1-1-2021

Bibliometric Analysis of Plant Disease Prediction Using Climatic condition

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Abstract

The changes in the climatic conditions are having beneficial as well as harmful effects on crop yields depending on the drastic changes. There can be a yield loss due to the occurrence of disease in crops. Apart from severe yield losses, infected yield can be harmful and threatening to living being's health as that is the source of food. This also affects the economy of the agricultural depended country. Disease prediction tools advance in the management of exertions for diseases in plants. Machine learning techniques help in elucidating complex associations between hosts and pathogens without invoking difficult-to-satisfy expectations. For the fungal diseases, analysis with multiple regression shows that meteorological parameters comprising of temperature, wind speed, and humidity were the key predictors of fungal attention. The paper discusses the bibliometric analysis of plant disease prediction from the Scopus database in analyzing the research by area, influential authors, institutions, countries, and funding agency. The 490 research documents are extracted from the year 2015 to 30th December 2020 from the database. Bibliometric analysis is the statistical analysis of the research published as articles, conference papers, and reviews, which helps in understanding the impact of publication in the research domain globally. The visualization analysis is done with open-source tools namely GPS Visualizer, Gephi, VOS viewer, ScienceScape, and wordcloud. The visualization aids in a quick and clear understanding of the different perspective as mentioned above in a particular research domain search.

Keywords: plant disease, prediction, regression model, climatic condition, bibliometric analysis.

1. Introduction

Agriculture is the mainstay of any country as it offers the food needs of the growing population across the world. Diseases in plants cause structural changes or lower development functions by varying the metabolic methods and biological methods of plants. The elementary cause of plant diseases are bacteria, fungi, and viruses. Plant diseases occur under the disease triangle scenario when pathogens, environment-based factors, and host plants are broadly quantified. The weather conditions and seasonal changes cause variation in the level of temperature, humidity, wind, etc. The changes in the climate condition are an important factor as they can helpful and harmful to crop production as both host and pathogen can be present and risk the cause of the disease in crops. So, in a favorable environmental condition along with the host and pathogen, the chances of infection of the disease are most likely. The loss in the yield further affects the seed quality and contamination of the grain. An appropriate care needs to be taken to avoid the major effects on plants as they, in turn, show their effect on the product quality, quantity, and productivity. The fast and accurate identification of disease severity will help to reduce yield losses. If climatic conditions are misinterpreted, they can impact the disease risk. The data showing the spatial coverage of crops with probabilistic climate change were developed by (Skelsey & Newton, 2015) in the future prediction of disease in wheat. The epidemics result in losses that attribute to widespread adoption of reduced and minimum tillage, decreased crop diversity, increased acreage of host crops, and wet, humid weather conditions during anthesis and early grain fill stages (Andersen et al., 2015). The multiple regression model equations based on temperature and vapor pressure with the epidemic climatic conditions help in the disease management programs (Manstretta & Rossi, 2015). The mean aggressiveness in the pattern of the epidemic climatic conditions was revealed with “Amplified fragment length polymorphism” (AFLP) markers showing the high genetic diversity within the pathogens. This shows that the disease can be a carryover from one season to another (Laloi et al., 2016).

With a binary logistic regression model, the connotation between the climatic condition and recovery along with topographical and environmental factors assessment showed significant results. High temperatures with low precipitation levels in the aridity conditions are key features resulting in the recovery of the infection in crops (Lione et al., 2017). Multiple regression analysis with meteorological parameters like temperature, humidity, and wind speed are key parameters in the prediction of the fungal concentration level. There was a negative correlation between fungal growth and sunlight (Kallawicha et al., 2017). The growth management was studied by (Yue et al., 2017) in the yield prediction considering above-ground biomass (AGB) based on the spectral parameters, such as specific bands, spectral indices (e.g., "Ratio Vegetation Index" (RVI), "Normalized Difference Vegetation Index" (NDVI), "Greenness Index" (GI) and "Wide Dynamic Range VI" (WDRVI)) and height of the crop. Numerous models combined with spectral parameters and crop height were evaluated. The height of the crop can be determined with the help of a snapshot hyperspectral sensor. This feature improves the estimation of AGB and is valuable input for mapping applications. This technique gives a helping hand in guidance for agricultural management. Weather forecast models help predict a week times condition. The system that can predict the occurrence of fungal diseases in crops based on the weather forecast is helpful to the farmers in the decision of spraying the fungicide (Shah et al., 2019; Smith et al., 2018; Vogelgsang et al., 2017).

The agroclimatic conditions vary for tropical and sub-tropical regions. So, the application of certain agrotechnology may not work for both regions or different varieties of crops (Ban et al., 2017). This affects the yield on the farm and in turn affects the economy of the country. If the weather condition is favorable for healthy yield then the country will gain profit from it. The influence of changes in the climatic condition situation assessment by Global Circulation Models indicated a gross income of US$25-84 per hectare for a country through crop yields (Hossain et al., 2018). A service Farm as a Service (FaaS) developed by (Kim et al., 2018) can confirm the disease in a plant with the captured images as well as offers predictive information about the possibility of disease and pests. The information obtained from the sensors and controllers that provide operation evidence is fetched for the service. Image processing has been done in several domains for classification purposes. These are used in the treatment of plant disease identification and further taking the preventive measure in curing them (Petrellis, 2018).

In the case of irrigation, there could be a negative yield anomaly in the yield prediction. In their work, (Zhu et al., 2019) estimated crop yields in the US-based on the impact of climate and irrigation for the 21st century. This accounts for uncertainty in climate parameters and the throughput of the crop. The ensemble in machine learning models with input parameters of weather, details of soil, management features, preliminary conditions, etc plays a vital role in the prediction of disease (Shahhosseini et al., 2019). Developing a predictive model with remote sensing facilitates precision agriculture while applying machine learning models (Diego et al., 2019). The total economic loss was used as a function of disease prediction based on yield, harvest area, and production (Bandara et al., 2020). An hourly time-step model (BLIGHTSIM) was developed by (Narouei-Khandan et al., 2020) to predict late blight in potato fields. The model uses temperature and relative humidity per hour as an input variable. There was a significant interface between average temperature and area under the disease progress curve (AUDPC) with this model. A wheat yield prediction model was developed by (Cao et al., 2020) with once-a-month climate data, satellite data showing “Vegetation indices”, and socio-economic factors. The best performance was achieved with “Ridge Regression”, “Random Forest”, and “Light Gradient Boosting” machine learning models. The main objective of the paper is to report a bibliometric analysis of the plant disease prediction with the regression model and climatic conditions.

2. Preliminary Data

Bibliometric analysis is the statistical analysis of the research published as articles, conference papers, and reviews, which helps in understanding the impact of publication in the research domain globally (Bongale et al., 2020). This is the first time to perform such a bibliometric analysis on plant disease prediction. This research paper is formulated by querying to Scopus database. The citation database is with a wide variety of fields domains viz science, technology, engineering, medicine, social sciences, arts, and humanities. The data is fetched from the Scopus database on 30th December 2020. The combination of Significant keywords queried in the search for the duration of 2015-2020 is shown in Table 1. The top ten keywords in the search are enumerated in Table 2 with the number of publications (NoP).

Table 1: The Search query for Scopus database.

Sr No	Search
1	Plant disease" and "disease prediction" and "regression model" or "viral disease" or "bacterial disease" or "fungal disease"
2	plant disease" and "disease prediction" or "regression model" and "weather condition" or temperature or humidity

Table 2: Top ten keywords with the number of publications.

Keyword	NoP	Keyword	NoP
Plant Disease	70	Physiology	41
Plant Diseases	61	Regression Analysis	41
Climate Change	51	Fungal Disease	38
Wheat	45	Crops	36
Microbiology	41	Forecasting	36

2.1 Initial Search Results

By employing the query mentioned in Table 1; the number of 490 publications is fetched from the Scopus database. Table 3 shows the NoP in different languages fetched in the search. Most of the publications are in the English Language accounting for 97.96%. Very few publications are in Chinese, Spanish, Portuguese and Russian language.

Table 3: Language of Publications.

Language	NoP	Percentage
English	480	97.96%
Chinese	6	1.22%
Spanish	2	0.41%
Portuguese	1	0.20%
Russian	1	0.20%

Table 4 shows the publication type in the article, review, conference paper, book chapter, and book. There the highest number of publications are in an article comprising 83.26% followed by 33 publications in a review. The conference publication comprises of 24 papers, while 16 and 9 publications in book chapter and book respectively.

Table 4 Type of Publications.

Publication Type	NoP	Percentage
Article	408	83.26%
Review	33	6.73%
Conference Paper	24	4.89%
Book Chapter	16	3.26%
Book	9	1.84%

2.2 Preliminary Data Analysis

The year publication trend is shown in Figure 1. The maximum publication of 139 are in year 2020. It is seen that there is a rise in this research area since 2018. The top ten influential authors contributing to the area of plant disease prediction are shown in Figure 2. Rossi V has 11 publications in his credit followed by Makowski D with 8 publication, Vicent A and Brun F with 7 publication each.

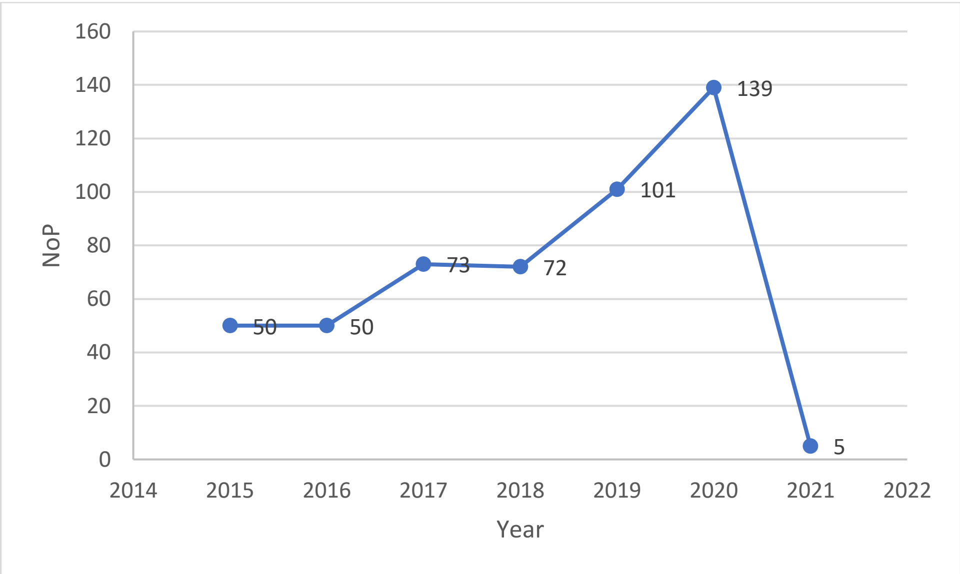

Figure 1: Yearly publication details in plant disease prediction.

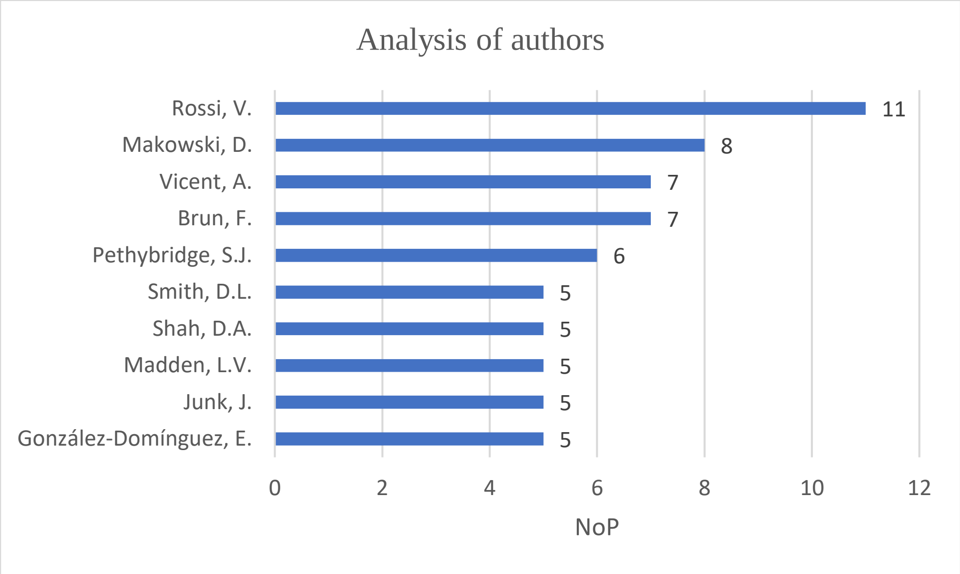

Figure 2: Top ten Influential author in plant disease prediction.

Figure 3 shows the top ten countries partaking in Scopus publications. United States (US) has a maximum number of publications of 128. India and China are having 63 and 52 publications respectively.

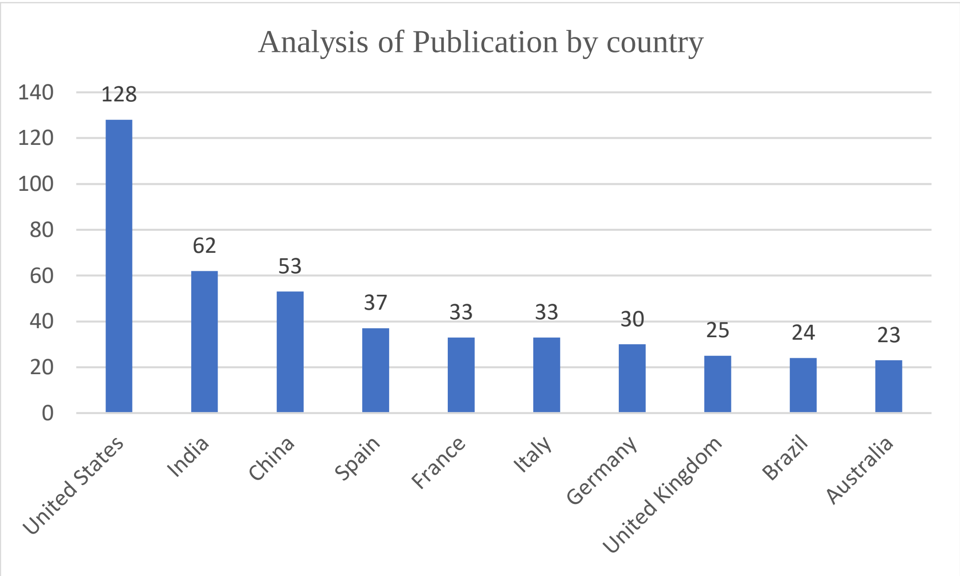

Figure 3: Top ten countries partaking in plant disease prediction from Scopus publications.

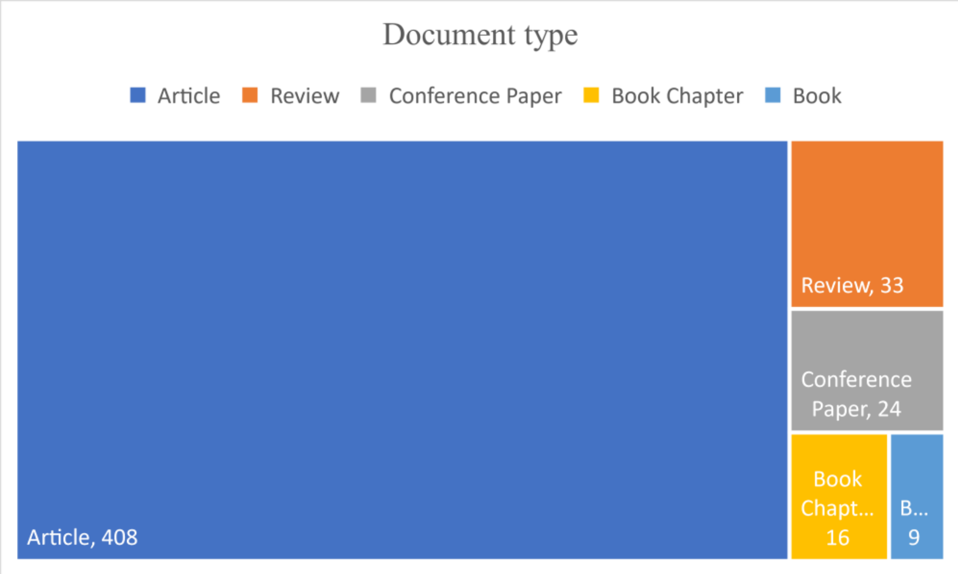

Figure 4: Types of document for publications in plant disease prediction.

The types of documents for publication are shown in Figure 4. The publications are highest in article type followed by documents in the review. The document by source analysis is shown in Figure 5. The CiteScore for 2015-2019 is shown in Figure 5(a). "Frontiers in Plant Science" is having the highest CiteScore of 7.8. Source normalized impact per paper by year (SNIP) is shown in Figure 5(b). Remote Sensing is having a SNIP value of 1.77. SCImago journal rank per year (SJR) is shown in Figure 5(c). "Frontiers in Plant Science" is having the highest SJR of 1.691.

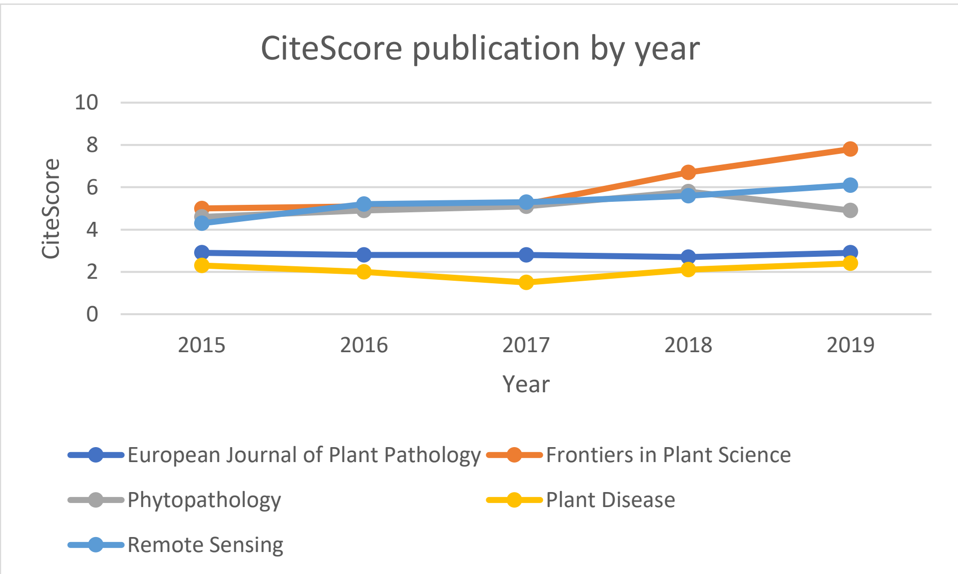

Figure 5 (a): CiteScore publication by year in plant disease prediction.

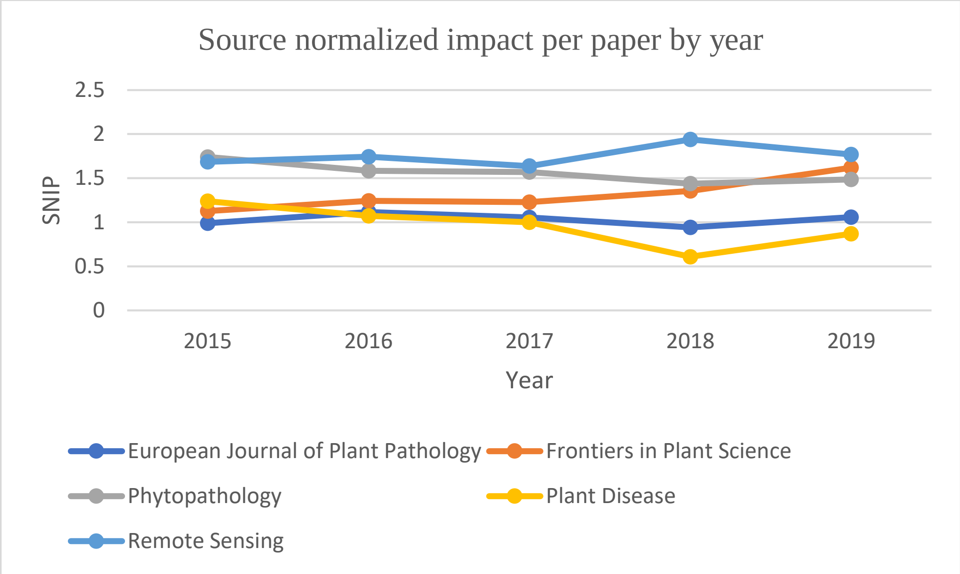

Figure 5 (b): Source normalized impact per paper by year in plant disease prediction.

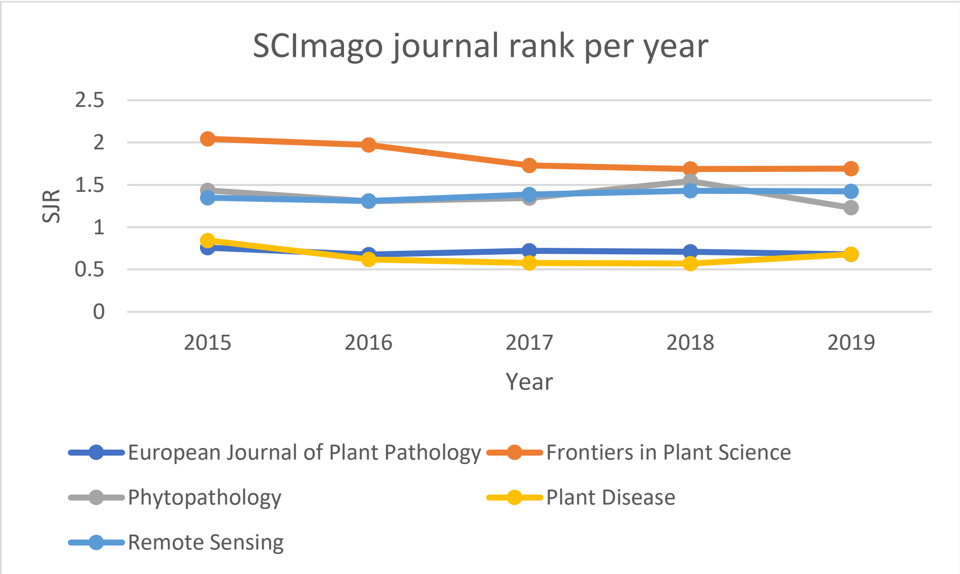

Figure 5 (a): SCImago journal rank per year in plant disease prediction.

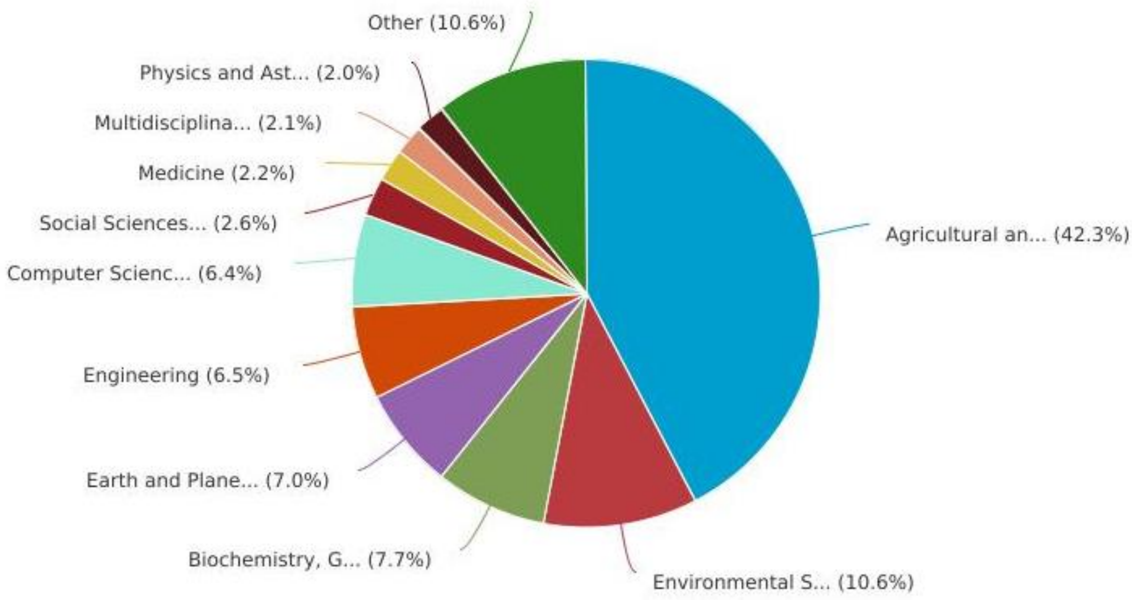

Figure 6: Analysis by subject area in plant disease prediction.

Figure 6 shows the analysis by subject area with Agricultural and Biological Sciences with the highest publication of 340 comprising of 42.3%. Followed by Environmental Science with 85 publications and Biochemistry, Genetics, and Molecular Biology with 62 publications.

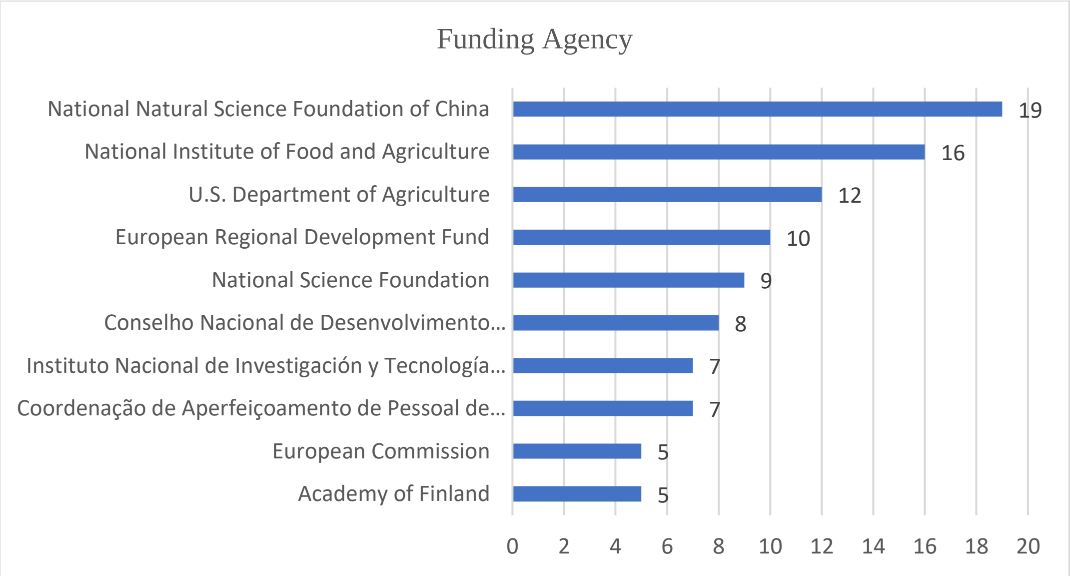

Figure 7: Top ten Funding agency plant disease prediction in Scopus.

Figure 7 shows the top ten funding agency analysis. National Natural Science Foundation of China is having the maximum funded project accounting for 19, followed by the National Institute of Food and Agriculture with 16 and the U.S. Department of Agriculture with 12 projects.

3. Bibliometric Analysis

The plant disease prediction, with its distinctiveness of literature and projecting researches with involved metrics therein, the bibliometric analysis is listed below:

3.1 Geographical region analysis

The maximum number of publications are from United States (US), India, and China. The geographical locations worldwide where the research on plant disease prediction is carried out is shown in Figure 8 using the GPS Visualizer tool of gpsvisualiser.com. This gives a global outlook towards the research.

Figure 8. Geographic locations of the study plant disease prediction.

3.2 Network Analysis

The network Visualization is done with help of visualizing tools of Gephi, ScienceScape, VOS viewer, and WordCloud.

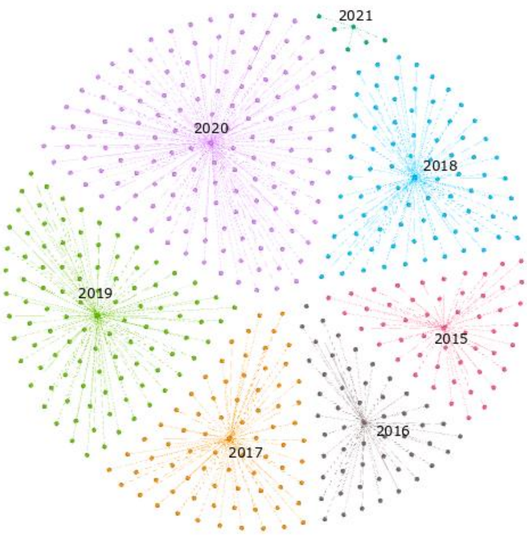

Figure 9: The Cluster of year and publication title in plant disease prediction from Scopus database.

Figure 9 shows the cluster of year and publication title in Scopus. The maximum publications of 139 are published in the year 2020 followed by 101 publications in 2019. Figure 10 shows the cluster of author and author keywords coappearing in the same paper. Climate change is seen to be the most significant keyword among the author keywords.

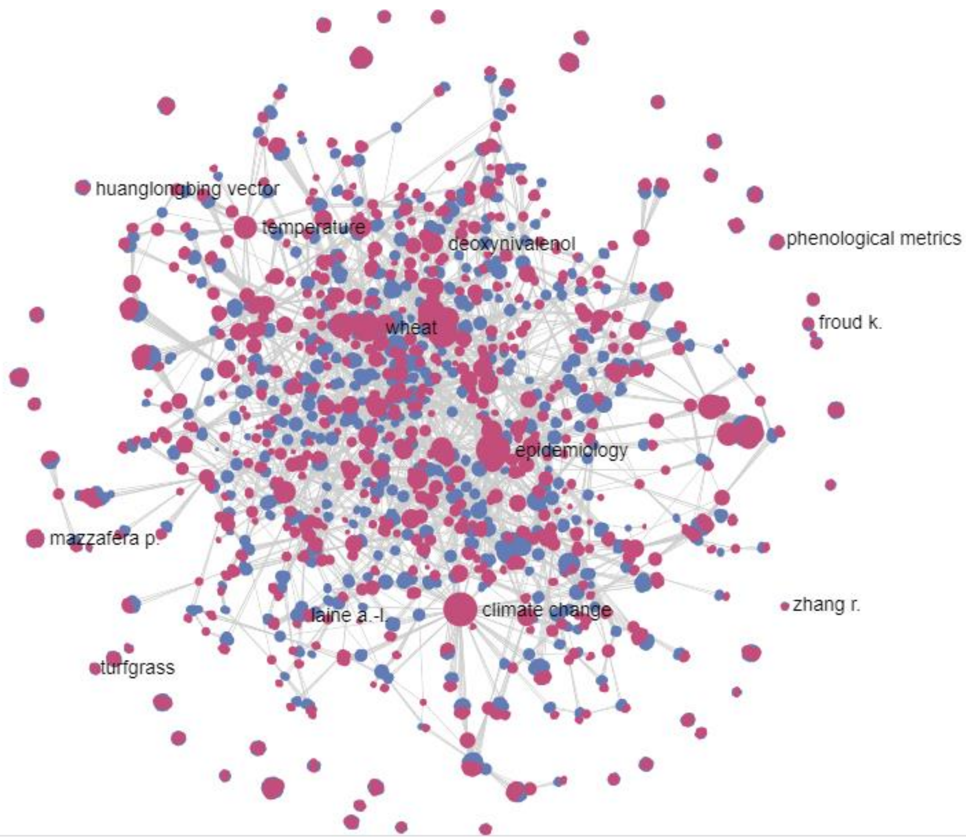

Figure 10: Author and author keyword coappearing in the same paper.

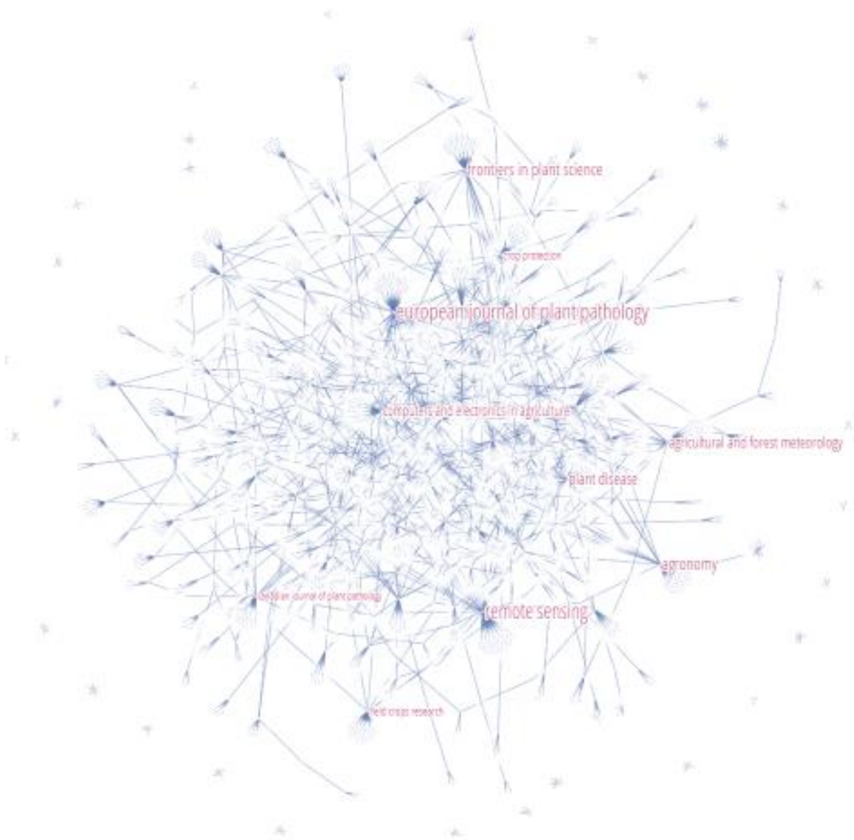

Figure 11: Source tile and author keyword coappearing in the same paper.

Figure 11 shows the cluster of source tile and author keyword coappearing in the same paper. European Journal of Plant Pathology, Frontiers in Plant Science, Phytopathology, Plant Disease, and Remote Sensing are seen to be the top five significant source titles. These source title can be seen in Figure 5 showing the CiteScore, SNIP, and SJR details.

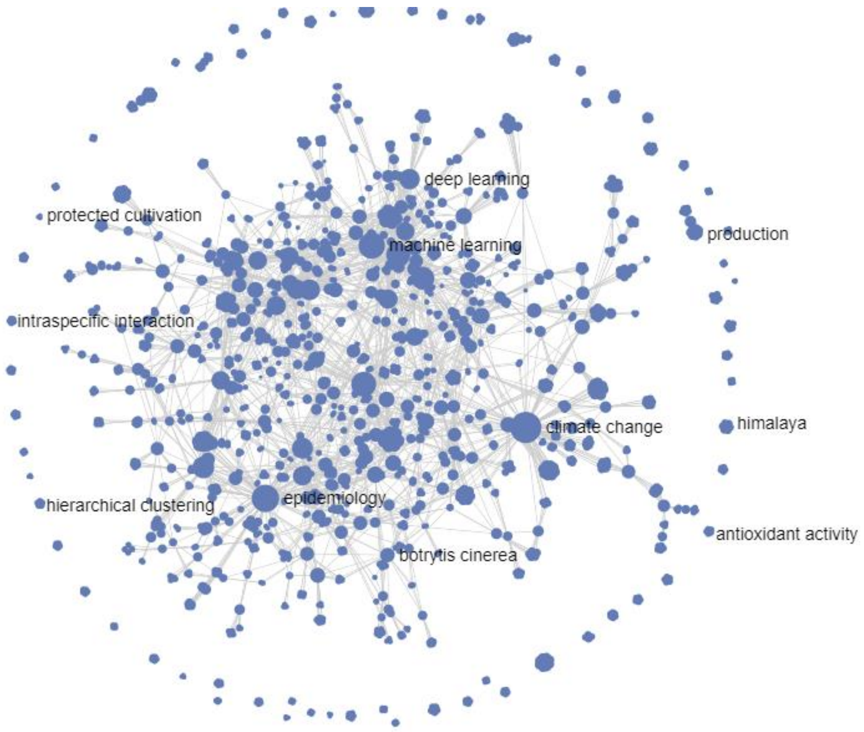

Figure 12: Author keywords coappearing in the same paper.

The author keywords coappearing in the same paper is shown in Figure 12. Climate change, machine learning, deep learning, epidemiology is among the most significant author keywords appearing here. The Cluster of co-occurrences of the keywords in the Scopus publication is shown in Figure 13. The interrelation between the keywords that are co-occurred in the research is linked together. Plant disease, climate change, and a regression model are the most co-occurring keywords.

Figure 14 shows the Sankey Graph – of main authors, main keywords, and main journals in the publications. The first column shows the influential authors, the second column shows the significant keywords they use and the third column shows the journal where the research is published. The interconnection of the terms is seen through the link. Figure 15 shows the tabular information of the Sankey Graph of Figure. 14. The details under each author, keyword, and journal with the NoP can be evaluated.

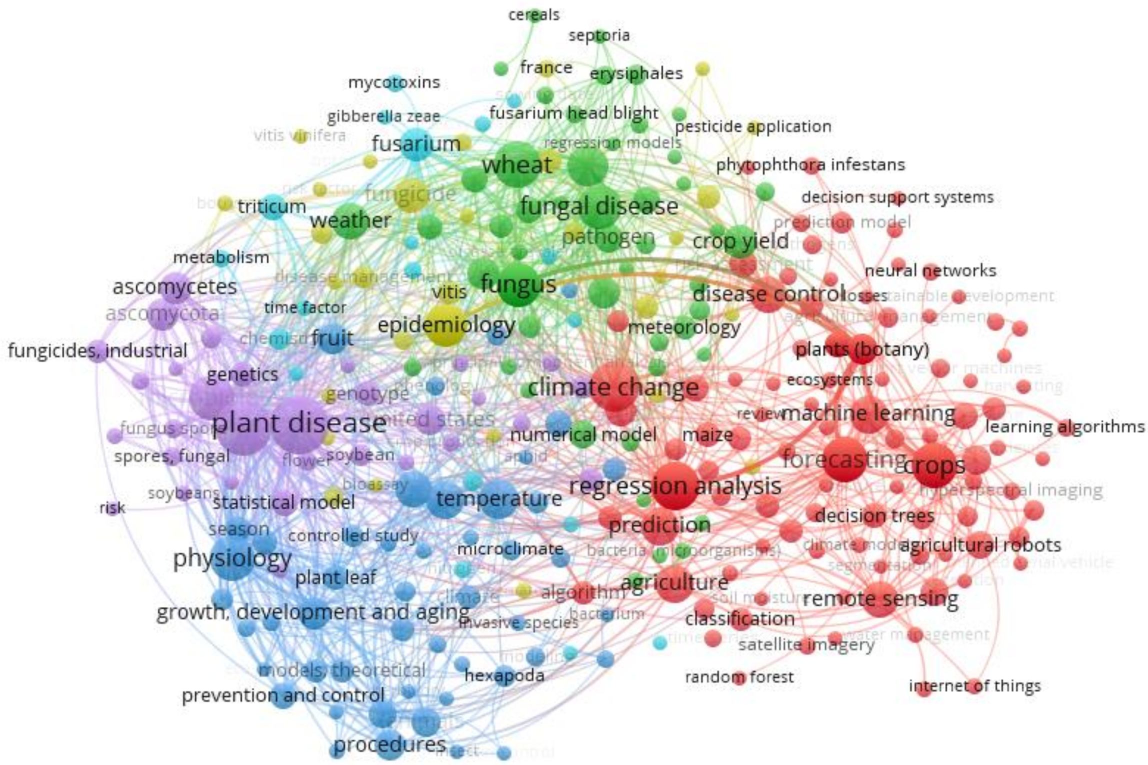

Figure 13: The Cluster of co-occurrences of the keywords in the Scopus publication.

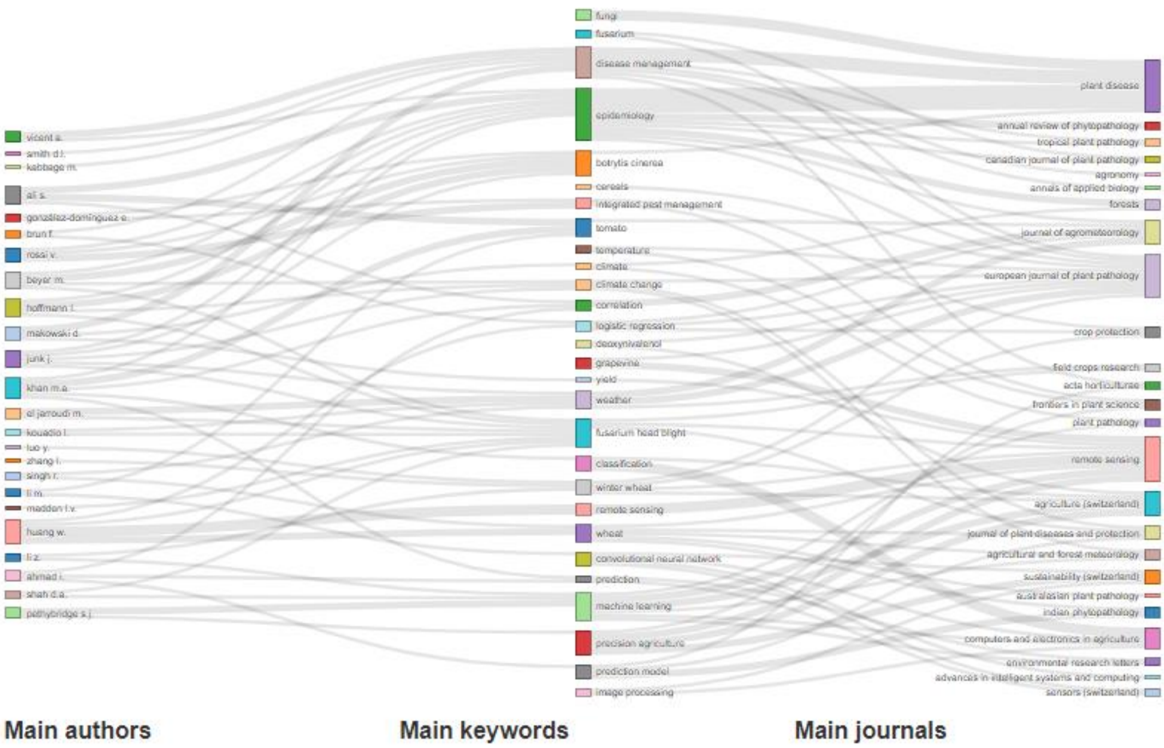

Fig 14: Sankey Graph -Main Authors, main keywords, and main journals.

Main authors

- rossi v. (11 papers)
- makowski d. (8 papers)
- brun f. (7 papers)
- el jarroudi m. (7 papers)
- vicent a. (7 papers)
- pethybridge s.j. (6 papers)
- gonzález-domínguez e. (5 papers)
- huang w. (5 papers)
- junk j. (5 papers)
- luo y. (5 papers)
- madden l.v. (5 papers)
- shah d.a. (5 papers)
- smith d.l. (5 papers)
- xu x. (5 papers)
- ahmad i. (4 papers)
- ali s. (4 papers)
- beyer m. (4 papers)
- cao x. (4 papers)
- caridad j.m. (4 papers)
- hoffmann l. (4 papers)
- kabbage m. (4 papers)
- khan m.a. (4 papers)
- kouadio l. (4 papers)
- li m. (4 papers)
- li z. (4 papers)
- marinas a. (4 papers)
- singh r. (4 papers)
- urbano f.j. (4 papers)
- wang y. (4 papers)
- zhang l. (4 papers)

Main keywords

- climate change (25 papers)
- epidemiology (22 papers)
- machine learning (18 papers)
- precision agriculture (13 papers)
- remote sensing (13 papers)
- wheat (13 papers)
- weather (12 papers)
- temperature (11 papers)
- disease management (9 papers)
- classification (8 papers)
- deep learning (8 papers)
- image processing (7 papers)
- prediction model (7 papers)
- winter wheat (7 papers)
- agriculture (6 papers)
- climate (6 papers)
- convolutional neural network (6 papers)
- deoxynivalenol (6 papers)
- fusarium (6 papers)
- fusarium head blight (6 papers)
- logistic regression (6 papers)
- prediction (6 papers)
- tomato (6 papers)
- yield (6 papers)
- botrytis cinerea (5 papers)
- cereals (5 papers)
- correlation (5 papers)
- fungi (5 papers)
- grapevine (5 papers)
- integrated pest management (5 papers)

Main journals

- plant disease (33 papers)
- phytopathology (17 papers)
- european journal of plant pathology (14 papers)
- remote sensing (13 papers)
- frontiers in plant science (9 papers)
- plos one (9 papers)
- agricultural and forest meteorology (8 papers)
- computers and electronics in agriculture (8 papers)
- agronomy (7 papers)
- crop protection (7 papers)
- field crops research (7 papers)
- canadian journal of plant pathology (6 papers)
- journal of agrometeorology (6 papers)
- agriculture (switzerland) (5 papers)
- scientific reports (5 papers)
- advances in intelligent systems and computing (4 papers)
- agronomy journal (4 papers)
- indian phytopathology (4 papers)
- journal of pest science (4 papers)
- journal of plant diseases and protection (4 papers)
- plant pathology (4 papers)
- sensors (switzerland) (4 papers)
- sustainability (switzerland) (4 papers)
- tropical plant pathology (4 papers)
- acta horticulturae (3 papers)
- annals of applied biology (3 papers)
- annual review of phytopathology (3 papers)
- australasian plant pathology (3 papers)
- environmental research letters (3 papers)
- forests (3 papers)

Figure 15: Tabular Information of Sankey Graph in Figure. 14.

2015

- climate change 4 papers
- remote sensing 2 papers
- temperature 2 papers
- logistic regression 2 papers
- environment 2 papers
- modelling 2 papers
- phenology 2 papers
- aphid 2 papers
- forewarning model 2 papers
- epidemiology 1 paper

2016

- epidemiology 3 papers
- climate change 2 papers
- temperature 2 papers
- phytophthora infestans 2 papers
- glycine max 2 papers
- pacific decadal oscillation 2 papers
- remote sensing 1 paper
- wheat 1 paper
- weather 1 paper
- disease management 1 paper

2017

- wheat 5 papers
- weather 5 papers
- climate change 3 papers
- epidemiology 3 papers
- climate 3 papers
- models 3 papers
- regression 3 papers
- yield 2 papers
- correlation 2 papers
- integrated pest management 2 papers

2018

- classification 4 papers
- image processing 3 papers
- fusarium 3 papers
- grapevine 3 papers
- data mining 3 papers
- climate change 2 papers
- winter wheat 2 papers
- deoxynivalenol 2 papers
- prediction 2 papers
- mycotoxins 2 papers

2019

- epidemiology 8 papers
- machine learning 7 papers
- climate change 5 papers
- precision agriculture 5 papers
- temperature 4 papers
- disease management 4 papers
- wheat 3 papers
- deep learning 3 papers
- prediction 3 papers
- extreme precipitation 3 papers

2020

- machine learning 10 papers
- climate change 8 papers
- remote sensing 8 papers
- epidemiology 7 papers
- precision agriculture 7 papers
- agriculture 4 papers
- weather 3 papers
- deep learning 3 papers
- image processing 3 papers
- winter wheat 3 papers

2021

- climate change 1 paper
- machine learning 1 paper
- deep learning 1 paper
- convolutional neural network 1 paper
- ann 1 paper
- plant diseases 1 paper
- regression model 1 paper
- thermal imaging 1 paper
- svm 1 paper
- agricultural advisors 1 paper

Figure 16: Top keywords by year.

Figure 16 shows the top keywords by year. The significant keywords used in the research in each year and the NoP with that keywords are seen under them. In 2015, there were maximum publication with keyword climate change whereas in 2020, there were 10 publications with machine learning as a keyword.

2015

- plant disease 4 papers
- european journal of plant pathology 4 papers
- phytopathology 3 papers
- acta horticulturae 3 papers
- plos one 2 papers
- field crops research 2 papers
- journal of plant diseases and protection 2 papers
- frontiers in plant science 1 paper
- agricultural and forest meteorology 1 paper
- journal of agrometeorology 1 paper

2016

- plant disease 7 papers
- european journal of plant pathology 2 papers
- agricultural and forest meteorology 2 papers
- computers and electronics in agriculture 2 papers
- journal of plant pathology 2 papers
- indian journal of science and technology 2 papers
- phytopathology 1 paper
- plos one 1 paper
- field crops research 1 paper
- agronomy journal 1 paper

2017

- plant disease 6 papers
- phytopathology 4 papers
- agricultural and forest meteorology 3 papers
- crop protection 3 papers
- field crops research 3 papers
- journal of agrometeorology 3 papers
- european journal of plant pathology 2 papers
- remote sensing 2 papers
- annals of applied biology 2 papers
- annual review of phytopathology 2 papers

2018

- plant disease 5 papers
- computers and electronics in agriculture 3 papers
- phytopathology 2 papers
- european journal of plant pathology 2 papers
- frontiers in plant science 2 papers
- crop protection 2 papers
- remote sensing 1 paper
- plos one 1 paper
- canadian journal of plant pathology 1 paper
- journal of agrometeorology 1 paper

2019

- phytopathology 5 papers
- plant disease 4 papers
- international journal of innovative technology and exploring engineering 3 papers
- european journal of plant pathology 2 papers
- remote sensing 2 papers
- frontiers in plant science 2 papers
- plos one 2 papers
- agronomy 2 papers
- sustainability (switzerland) 2 papers
- forests 2 papers

2020

- remote sensing 8 papers
- plant disease 7 papers
- agriculture (switzerland) 5 papers
- agronomy 4 papers
- canadian journal of plant pathology 4 papers
- frontiers in plant science 3 papers
- computers and electronics in agriculture 3 papers
- scientific reports 3 papers
- indian phytopathology 3 papers
- phytopathology 2 papers

2021

- advances in intelligent systems and computing 2 papers
- agricultural and forest meteorology 1 paper
- journal of environmental management 1 paper
- smart innovation, systems and technologies 1 paper

Figure 17: Top journals per year.

Figure 17 shows the top journals in each year where publications are done in Scopus. There are 5 papers in plant disease and Phytopathology respectively in 2018 and 2019. There are 8 publications in remote sensing in the year 2020.

Figure 18: The words in the publication are visualized with wordcloud in plant disease prediction.

The word that is more frequently used in the publications for the plant disease prediction is visualized through wordcloud as shown in Figure 18. The significant keywords that are used more in the research are shown with higher font size. The words “plant”, “breeding”, “phenotyping”, “crop”, “genetic”, “field data” are the most commonly used words in this research area.

3.3 Statistical analysis of publication citation

The yearly citation of the publications is shown in Table 5 with the publications in the area of plant disease prediction. The total citation for the 490 publications is 3123 for Scopus data. Table 6 shows the list of the topmost five papers with citations received by them in the Scopus database. Article “Translating High-Throughput Phenotyping into Genetic Gain” is a highly cited document with 144 citations.

Table 5: Analysis of citations for publications in plant disease classification.

Year	<2016	2016	2017	2018	2019	2020	>2020	Total
No of citations (Scopus)	18	113	238	405	833	1433	83	3123

Table 6: A citation analysis of the top ten publications in plant disease classification in Scopus and WOS

Sr No	Publication title	Yearly citations received by the publication							
		<2016	2016	2017	2018	2019	2020	>2020	Total
1	“Translating High-Throughput Phenotyping into Genetic Gain”	0	0	0	6	61	73	4	144

2	"Estimation of winter wheat above-ground biomass using unmanned aerial vehicle-based snapshot hyperspectral sensor and crop height improved models"	0	0	1	29	39	39	0	108
3	"Recent progress of hyperspectral imaging on quality and safety inspection of fruits and vegetables: A review"	0	15	20	28	23	11	1	98
4	"Perspectives for Remote Sensing with Unmanned Aerial Vehicles in Precision Agriculture"	0	0	0	0	22	64	2	88
5	"A critical review of plant protection tools for reducing pesticide use on grapevine and new perspectives for the implementation of IPM in viticulture"	0	0	4	12	27	31	1	75

Conclusion

The bibliometric study of plant disease prediction is based on the research publication data fetched from the Scopus database. The subject area of "Agricultural and Biological Sciences" has the highest publication followed by "Environmental Science" and "Biochemistry, Genetics, and Molecular Biology". "Plant disease" journal is having the maximum number of publications in this research area. The key research contributors in the articles and conference papers are from United States, India, and China amongst the other countries. China is having the maximum funded research work on plant disease prediction. The network visualization tools help in highlighting the significant keywords with influential authors publishing in the source title, year of publication in the research area. Plant disease prediction is an important part as it succors to the disease management of the crop and leads to the healthy and good quality and quantity of the yield. This benefits society with the increasing demands of food globally and supports the economy. This bibliometric survey is very useful for new upcoming researchers to find the research gap in the field of plant disease prediction.

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