su, W.H.; Zhang, J.; Yang, C.; Page, R.; Szinyei, T.; Hirsch, C.D.; Steffenson, B.J. Automatic Evaluation of Wheat Resistance to Fusarium Head Blight Using Dual Mask-Rcnn Deep Learning Frameworks in Computer Vision. *Remote Sens.* **2021**, *13*, 26. [\[CrossRef\]](#)
86. Huang, L.; Wu, K.; Huang, W.; Dong, Y.; Ma, H.; Liu, Y.; Liu, L. Detection of Fusarium Head Blight in Wheat Ears Using Continuous Wavelet Analysis and Pso-Svm. *Agriculture* **2021**, *11*, 998. [\[CrossRef\]](#)
87. Fernández-Campos, M.; Huang, Y.T.; Jahanshahi, M.R.; Wang, T.; Jin, J.; Telenko, D.E.; Góngora-Canul, C.; Cruz, C. Wheat Spike Blast Image Classification Using Deep Convolutional Neural Networks. *Front. Plant Sci.* **2021**, *12*, 1054. [\[CrossRef\]](#)
88. Gu, C.; Wang, D.; Zhang, H.; Zhang, J.; Zhang, D.; Liang, D. Fusion of Deep Convolution and Shallow Features to Recognize the Severity of Wheat Fusarium Head Blight. *Front. Plant Sci.* **2021**, *11*, 2075. [\[CrossRef\]](#) [\[PubMed\]](#)
89. Mustafa, G.; Zheng, H.; Li, W.; Yin, Y.; Wang, Y.; Zhou, M.; Liu, P.; Bilal, M.; Jia, H.; Li, G. Fusarium Head Blight Monitoring in Wheat Ears Using Machine Learning and Multimodal Data from Asymptomatic to Symptomatic Periods. *Front. Plant Sci.* **2022**, *13*, 2341. [\[CrossRef\]](#)
90. Żelazny, W.R.; Chrpová, J.; Hamouz, P. Fusarium Head Blight Detection from Spectral Measurements in a Field Phenotyping Setting—A Pre-Registered Study. *Biosyst. Eng.* **2021**, *211*, 97–113. [\[CrossRef\]](#)
91. Zhang, D.; Wang, Z.; Jin, N.; Gu, C.; Chen, Y.; Huang, Y. Evaluation of Efficacy of Fungicides for Control of Wheat Fusarium Head Blight Based on Digital Imaging. *IEEE Access* **2020**, *8*, 109876–109890. [\[CrossRef\]](#)
92. Li, W.; Liu, Y.; Chen, H.; Zhang, C.C. Estimation Model of Winter Wheat Disease Based on Meteorological Factors and Spectral Information. *Food Prod. Process. Nutr.* **2020**, *2*, 5. [\[CrossRef\]](#)
93. Liu, L.; Dong, Y.; Huang, W.; Du, X.; Ren, B.; Huang, L.; Zheng, Q.; Ma, H. A Disease Index for Efficiently Detecting Wheat Fusarium Head Blight Using Sentinel-2 Multispectral Imagery. *IEEE Access* **2020**, *8*, 52181–52191. [\[CrossRef\]](#)
94. Xiao, Y.; Dong, Y.; Huang, W.; Liu, L.; Ma, H.; Ye, H.; Wang, K. Dynamic Remote Sensing Prediction for Wheat Fusarium Head Blight by Combining Host and Habitat Conditions. *Remote Sens.* **2020**, *12*, 3046. [\[CrossRef\]](#)
95. Liu, L.; Dong, Y.; Huang, W.; Du, X.; Ma, H. Monitoring Wheat Fusarium Head Blight Using Unmanned Aerial Vehicle Hyperspectral Imagery. *Remote Sens.* **2020**, *12*, 3811. [\[CrossRef\]](#)
96. Xiao, Y.; Dong, Y.; Huang, W.; Liu, L.; Ma, H. Wheat Fusarium Head Blight Detection Using UAV-Based Spectral and Texture Features in Optimal Window Size. *Remote Sens.* **2021**, *13*, 2437. [\[CrossRef\]](#)
97. Zhang, H.; Huang, L.; Huang, W.; Dong, Y.; Weng, S.; Zhao, J.; Ma, H.; Liu, L. Detection of Wheat Fusarium Head Blight Using UAV-Based Spectral and Image Feature Fusion. *Front. Plant Sci.* **2022**, *13*, 3524. [\[CrossRef\]](#)
98. Feng, Z.H.; Wang, L.Y.; Yang, Z.Q.; Zhang, Y.Y.; Li, X.; Song, L.; He, L.; Duan, J.Z.; Feng, W. Hyperspectral Monitoring of Powdery Mildew Disease Severity in Wheat Based on Machine Learning. *Front. Plant Sci.* **2022**, *13*, 828454. [\[CrossRef\]](#)
99. Guo, W.; Yang, Y.; Zhao, H.; Song, R.; Dong, P.; Jin, Q.; Baig, M.H.A.; Liu, Z.; Yang, Z. Winter Wheat Take-All Disease Index Estimation Model Based on Hyperspectral Data. *Appl. Sci.* **2021**, *11*, 9230. [\[CrossRef\]](#)

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