



Article

Bibliometric and Social Network Analysis on the Use of Satellite Imagery in Agriculture: An Entropy-Based Approach

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Abstract: Satellite imagery is gaining popularity as a valuable tool to lower the impact on natural resources and increase profits for farmers. The purpose of this study is twofold: to mine the scientific literature to reveal the structure of this research domain, and to investigate to what extent scientific results can reach a wider public audience. To meet these two objectives, a Web of Science and a Twitter dataset were retrieved and analysed, respectively. For the academic literature, different performances of various countries were observed: the USA and China resulted as the leading actors, both in terms of published papers and employed researchers. Among the categorised keywords, "resolution", "Landsat", "yield", "wheat" and "multispectral" are the most used. Then, analysing the semantic network of the words used in the various abstracts, the different facets of the research in satellite remote sensing were detected. The importance of retrieving meteorological parameters through remote sensing and the broad use of vegetation indexes emerged from these analyses. As emerging topics, classification tasks for land use assessment and crop recognition stand out, alongside the use of hyperspectral sensors. Regarding the interaction of academia with the public, the analysis showed that it is practically absent on Twitter: most of the activity therein stems from private companies advertising their business. This shows that there is still a communication gap between academia and actors from other societal sectors.

Keywords: agrometeorology; GNSS; landsat; MODIS; NDVI; natural language processing; network null-models; sentinel; UAV; vegetation index



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1. Introduction

1.1. A Help from Above: The Use of Satellite Imagery in Agriculture

In sustainable agriculture, the necessity of having lower exploitation of agronomic inputs and natural resources must be reconciled with high production standards, increasing profits for farmers [1] and providing social benefits [2]. In this context, satellite platforms play an important role in two main application branches: agricultural machinery geolocation and navigation and field remote sensing (RS). Among other applications, satellites dedicated to the Global Navigation Satellite System (GNSS) allow for in-field georeferenced observations, Variable Rate Technology (VRT) treatments and the automation of tractor-driving systems [3,4]. Satellite remote sensing currently includes numerous constellations capable of providing a wide range of imagery products which Precision Agriculture (PA) makes use of in many different applications [5].

The launch of the NASA Landsat-1 satellite in 1972 represents the first step in the evolution of satellite remote sensing for applications in agriculture [6]. Meanwhile, the year 2008 marked the beginning of the era of microsatellites and satellite constellations. From then on, it has been possible to obtain usable and accurate imagery with a high acquisition frequency and large area coverage [7]. Nowadays, private companies are launching their own agriculture-focused satellites alongside national space agencies [8].

Satellites provide information by measuring the electromagnetic radiation reflected or emitted from the earth's surface. They are equipped with a wide range of sensors that allow spatial and multitemporal monitoring of soil and crop features throughout all the phenological stages. These sensors can be active or passive [5]. Active sensors, radar and lidar, use an artificial source of energy to illuminate objects on the ground and detect their reflected response or backscattering. Passive sensors detect the amount of radiation reflected or emitted by bodies in specific intervals of the spectrum e.g., the visible region (VIS, 380–750 nm), the near-infrared (NIR, 0.7–1.3 μm), the short infrared (SWIR, 1.3–2.5 μm) and/or the thermal infrared (TIR, 7–20 μm) [9]. Each type of sensor has a typical application in field monitoring. Radar and lidar can be used for soil moisture estimation or the evaluation of vegetative growth. Panchromatic sensors, synthesising the red, green and blue (RGB) bands, can produce images with a high spatial resolution for drafting maps or the construction of digital terrain models (DEM) [10]. Though DEMs can be generated from 2D-RGB images, this requires some specific characteristics of the imagery (e.g., sufficient overlap between two adjacent images). A typical processing approach can be performed through photogrammetric techniques, like the so-called Structure from Motion (SfM) technique [11]. Multispectral sensors record several spectral bands (typically 3–12) with a high amplitude (15–90 nm), useful for the calculation of traditional vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) or for plant species recognition [5]. Hyperspectral sensors measure the spectral response in a very high number (often hundreds) of bands with a finer amplitude (5–10 nm). Thus, they can identify absorption peaks related to certain components (e.g., photosynthetic pigments) and allow the calculation of more specific indices or the retrieval of soil organic matter. Thermal sensors estimate the temperature of vegetation and soil for evaluating soil water content, detecting crop water stress and irrigation scheduling [9].

In the last years, satellite imagery has come to the fore as both a research tool and as a support to many stakeholders in the agricultural supply chain. Thus, the application of this technology for several crop practices, such as fertilisation [12], irrigation [13] and harvest [14], could allow sustainable management of agricultural systems. This has been also possible thanks to recently created ad hoc web services. Applications range from the recognition of plot boundaries [15] and those providing interoperability between drones and satellite data [16], up to decision support systems (DSS) with customizable packages [17].

In the choice of satellite products for research or technical purposes, spatial resolution is a compromise between imagery costs and the accuracy necessary for crop monitoring [10]. Extensive crops, such as cereals, can be monitored with appreciable results using intermediate spatial resolutions (5–10 m per pixel) [12], while for crops with discontinuous coverage, the presence of inter-rows requires the need for a greater resolution, as in the case of vineyards. Thus, to discriminate crops without altering the information due to the co-presence within the same pixel of the canopy and bare soil/grass, a sub-metric detail (<0.1 m per pixel) is required [18]. Where it is not possible to provide such detail due to sensor limitations, another way to tackle the issue of coarse resolution and mixed pixels containing various attributes is the use of sub-pixel classification [19]. In the same way, timely monitoring is a key issue for agricultural activities and for this reason satellite revisit time (the frequency of platform passage over the same area) can be a discriminating factor in the choice of satellite imagery [10]. Retrieving the beginning of a phenological phase or verifying field operations requires high temporal resolution. This has been guaranteed in the last decade by open data (e.g., Sentinel-2 with 5 days of revisit time) [20] or commercial solutions such as WorldView or Pleiades, which provide daily images [5].

1.2. Satellite Imagery for Agriculture through Different Information Sources

The importance of the use of satellite RS in agriculture is significant considering the wide range of available applications, sensors and resolutions. Understanding the main developments in the use of satellite imagery in agriculture is crucial for synthesising

the existing knowledge base, advancing the line of research and making better use of this technology. In this context, literature reviews are increasingly becoming important due to the fast-growing pace of scientific production [21]. But traditional review papers focus only on the content of publications and may suffer from the subjective biases of the researchers involved in the process [22]. By contrast, bibliometrics applies quantitative analysis and statistics to perform a systematic, objective and reproducible analysis of the unstructured and large body of information [23]. It can be used to detect the most influential authors/journals/institutions/countries, the principal research streams, the emerging and trending topics and to show a clear overview of a research topic [24]. In doing this, bibliometrics takes advantage of scientific methods such as Social Network Analysis (SNA) [25].

Two-way communication between scientists and the public should be incorporated into effective communication and scientific outreach efforts to improve not only the reputation of particular innovations but also appropriate further development by listening to audiences and tailoring innovations to their needs [26]. A virtual forum where this type of communication can be implemented is represented by online social network platforms [27]. In this sense, it could be very interesting to look at how the use of satellite imagery in agriculture is presented in online social networks.

1.3. Aim of the Study

To the best of the authors' knowledge, only a few studies have exclusively addressed the use of satellite platforms and sensors for agricultural applications leveraging academic databases [28,29]. Moreover, there are still no research papers that exploited informetric analysis (scientific literature and information retrieved from online social networks) to summarise the research field under investigation. Thus, the first aim of the work is to mine the scientific literature from the first appearance of the technology in scholarly articles until today to reveal the structure of this research domain. The study is based on the following research questions (RQs):

1. What are the most influential countries and journals and the key papers in the field?
2. What is the spectrum of the terminology related to the use of satellite imagery in agriculture and what are the relations among them?
3. What are the main research streams and emerging topics?

By answering the above questions, this paper aims to provide researchers with a comprehensive and objective framework of the topic. It also supports the scientific process by offering research directions and identifying hotspots.

Additionally, the discourse on the use of satellite imagery in agriculture is investigated within one of the most popular social network platforms: Twitter. The choice of Twitter is for two main reasons: it is an easy-to-use tool to spread news and scientific results, and for the completeness of the available data. Two further RQs aim to broaden the study:

4. Who talks about satellite imagery for agriculture on Twitter and for what purpose?
5. What are the cutting-edge dynamics and development trends discussed?

This analysis allows the examination of the communication and outreach of the research topic outside academia, providing a point of view that is more oriented to practical applications.

2. Materials and Methods

2.1. WOS Dataset Description

2.1.1. Scientific Paper Search

The authors performed a comprehensive literature search using the Web of Science (WoS-Clarivate Analytics) search engine to extract peer-reviewed studies related to the use of satellite imagery in agriculture from the technology's first appearance in the literature up to the current moment. The guiding approach is similar to the PRISMA methodology [30], with the only differences due to the nature of the data sources. Indeed, in the present case

the removal of duplicates is not necessary (duplicates are not present WoS), nor full-text evaluation (data mining is based on title, abstract and keyword).

The query was '(TS = ("Agric*")) AND (TS = ("Satellite"))', i.e., all papers having "satellite" and all words beginning with "agric-" in the topic. The research words have been deliberately chosen not to be too specific in order to encompass all the works related to the topic without risking any item being excluded. Then, a filtering step was conducted by exploiting the exclusion criteria directly available in the WoS search engine; that is document type, language and publication year. Original articles, review articles, book chapters, editorial material and data papers published in the English language were selected. Regarding timespan, the investigation encompassed the entire body of literature from 1977 to mid-2022 (30 June). The search query generated 8526 records with publication data containing information on the "Author, Title, Source", "Abstract, Keyword, Addresses" and "Cited References and Use" categories, resulting in 72 fields. Records not relevant to the research goal (e.g., satellite RNA in plant pathology), were excluded in a data cleaning step (more details in the following sections).

2.1.2. Data Cleaning

As with any dataset, WoS extraction is affected by some noise: for instance, some records do not display the abstract or others do not display the publication year. Additionally, it occasionally happens that some papers that are not related to the research field under investigation are included: for instance, the terms "satellite" and "agriculture" are used in the context of archaeology (for satellite settlements and their agricultural activities) or in urban studies (for urban pattern management).

To get rid of those records that may put the coherence of the dataset at risk, the following procedure was implemented. Each record in the dataset is provided with at least a single Research Area (RA), i.e., the field of the research. A manual selection of the most relevant for the research was performed choosing Remote Sensing, Agriculture, Imaging Science & Photographic Technology, Science & Technology-Other Topics, Engineering, Computer Science, Geochemistry & Geophysics, Plant Science, Instrument & Instrumentation. To be maximally conservative, only papers with all the RAs in this list were selected. The resulting dataset displayed 1933 papers.

When performing the analysis, authors observed a posteriori that some recurrent keywords were unrelated to the topics under analysis. Even limiting the analysis to the RAs above, some applications to cell biology and marine science remained in the dataset. Therefore, authors excluded those papers including the words "dna", "rna", "clone" and "virus" from the dataset. To limit analysis to agriculture, "ocean", a recurrent term referring to coast monitoring, and "aerosol", a frequent keyword related to atmospheric science, were also excluded. The final dataset included 1830 papers. While this approach could be considered particularly strict, further analyses prove that it minimises the presence of noise.

2.1.3. Twitter Dataset Description

Messages published on Twitter focusing on the same topics were analysed. In particular, using the GET/2/tweets/search/all API [31] with Academic Access [32], authors accessed all messages containing the keywords used for retrieving the WoS dataset, from the very first message of Twitter in 2006 until 1 July 2022, mirroring the WoS query. More in detail, the query was "(agriculture OR agricultural OR agriculturalist OR agriculturalist OR agriculturalist OR agriculturalists OR agronomy OR agronomics OR agronomic OR agronomist OR agronomists) satellite".

The result was a dataset made up of 57,638 messages. Again, to mirror the analysis performed on the WoS dataset, all messages containing terms referring to "dna", "rna", "clone", "virus", "ocean" and "aerosol" were excluded, resulting in 55,768 different tweets posted by 42,397 different accounts, as identified by their unique author id.

2.2. Data Analysis

The analysis of the WoS dataset was divided into two main parts: the first part analysed descriptive statistics, which highlighted interesting trends of the production in the field of satellite imagery in agriculture and the relevance of scientific production of various countries and researchers; the second analysis was dedicated to the semantic network, as obtained from the abstract of the papers. While the former is more straightforward, the main steps of the methodology of the latter will be introduced in the following sections.

Since only limited information regarding the authors of posts on Twitter is available, most of the first part of the WoS analysis was neglected on the Twitter dataset. Nevertheless, the analysis of semantic networks was performed on Twitter's new content messages, i.e., those that are not retweets. It is worth mentioning that this approach is similar, but different, to others in the literature. For instance, in [33] the semantic network was inferred using only a tweets' hashtags.

The procedure used to get the semantic networks is pictorially represented in Figure 1. While Figure 1 shows the procedure for WoS, the one used for Twitter is perfectly analogous, just replacing WoS IDs with Tweet IDs and the abstracts with tweets' texts.

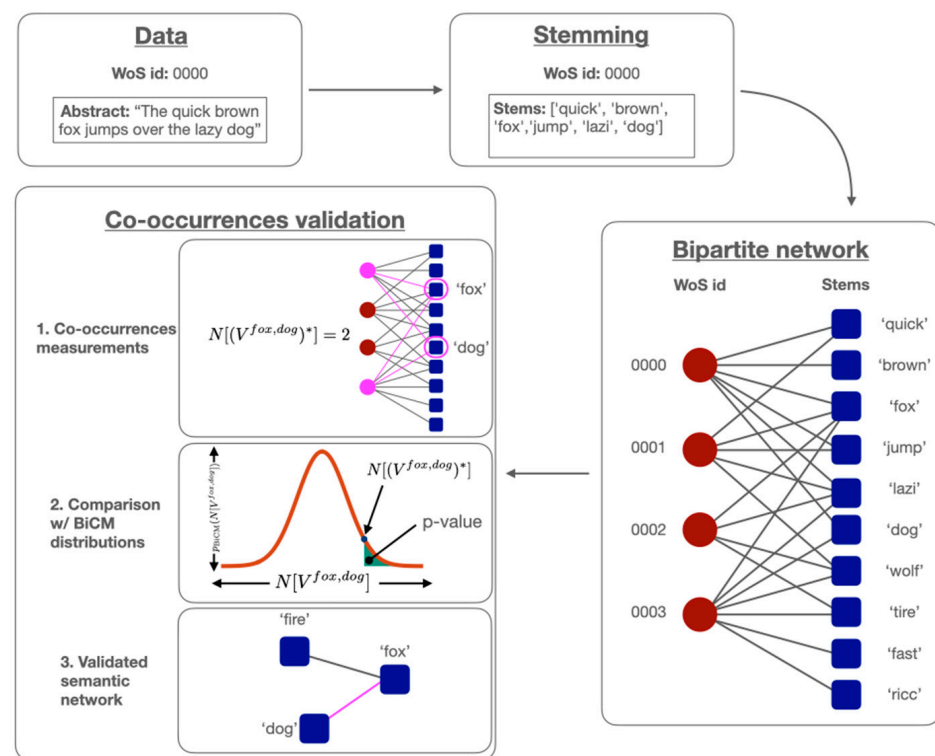


Figure 1. Pictorial representation of the procedure for inferring a semantic network from WoS data. Quantities marked with an asterisk (*) indicate values measured on the real system.

First, the text of each abstract is considered and divided into stems, using nltk Python module [27]. Then, a bipartite network of abstracts, as identified by WoS IDs, and stems is built. The information contained in the bipartite network is subsequently projected into the layer of stems and finally validated: the projection process is obtained by comparing the value measured in the real networks with the distributions expected by a maximum-entropy benchmark. In the following, each step of this procedure is described in detail.

2.2.1. Stemming Words from the Abstracts and Tweets

All the various texts—be they be scientific paper abstracts or Twitter posts—were automatically analysed using the Natural Language Processing (NLP) tools provided by the nltk Python module [34]. At first, all single words were detected by removing punctuation,

numbers (still considering alpha-numeric entries) and stop words. The English stop words list used is the one present in the nltk submodule nltk.corpus and includes pronouns, demonstrative adjectives, prepositions, auxiliary verbs and similar items [34].

Then, the Snowball stemmer [34] was used. A stemmer reduces a word to a “stem” by cutting prefixes and suffixes. The rationale is to reduce the different conjugations or declensions of the same word to the same stem, in order to correctly count the occurrence of the same concept. For instance, “crop”, “crops” and “cropping” are all stemmed by Snowball procedure to the same stem “crop”.

During the analysis, the stem association performed by nltk was inspected by manually checking the most frequent stems. The 100 most common terms were examined: for each term, the 5 following and 5 preceding terms in alphabetic order (i.e., the most similar ones) were checked using edit distance. In a nutshell, the edit distance counts how many characters have to be removed or substituted to pass from a word to the following one [34]. Finally, the authors manually verified if nltk missed a possible association between the more frequent word and the most similar ones, selecting couples of stems for which the edit distance is lower than 3 (i.e., selecting couples in which the two stems differ for a maximum of 2 characters).

The test procedure was applied to 1000 couples of stems. Less than 1% of the comparisons were not correctly recognized by nltk. The impact of missed association was so limited that the nltk procedure was considered reliable. Due to the large number of stem couples requiring verification, the result from nltk was considered as provided by the Python module. When, in the following, an incorrect association is found, it will be stressed and commented on.

Finally, each text was associated with the (filtered) stems of the words in it: in the case of WoS, each abstract was identified by the relative paper WoS ID; in the case of Twitter each message was identified by its tweet ID.

2.2.2. Bipartite Networks, Entropy-Based Null-Models and Validated Semantic Networks

To identify non-trivial similarities in the way concepts and ideas are used in the various abstracts, the association between research papers and stems was represented as a bipartite network [35]. In a bipartite network, nodes are divided into two sets, called layers, and edges can only connect nodes from different layers. Papers and stems were described as the two layers of a bipartite network: an edge connecting a stem to a paper was present if the stem was used in the paper’s abstract.

The target of the analysis is to infer non-trivial similarities among stems, given their usage in the various corpora of texts. The main premise is that two stems (and, of course, the related words) are related if they are both used in many scientific abstracts. Therefore, for every couple of stems, the number of abstracts in which they both appear was counted. In bipartite networks, these are called co-occurrences.

Nevertheless, a high value of the co-occurrences between two nodes on the same layer may be due only to the presence of two frequent stems within particularly verbose abstracts. Therefore, a proper benchmark for the analysis of the observed co-occurrences is needed.

In the study, an Information Theory technique was used to discount the information coming from the frequency of words and the number of stems in each abstract (see [36] for a review).

To simplify, the idea is to start from a real network and define the set of all possible graphs having the same number of nodes and all possible link configurations (the ensemble). The quantity of uncertainty of the system is accounted for by the function named Shannon (or Information) entropy (Equation (1):

$$S = - \sum_{G \in \Gamma} P(G) \ln P(G) \quad (1)$$

where G is a graph in the ensemble and $P(G)$ is the probability of observing the graph G .

The main target of this construction is to provide a maximally random benchmark but for some network properties observed in the real system. Therefore, a constrained maximisation of the Shannon entropy associated with the system can be performed, where the constraints are exactly those defining properties observed in the real network.

Remarkably, the same approach was used in [37] to derive the canonical ensembles in Statistical Physics from Information Theory. The adaptation of this framework to complex networks permitted the extension of constraints from global, as the total energy in Statistical Physics, to local ones, as the number of connections per node [38–40].

The framework described above can be applied to bipartite networks: in this case, it is possible to constrain the number of connections (i.e., the degree) for nodes in both layers. The related model is called Bipartite Configuration Model (BiCM, [41]) and it is implemented in the NEMtropy Python module described in [42].

Therefore, given a real network, the observed co-occurrences can be compared with their BiCM distributions. If the BiCM probability of observing the value measured in the real network is particularly low (i.e., the relative p -value is statistically significant), then the ingredients of the BiCM cannot explain the deviation from the model and the relative co-occurrences are validated [43]. The result of the validated projection procedure is a monopartite network (i.e., a network in which nodes are all of the same nature) in which an edge represents a non-trivial similarity.

The validation procedure is present in the NEMtropy Python module mentioned above.

3. Results and Discussion

3.1. WoS Dataset

3.1.1. Descriptive Statistics

Country Performances

Analysing the number of publications per year throughout the investigated period (1977 to mid-2022) (Figure 2), it becomes immediately evident that the number of publications has experienced rapid growth in the last two decades. In fact, from 2017, the number of publications breaks through the threshold of 100 published per year; the trend is further accentuated in 2022, 130 research works already published by mid-year.

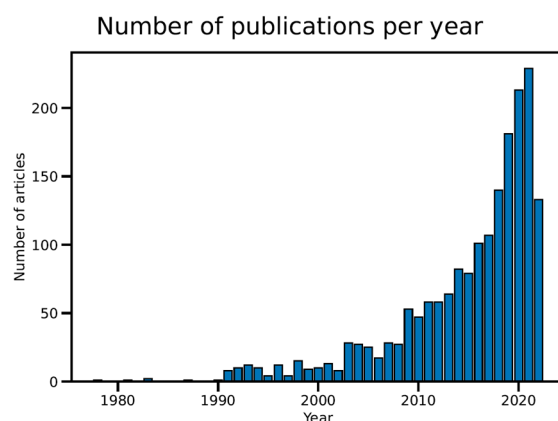


Figure 2. Number of publications per year (1977–mid 2022).

The most active country in the period encompassed by this study is the USA, with over 400 publications (Figure A1). The People's Republic of China (PRC) and India are positioned in the second and third place of the ranking, respectively, with more than 200 and 150 published research works. In a more detached group, there are some European countries (Germany, Italy and Spain with <150 publications). Looking at the data per decade (Figure 3), the USA remained the leading country for three decades (1991–2000, 2001–2010, 2011–2020) and then was finally overtaken by PRC in 2021–2022. India ranked second in 1991–2010, then fell fourth (2011–2020) and has recently returned to third place. Italy has risen from seventh to fourth over time while England gradually dropped out of

the top 20. Other countries, like Germany and France, steadily occupy positions in the top 10 over the period. Data for the period 1977–1990 are not shown as there are a small number of publications.

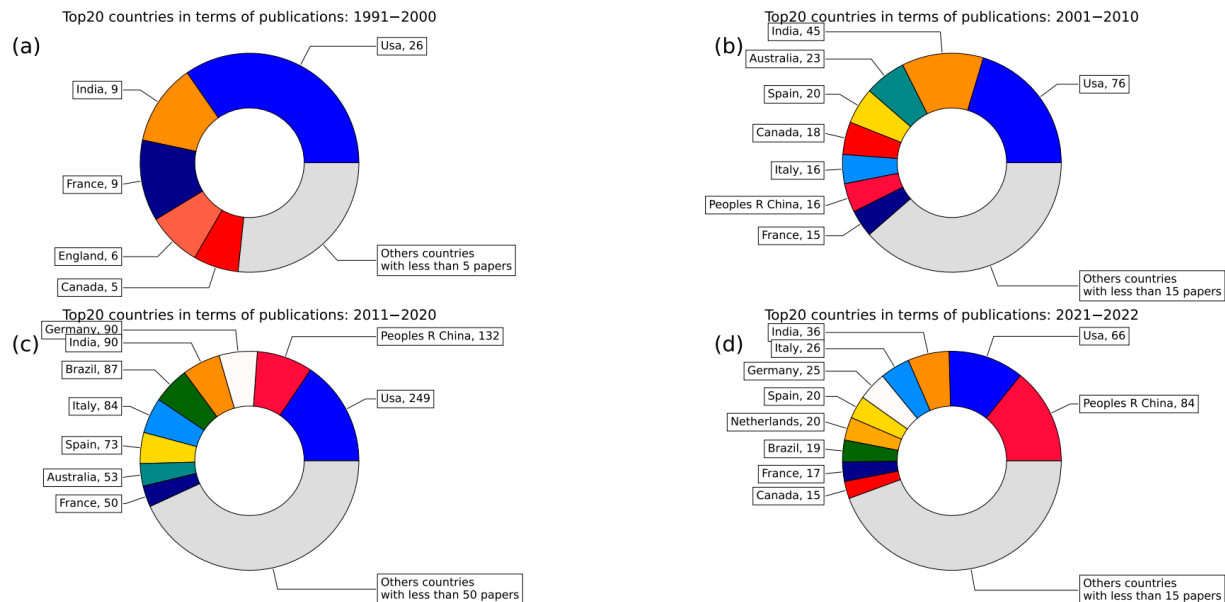


Figure 3. Top 20 countries in terms of publications 1991–2000 (a), 2001–2010 (b), 2011–2020 (c), 2021–mid2022 (d).

Ranking the number of researchers dealing with satellite imagery in agriculture (1977 to mid-2022) (Figure A2) mirrors the previous findings, with the top three positions occupied by the same countries, USA, PRC and India, with more than 1000, 800 and 500 researchers, respectively. Brazil, Italy and Germany complete the top 6 with Italy holding the fifth position in both rankings. Shifting from the number of researchers to the number of publications, Brazil passes from rank 4 to rank 7 while Germany from rank 6 to rank 4. This probably occurs because in Brazil more research groups are dealing with the current research topic than in Germany and/or the scientific papers are authored on average by a higher number of authors in Brazil than in Germany. Throughout the time frame of the analysis (Figure 4), the USA remains in the very first positions (1 and 2) while a dizzying growth of PRC (out of the top 20 in 1991–2000) is evident, outperforming the USA in 2021–2022. India is also remains in the top positions (rank 3 in 2021–2022), overcoming a slight decline in the decade 2011–2020 (rank 5). Brazil also had strong growth especially in 2011–2020 while countries like Italy, France, and Germany have always been present in the top 10. Pakistan has recently entered the top 10 for the first time.

Nevertheless, the number of publications and researchers per country is not the end of the story. What is crucial is the impact of the research produced in each country. A proxy of the quality of research is given by the number of citations received. Such a measure is not accurate on its own, since the number of citations may be due to the institute, the country researchers come from, or the audience (for instance, see [44]).

WoS dataset is quite limited. As such, to gain sufficient statistics, focus was placed on countries that released more than 80 papers in the entire time window (Figure 4a) and the distribution of the citations per paper was considered (Figure 4b).

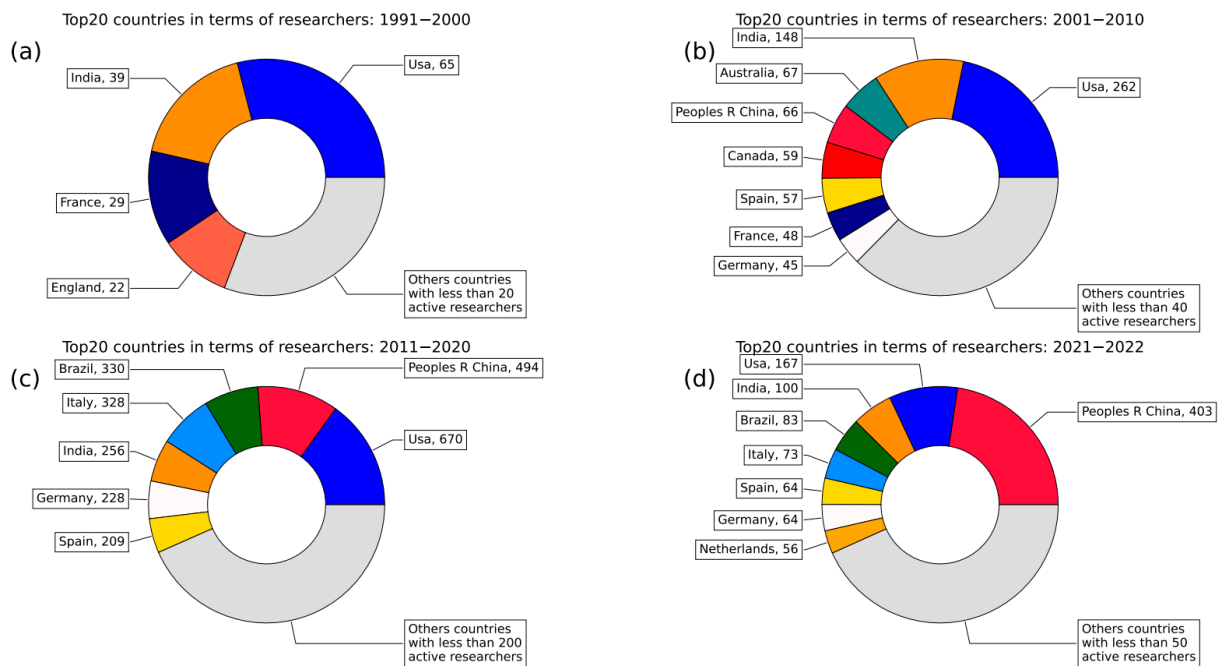


Figure 4. Top 20 countries in terms of researchers 1991–2000 (a), 2001–2010 (b), 2011–2020 (c), 2021–mid2022 (d).

In the right panel, boxplots, i.e., an intuitive way of comparing different distributions, were displayed. The edges of each box are the first (Q1) and the third (Q3) quartiles of the represented distribution, while the orange line represents the median. If the Interquartile Range is defined as $IQR = Q3 - Q1$, the whiskers are taken at 1.5 IQR from the edges of the box. In the plot, outliers were not represented to make the plot clearer. The boxplots are ordered according to the median of each distribution.

In Figure 5, it can be observed that the impact of the research from China and India underperforms that of other countries, despite the strong efforts in terms of publications (see Figure 3) and researchers (see Figure 4).

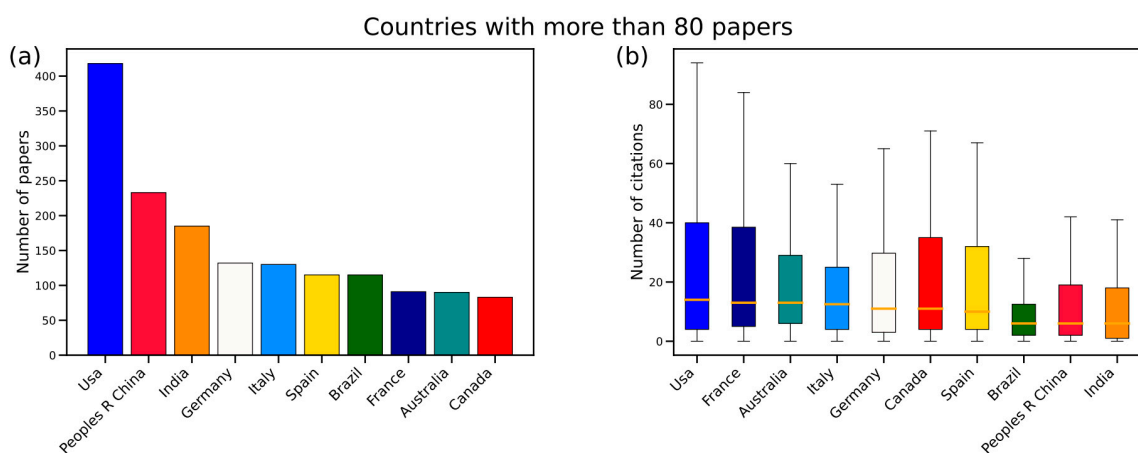


Figure 5. Quality of research: countries with more than 80 papers (1977–mid2022) (a) and distribution of the citations per paper (b).

Journal Performances

Among the journals that present the highest number of publications across the period under analysis (1977–mid2022), there are three that outperform all others in terms of published items (for journal abbreviation see Table S1). These are the International Journal

of Remote Sensing (Int. J. Remote Sens. - Taylor & Francis), the International Journal of Applied Earth Observation and Geoinformation (Int. J. Appl. Earth Obs. Geoinf. - Elsevier) and Computers and Electronics in Agriculture (Comput. Electron. Agric. - Elsevier), with 307, 157 and 107 publications, respectively (Figure 6a). Taylor & Francis places only one journal in the top 10 while three other publishers feature more than one: Elsevier (3, those mentioned above and Geoderma), MDPI (2, Agronomy and Agriculture) and Springer (2, Precision Agriculture and Scientific Reports). This picture shows that there are long-established scientific publishers but also new players who are emerging in this sector, such as MDPI and PLOS.

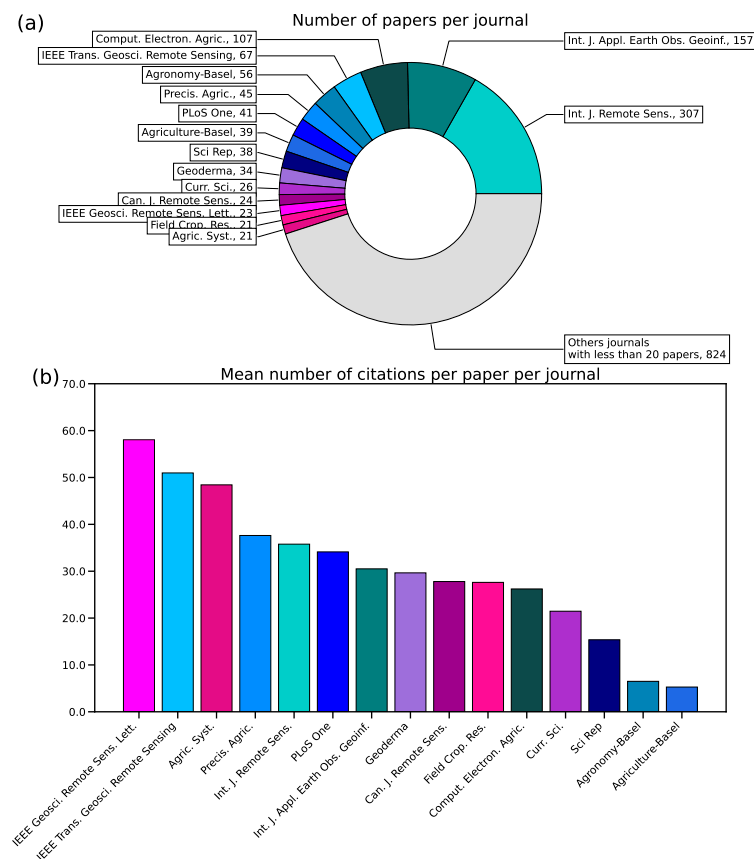


Figure 6. Journal performances: number of papers per journal (a) and mean number of citations per paper per journal (b). In panel (b), only journals with at least 20 papers are reported.

Focusing on the impact of each journal, the average number of citations per paper published in the journal was considered. To have sufficient statistics, only the journals most present in the WoS dataset were considered (Figure 6b). A partial reshuffling of the results reported in the top panel of Figure 6a can be noted immediately. Indeed, the ranking of journals with the highest average number of citations is dominated by IEEE journals (IEEE Geoscience and Remote Sensing Letters and IEEE Transactions on Geoscience and Remote Sensing) with 58.04 and 50.97 citations per paper on average, closely followed by Agricultural Systems with 48.43 citations per paper on average. All other journals have a lower number of citations ranging between 38 and 5, on average. On the contrary, two journals positioned in the top ranking in terms of publications number fall back many positions when analysing the average citations: Computers and Electronics in Agriculture and Agronomy. A possible explanation could be the specificity of the research topic covered by the journals, like agriculture (which, moreover, is not one of the most debated themes at the international level), and, in the case of Agronomy, due to the recent appearance of the journal at the front of the international stage (first impact factor in 2018).

The panels (a) and (b) of Figure 7 show the citation's distribution within all citation indexes in WoS and the distribution of the number of papers per author, respectively. The distribution is, roughly speaking, a power law, i.e., $P(x) \sim x^{-\alpha}$. Such an observation seems to suggest that the process is a multiplicative one, i.e., if the number of publications at time t of a certain author is P_t , then its value at $t + 1$ is $P_{t+1} = \varepsilon P_t$, where ε is a certain factor [35]. In this sense, the right panel of Figure 7 seems in agreement with the dynamic suggested by Kauffman of the “adjacent possible” [45]: while the original idea derived from the context of molecular and biological evolution, it was also applied for modelling the rise of innovations (for instance, see [46]).

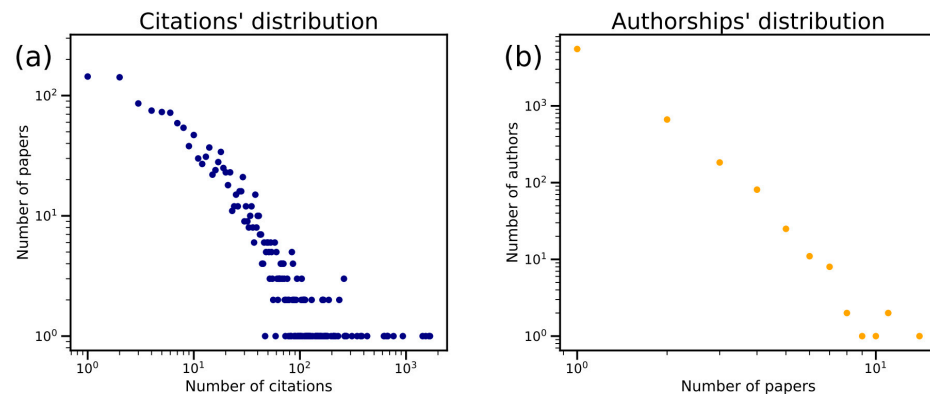


Figure 7. Citations' and authorships' distributions throughout the WoS dataset (1977–mid2022).

The main idea is that innovation proceeds in single steps on a path sketched by previous contributions. In this sense, the “adjacent possible” is the set of unknown items that are at a single innovation step from the current stage of evolution. Since all new objects in the adjacent possible can be reached by a recombination of existing ones, when a new item is discovered or created, the bound of the adjacent possible is updated and expanded. Modelling of such a hypothesis appeared in [46] and is based on power-law distributions observed in various real systems; the power-law distributions in Figure 5 support the finding therein.

The main hypothesis of Figure 7a is that the greatest number papers received a limited number of citations (left top angle), while a smaller number had a great number of citations (bottom right angle). Analogously, in Figure 7b, a limited number of authors wrote just a single paper, while a few wrote more than 10 papers on the examined subject. Finally, the power law sense is that the frequency of papers receiving n citations is proportional to the frequency of papers receiving δ_n via a (negative) power of δ .

3.1.2. Most Cited Papers

Among the top 50 publications in terms of citation, 20 items strictly connected with the field of application of the study were selected. The exclusion criteria cut off studies (i) on a global scale, (ii) citing the search keywords < 5 times throughout the document and/or not including them in the core of the document (iii) out of the aim and scope of Agronomy. The results are presented in Table 1. The most cited papers are published in the period between 1996 and 2017. If it may not be surprising that the papers published in the past decades collect many citations; for those published more recently it can be a distinctive sign of the quality of the research or at least of the novelty of the topics covered. Indeed, it is remarkable that the oldest most influential paper is relatively recent (i.e., 27 years ago). In the scientific literature, the importance of the first mover advantage is often stressed, i.e., the fact that older papers get more citations just because they are present in the literature for a greater amount of time [47]. In this case, the situation is different: the most cited paper is only 10 years old in a dataset 45 years long. Such an effect is probably due to the rapid evolution of the available satellite technology that may have resulted in making older papers outdated relatively quickly.

Table 1. Top 20 papers in terms of citations. Authors, year, title and journal are also reported.

AGRICULTURAL RANKING	AUTHORS	YEAR	TITLE	JOURNAL	CITATIONS
1	Scanlon et al.	2012	Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley	PNAS	674
2	Kussul et al.	2017	Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data	IEEE Geosci. Remote Sens. Lett.	665
3	Morton et al.	2006	Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon	PNAS	618
4	Macedo et al.	2012	Decoupling of deforestation and soy production in the southern Amazon during the late 2000s	PNAS	374
5	Gomez et al.	2008	Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study	Geoderma	346
6	Solberg et al.	1996	A Markov random field model for classification of multisource satellite imagery	IEEE Trans. Geosci. Remote Sensing	309
7	Lee et al.	2010	Sensing technologies for precision specialty crop production	Comput. Electron. Agric.	272
8	Moulin et al.	1998	Combining agricultural crop models and satellite observations: from field to regional scales	Int. J. Remote Sens.	267
9	Carlson et al.	2012	Committed carbon emissions, deforestation, and community land conversion from oil palm plantation expansion in West Kalimantan, Indonesia	PNAS	260
10	Ren et al.	2008	Regional yield estimation for winter wheat with MODIS-NDVI data in Shandong, China	Int. J. Appl. Earth Obs. Geoinf.	217
11	McNairn and Brisco	2004	The application of C-band polarimetric SAR for agriculture: a review	Can. J. Remote Sens.	208
12	Forkuor et al.	2017	High Resolution Mapping of Soil Properties Using Remote Sensing Variables in South-Western Burkina Faso: A Comparison of Machine Learning and Multiple Linear Regression Models	PLoS One	187
13	Johnson et al.	2003	Mapping vineyard leaf area with multispectral satellite imagery	Comput. Electron. Agric.	179
14	Castillejo-Gonzalez et al.	2009	Object- and pixel-based analysis for mapping crops and their agro-environmental associated measures using QuickBird imagery	Comput. Electron. Agric.	172
15	Lopez-Granados	2011	Weed detection for site-specific weed management: mapping and real-time approaches	Weed Res.	168
16	Delegido et al.	2013	A red-edge spectral index for remote sensing estimation of green LAI over agroecosystems	Eur. J. Agron.	164
17	Muller et al.	2013	Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees	Agric. Syst.	163
18	Serra et al.	2003	Post-classification change detection with data from different sensors: some accuracy considerations	Int. J. Remote Sens.	162
19	Burke and Lobell	2017	Satellite-based assessment of yield variation and its determinants in smallholder African systems	PNAS	156
20	Arvor et al.	2011	Classification of MODIS EVI time series for crop mapping in the state of Mato Grosso, Brazil	Int. J. Remote Sens.	155

Among the most recent publications (2017), it is worth mentioning the work by Kussul et al. [48] dealing with the classification of crop type through deep learning techniques. This paper gained 665 citations. In addition to this study, the topic of regional-level crop classification or monitoring and the land use changes towards cropland [49–52] is the backbone of the most-cited-paper group. The retrieval of soil properties and soil carbon appears to be another trending topic [53,54] while, despite the number of citations (674), the study by Scanlon et al. [55] on irrigation sustainability is the only one dealing with soil water retrieval. Regarding crop type, Ren et al. [56] estimate winter wheat yield with

MODIS-NDVI data and Johnson et al. [57] exploit multispectral imaging to map the leaf area in a vineyard. Contrary to what one might expect, there are only three review studies among the top 20 cited publications [58–60].

3.1.3. Most Used Keywords

Following the methodology reported in Section 2.2.1, the most frequent stems were retrieved in the publication abstracts, driven by a list of relevant keywords categorised into groups (Table A1). All the driving keywords suggested by the authors are retrieved as stems in the WoS dataset, except for “pruning” and “fertilisation” (in this last case the word is stemmed as “fertil” so as not to mislead with the adjective “fertile”). Among the most used keywords (Table A2), the stem “resolut” in the imagery features group is by far the most frequent (518 records), occupying rank #34 in the overall stem count. “Landsat” in combination with the “MODIS” (Moderate Resolution Imaging Spectroradiometer) instrument results in the most widespread satellite platform (290 and 155 records, respectively). The NASA/USGS Landsat program (from Landsat 1 to Landsat 9) provides the longest continuous space-based record of Earth’s land in existence while MODIS is a key instrument aboard the Terra and Aqua satellites. Other types of satellite with a stem frequency higher than 20 are “Quickbird”, a high-resolution commercial Earth observation satellite, owned by DigitalGlobe, launched in 2001 and reentered in 2015; “Rapideye”, a constellation of five satellites owned by Planet, launched in 2008 and deactivated in 2020; and “Terra”, the NASA flagship of the Earth Observing System, launched in 1999. The ESA platforms for agricultural applications Sentinel-2 (instrument on board: Multispectral Instrument - MSI) and Sentinel-1 (instrument on board: single C-band synthetic aperture radar - C-SAR) ranked in the second and third position of the satellite category with an overall frequency of 193, respectively (“Sentinel” + “Sentinel-2” + “Sentinel-1”; for frequencies, see Table A2). The significant difference in frequency values between Landsat and Sentinel stems is certainly due to the Landsat’s earlier launch date (1972) in comparison with Sentinel-1 (2014) and Sentinel-2 (2015). This means that Landsat has been broadly used for a much longer time and proves its established popularity among researchers but, on the other hand, use of the Sentinel constellation for agricultural applications is increasing rapidly. Regarding crop management, “yield” monitoring/forecasting and the “harvest” stage are particularly investigated by researchers while “wheat” is the top-ranking crop. The NDVI (Normalized Difference Vegetation Index) is used as a reference in many studies and results in the most used vegetation index (288 records). This is in accordance with the broad use of the “multispectral” sensor. In the image processing topic, the “classification” task achieved the best performance, as did “radar” among sensors (220 and 134 records, respectively). The keywords belonging to the electromagnetic spectrum group are not present in the top 10, likely because, as with other terms (i.e., those relating to artificial intelligence), researchers followed the general rule of not mentioning acronyms in the abstract.

Analysing the results in Sections 3.1.2 and 3.1.3, some considerations on trending topics can be outlined. The classification task on regional and field scales for land use or crop recognition seem to be among the most explored research issues. Landsat imagery is widely used. Crop management is focused particularly on yield/monitoring and, among crops, on wheat, which is one of the most important staple crops with 761 million tons produced worldwide [61].

3.1.4. Semantic Networks

In the following, authors analyse the semantic network resulting from the validation procedure, described in Section 2.2.2, as applied to the abstracts of the WoS dataset. To summarise, if a couple of stems appear together in a great number of papers that cannot be explained only by the frequency of the stems in the analysed abstracts and by the verbosity of each abstract, a link connecting those stems is present in the validated projection. The result of the projecting procedure is quite strict [43]: the validated stems are just 751 (over 14,294 different stems of the entire dataset), 5.25% of the total.

As shown by the plot in Figure 8, the network displays a Largest Connected Component (LCC) including nearly 43% of all stems (322 nodes), a smaller one including 60 nodes, and finally smaller subgraphs made of small cliques. To observe the mesoscale organisation of the system, the Louvain community detection [62] was run. The community detection returns 11 communities (see Table A3 for more details) with more than 10 nodes; 2 of them partition the second largest component. Focus will be placed on the largest connected component and the second largest one as they are the only components providing a rich relation structure among stems. Nevertheless, regarding the second largest component (bottom right corner of Figure 8), it should be noted that the two communities do not fall fully within the aim of the study. The one on the right represents the “Geolocation and navigation” community (i.e., the first three nodes are “navig”, “GNSS” and “posit”) encompassing field positioning, robotics and steering. As said before, although these are pivotal applications in agriculture, they do not exploit satellite imagery and thus are excluded from the study’s aim. The other community is labelled as “Unmanned Aerial Vehicle” (UAV) and contains stems related to drones, dedicated sensors (“RGB” and “lidar”) and typical UAV-derived imagery products as “DEM” (Digital Elevation Model). Many of the publications retrieved in the dataset dealing with UAVs seem to mention satellites as merely another RS platform, often to enhance the advantages of drones. Data comparison between satellite and UAV platforms for calibration/validation or upscaling/downscaling processes seems to be quite rare considering both the absence of the keyword “interoperability” in the validated network and the fact that this community is part of a connected component different from LCC. However, the two communities are closely related, and this agrees with their integrated involvement in PA activities on field/parcel scales.

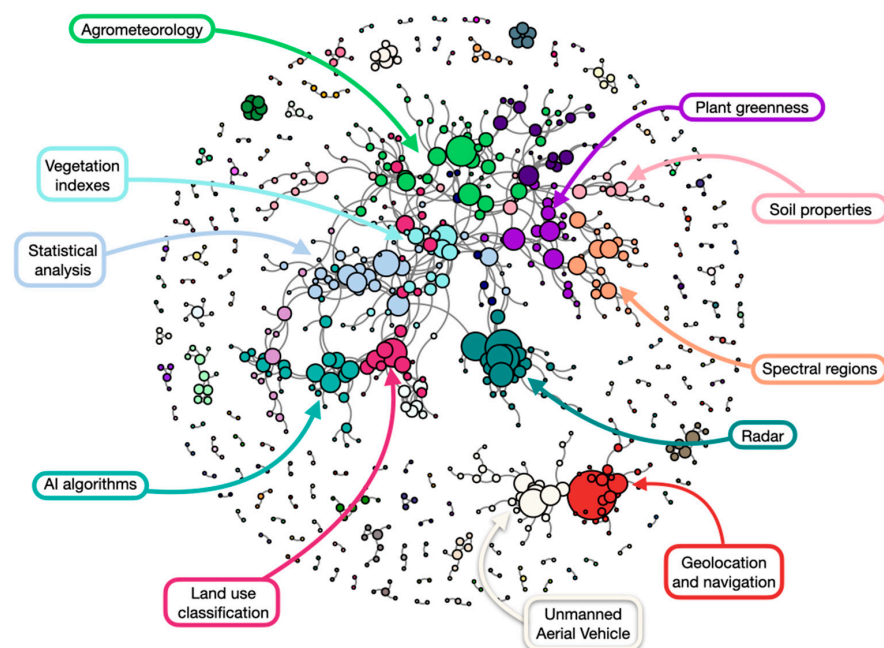


Figure 8. WoS dataset semantic network. The arrows mark the communities mentioned in the legend.

Shifting to LCC, it can be noted that the largest community (47 nodes), labelled as “Agrometeorology”, occupies a central position within the network and it is well connected with numerous links to almost all others. This community collects terms related to agrometeorological parameters and retrieval methods influencing crop growth; as such, it is at the centre of the network as weather conditions are the main driving factors of agricultural activity. Two other large communities with the same number of nodes (31) are “Radar” and “Soil properties”. These occupy a peripheral space of LCC and do not appear to be closely connected with other communities. The “Radar” community presents numerous nodes that highlight the main radar platforms used in the agricultural sector (Radarsat-2, Sentinel-1

and ALOS with the Palsar instrument). Instead, the “Soil properties” community has a tree structure, starting from stem nodes relating to the soil organic content and electrical conductivity. The latter, in turn, branches into indications about texture (“clay”), salinity (“salin”) and nutrient availability (“pH”, “phosphorus”).

In the bottom part of Figure 7, two communities that are strictly linked can be noticed: “Land use classification” and “Artificial Intelligence (AI) algorithms”. The latter comprises stems from both machine learning (“svm”, “rf”) and deep learning (“ann”, “cnn”) algorithms, which are often used for land use classification tasks. It is worth noting that in the “Land use classification” community, a missed identification of stems occurs, as presented in Section 2.2.1: “classif” and “classifi” (Table A3) refer to the same concepts, as they are stems of “classification”, “classify” and “classifier”, and their conjugations. The retrieving of chlorophyll and nitrogen content is the main core of the “Plant greenness” community, which is connected to the “Spectral regions” community, where portions of the electromagnetic spectrum typically employed in agricultural tasks are reported (“red”, “infrar”, “nir”). Finally, despite its modest size (22 nodes), the “Vegetational indexes” community lies at the centre of LCC. The large number of links with other communities is justified by the broad use of vegetation indexes in processing satellite imagery for agricultural research activities.

Focusing on the Sentinel-2 satellite, it must be highlighted that the community that includes this platform is not reported (<10 nodes). However, due to the role that Sentinel-2 plays in agricultural applications, the authors analysed its community and compared it with the one including Sentinel-1 (“Radar” community). The stems of the two communities show that, in the case of Sentinel-1, the scientific discourse revolves around the acquisition of radar imagery (“apertur”, “backscatt”, “vv”), while for Sentinel-2, the researchers’ focus is pointed at the extraction of informative data from images, often through machine learning and deep learning techniques (“svm”, “rf”, “neural”, “convolut”).

To consider arguments connecting different fields, as represented in terms of communities of stems, the node betweenness is considered (an index counting the number of shortest paths that pass through each node [35]). Table 2 reports the betweenness for both overall network stems and stems related to the driving keywords selected by the authors. The values are normalised such that the node with the greatest betweenness has a value of 1 and the one with the lowest a value of 0. As could be expected, the terms of the overall network connecting the various communities are mainly generic and related to image analysis (“coeffici”, “index”, “correl”, “classif”) or other sorts of ubiquitous in the use of satellite imagery in agriculture (“moistur”, “soil”, “leaf”).

Table 2. Betweenness of stems in WoS semantic network. The top 10 stems, in terms of betweenness, within the entire semantic network (left columns) and the list of stems selected by the authors (right columns) are reported.

Overall Top 10		Selected Top 10	
Stem	Betweenness	Stem	Betweenness
coeffici	1	modi	0.346
moistur	0.838	thermal	0.332
soil	0.779	yield	0.269
leaf	0.73	radar	0.26
index	0.662	wheat	0.174
kappa	0.646	evi	0.136
correl	0.565	resolut	0.125
backscatt	0.547	hyperspectr	0.1
temperatur	0.535	ndvi	0.075
classif	0.512	landsat	0.061

All selected stems show lower values of betweenness. Not surprisingly, all are more specific. As such, they are quite central in their community, but are limitedly connected outside.

3.2. Twitter Dataset

3.2.1. Descriptive Statistics

Similar to what was observed in Figure 2, the volume of messages on Twitter targeting the use of satellite imagery in agriculture has experienced a rapid increase since the foundation of the platform, as can be observed from Figure 9. Differently from the WoS dataset, there is an evident decrease in 2021 that is not present in the WoS dataset. It is likely that this decline occurs since Twitter is intensively used to advertise activities like workshops, conferences and live events. Due to the COVID-19 pandemic, most of those activities were cancelled in 2021, if they did not undergo significant limitations.

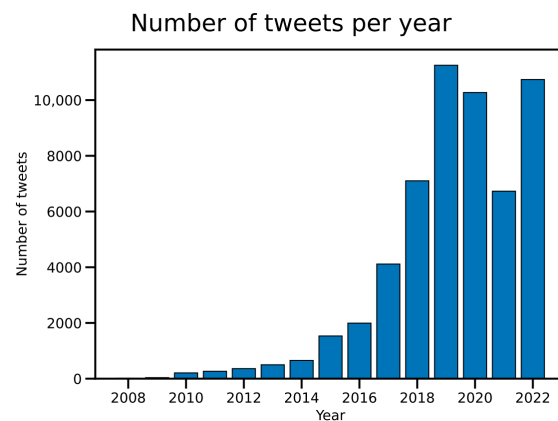


Figure 9. Number of tweets per year (2008–mid2022).

Analogously to Figure 7, in Figure 10, some distributions regarding the Twitter dataset are represented. Specifically, Figure 10 shows the number of retweets (i.e., sharings) per message (Figure 10a) and the number of original messages (i.e., tweets) per account (Figure 10b). In Figure 10, panels (a) and (b) are analogous to the number of citations per paper (Figure 7a) and the number of papers per author (left panel, Figure 7b). As in the case of the WoS dataset, the distributions displayed in Figure 10 are power laws, thus providing additional confirmations about the “adjacent possible” interpretation formulated in [46].

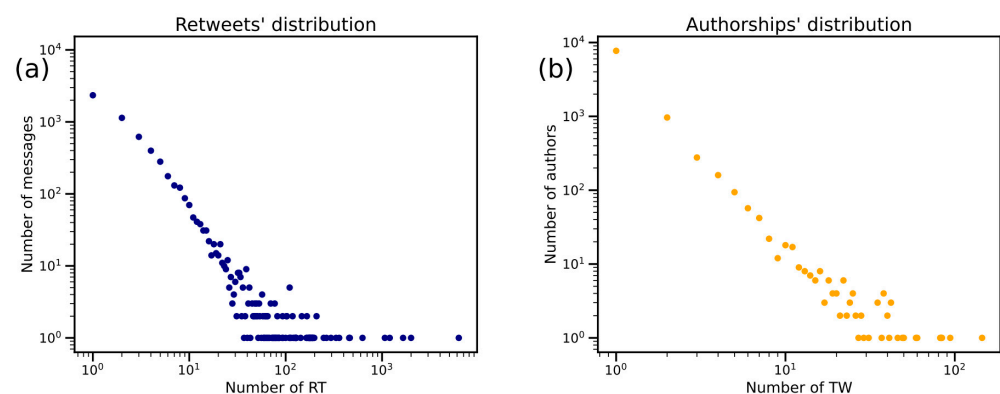


Figure 10. Retweets and authorships’ distributions throughout the Twitter dataset (2008–mid2022).

3.2.2. Semantic Network

Similar to the analysis of Section 3.1.4, the authors analysed the semantic network resulting from the validation procedure, applied to the Twitter posts. Firstly, tweets containing original contents (all messages that are not retweets) were selected. Then, each message was reduced to stems (including hashtags and emoticons; emoticons were not stemmed but were considered in the bipartite network). Finally, the procedure involved building a bipartite network of tweet IDs (the unique identifier of each tweet message)

and stems (as obtained with the procedure described in Section 2.2.1) and validating the projection on the layer of stems, using BiCM as a benchmark.

The resulting network includes 4767 nodes and 17,843 links. In this case, the network is composed of a Largest Connected Component (pictorially represented in Figure 11), including nearly 72.5% of the nodes of the entire network.

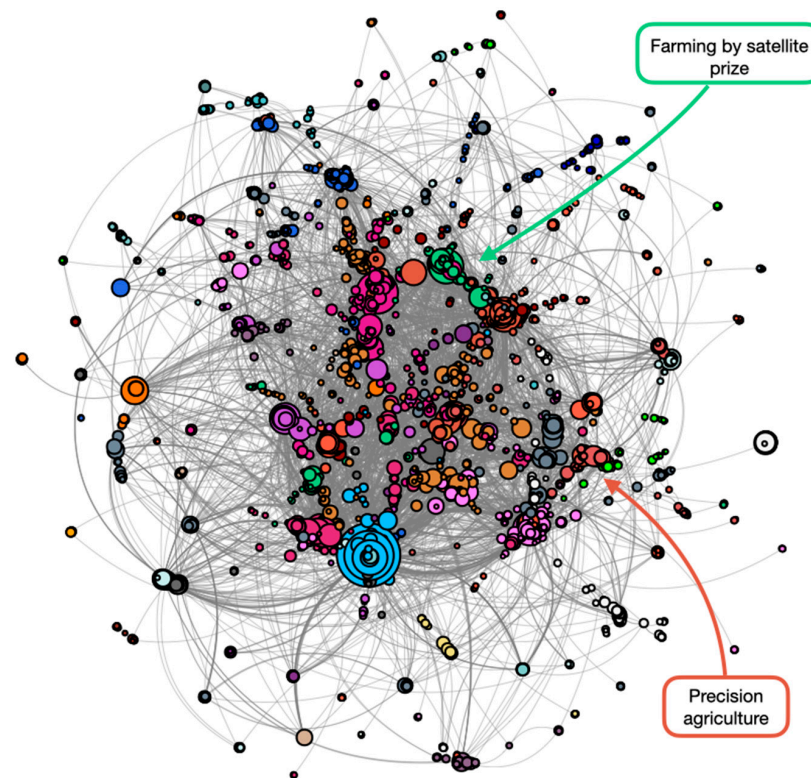


Figure 11. Twitter dataset semantic network. The arrows mark the communities mentioned in the legend. Other communities are related to arguments different from the result of academic research in the use of satellite imagery in agriculture and therefore are neglected. As it can be seen, academic achievements represent a small portion of the semantic network that, instead, is mostly populated by arguments related to the presentation of new products by private companies.

To detect the mesoscale organisation of the network, the Louvain algorithm for community detection [62] was run. The algorithm returned 329 communities, but only 14 have more than 100 nodes. Indeed, the communities found are much larger than those observed in the WoS dataset (the most numerous one accounts for 255 nodes). As the communities become larger, their identification in terms of main topics suitable for research purposes becomes tougher, since many subtopics contribute to the same community.

The volume of messages in the network is caused primarily by the massive number of tweets posted by private companies that use Twitter as a showcase to promote their activities. The enterprise's core business includes the satellite and space industry in general but also specific activities such as providing satellite data through dedicated web platforms directly to farmer and developing nations. Companies that deal specifically with the agricultural sector are committed to making new technologies (not just satellite data) more accessible to farmers. A secondary high volume of messages come from national space agencies that announce the successful launch of new satellites (i.e., the hyperspectral satellite Prisma through the Vega launcher in 2019).

Moving to agriculture-oriented topics, only two communities worthy of being commented on for the aim of the study were found in the network, labelled as "Farming by satellite prize" (220 nodes) and "Precision agriculture" (129 nodes). The "Farming by satellite prize" community bears witness to the intense technology transfer and communication

activity put in place by European institutions about their space programs. It comprises, among the most significant stems, “copernicus”, “egno” and “fbs prize”. The prize aims to support young innovators delivering applications and services based on Galileo, EGNOS (European Geostationary Navigation Overlay System) and Copernicus that will contribute to the evolution of agriculture. The “Precision farming” community emerges as the only cluster with technical stems but, regarding the use of satellite images in agriculture, they can be considered quite generic. The stems “water”, “veget”, “organicfarm” and “crophealth” represent the community core with a frequency of 34, 31, 29 and 26, respectively.

As in Section 3.1.4, to consider arguments connecting different fields, the node betweenness for both overall network stems and stems selected through the driving keywords was considered (Table 3). The stems in the overall network with the highest betweenness values (“iot”, “co2”, “ecosensenow”) refer to generic terms outside the use of satellite imagery in agriculture. This is probably due to the diversified activities carried out by private companies that animate the debate on Twitter in this sector. Switching on the selected stems, the betweenness has low values except for “radar” and “ai”. In the first case, the good value of betweenness is related to the extensive advertising that ISRO commissioned for its radar satellite launches. Since the stem “ai” is often present in communities driven by private companies, the betweenness of AI techniques could derive from business solutions outside the topic under investigation.

Table 3. Betweenness of stems in the Twitter semantic network. The top 10 stems with the overall greatest betweenness (left columns) and the top 10 selected stems (right columns) are reported.

Overall Top 10		Selected Top 10	
Stem	Betweenness	Stem	Betweenness
iot	1.000	radar	0.400
co2	0.933	ai	0.303
ecosensenow	0.903	yield	0.164
imag	0.682	thermal	0.101
earth	0.669	resolut	0.092
fire	0.641	landsat	0.055
emiss	0.633	rice	0.044
launch	0.628	pest	0.043
farm	0.627	harvest	0.040
prize	0.621	aqua	0.039

4. Conclusions

To the best of the authors’ knowledge, this is the first study performing an informetric analysis on the use of satellite imagery in agriculture leveraging both a scientific literature dataset and a non-academic information source.

In the Introduction, 5 research questions (RQ) were proposed to better organise the presentation of the results. The first 3 regarded the analysis of the scientific literature related to remote sensing in precision agriculture, while the subsequent 2 tackled the presence of the same subject on Twitter. To highlight non-trivial relations and the evolution of satellite imagery in agriculture within scientific research (answering the first 3 RQs), papers were downloaded from the Web of Science by selecting “agriculture” (and its conjugations) and “satellites” in the abstract, title and keywords. After a deep data cleaning, necessary to avoid papers related to distant fields, descriptive statistics and the semantic network of stems were extracted.

First, the performances of countries, journals and the most influential papers were analysed, answering RQ1. Regarding the evolution of the scientific field, a rapid growth in the production of papers was observed during the years, due, essentially, to the evolution of technology for satellite imagery access and their automated analysis. It is noteworthy that the predominance of the USA in this field has been challenged by China in the last

few years, both in terms of publications and in employed researchers. Nevertheless, the research impact of US publications remains much higher than those of China.

When analysing the most frequent scientific journals, authors observed that those related to long-established editors (Elsevier – Amsterdam, the Netherlands; IEEE – New York, NY, USA) are challenged by more recent ones (MDPI, PLOS). Nevertheless, the study of the distribution of citations showed that long-established editors still attract the greatest attention.

Mainstream topics were retrieved from the analysis of the most cited papers and most frequent abstract keywords selected through a tailored list. It follows that radar and multispectral sensors are broadly used, and among the latter in particular MODIS, a key instrument aboard the Terra and Aqua NASA satellites. Another milestone of the agricultural research task is represented by the computation of the NDVI vegetation index through satellite imagery. Among crops, wheat often plays a key role in different studies with a focus on yield forecasting.

To answer RQs 2 and 3 (the analysis of the terminology used in the scientific literature and the relation among the various terms, and the inference of emerging trends), the semantic network, as extracted from the abstract of the various papers, was then analysed. All words from the abstract of each paper were collected, stop words and punctuations were removed, then all retrieved words were “stemmed”. The rationale was to focus on the concepts and not on the single word. As such, different conjugations of the same word were reduced to the same stem.

Finally, the non-trivial co-occurrences of stems in papers’ abstracts were filtered via an entropy-based approach. This approach resides in comparing the observations to a benchmark that is maximally random but for some information of the real system.

The result is a network of stems that are connected if they are often used together in the various abstracts. Thus, it is possible to detect different communities related to the various subfields of the research.

From the network analysis, the large size of the “Agrometeorology” community emerges, confirming the importance of RS retrieval of meteorological parameters in the agricultural sector. This is a base for further studies. Though having a smaller dimension, it is worth noting that the “Vegetation indexes” community is well connected with others. Moreover, some indexes (i.e., EVI and NDVI) included in this community have low values of betweenness; nodes with low values of betweenness are well-connected in their community, but relatively loosely linked to nodes in other communities.

Integrating all information into a coherent view, it is remarkable that the most cited papers are quite recent: for instance, the most cited paper is only 11 years old. In this sense, it seems that the “first mover advantage” (the fact that older papers gather more citations just for the fact of being in the literature for a longer time) is not relevant here. Instead, likely due to the rapid growth of the present field of research, older papers may have become outdated relatively quickly and have therefore not exploited their time advantage. On the other hand, the network of validated stems highlights the presence of emerging topics. Analysing the stems retrieved from recently published papers, classification task for land use assessment and crop recognition stands out as a pervasive and cutting-edge topic, together with the use of hyperspectral sensors and RS retrieval of plant responses to environmental cues (i.e., fluorescence).

Nonetheless, the academic contribution is just one facet of the impact of RS in PA. To exploit the impact of these novel tools on practitioners, data from online social networks, specifically Twitter, chosen for its use by private companies and for its data availability, were also analysed. The research aimed to infer the different purposes in the online debate on remote sensing in precision agriculture (RQ4) and the analysis of the dynamic and the development of the various topics (RQ5). When downloading the data from Twitter API, the search queries mirrored those used for the WoS data retrieval to provide an easy comparison between results. Indeed, some descriptive statistics are quite similar (such as the retweet/citations distributions), but there are also evident differences, like a clear decline in the number of tweets in 2021. This behaviour is not present in the academic

production and is likely because companies on Twitter often advertise public events, which were almost certainly cancelled or postponed during the COVID-19 pandemic. One of the main findings of the study is that Twitter is largely used by private companies and national space agencies for informational and promotional purposes. On the contrary, it does not seem to be very popular among researchers to share and spread scientific findings outside academia.

From a scientific point of view, future challenges concern the availability of satellite imagery with high resolution and shortened revisit times. The processing bottleneck related to the increasing amount of data may increase but agricultural RS tasks will benefit from these new achievements, paving the way for more accurate or newer applications. In this sense, researchers could focus on developing new models (i.e., crop growth) which embed various types of satellite data or on associating plant spectral signatures to crop features or status, such as variety or disease-induced stress.

From the bibliometric point of view, the present analysis shows a novel and promising application of entropy-based null-models for the detection of semantic networks. Similar procedures have been applied to Twitter datasets [33,63], where the workflow was limited to the usage of hashtags. In this study, the attention is placed on the entire abstract in the case of the WoS dataset, or on the entire text of the message in the case of the Twitter dataset.

Regarding the bibliometric analysis of remote sensing in precision agriculture, while this research focuses on Twitter and WoS, other data sources could complement the analysis. For instance, for the academic facet, Google Scholar includes other documents from grey literature, e.g., Ph.D. and Master's theses, and may reinforce or open up new clusters of stems in the semantic network. However, due to the tendency of Google Scholar to include different data, including not necessarily peer-reviewed publications, the risk of adding uninformative noise to the dataset is quite high. Even focusing on a "cleaned" source like Web of Science, the presence of noise was quite strong, and adding grey literature may introduce an additional source of noise. Nevertheless, analysing data from Google Scholar could be of interest in order to highlight similarities and differences with WoS. Analogously, regarding the online social network side, it could be interesting to study the data from other social networks like Facebook. Though the data availability and the detail about the data of its users is quite limited in this case, it could represent an interesting source to be investigated.

The main aim of PA research is to provide more efficient tools to lower the impact on natural resources and, at the same time, increase profits for farmers. In this study, the limited presence of academia promoting its scientific advancements in online social networks is highlighted. Online social networks represent a novel and unprecedented way to target practitioners and private individuals. Therefore, if academia will not exploit this opportunity, achievements in the use of satellite imagery will struggle to reach a wider audience and their effectiveness may be subject to limitations.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy13020576/s1>. Table S1: Journal title, ISO abbreviation and publisher appearing in the manuscript.

Author Contributions: Conceptualization, R.D. and F.S.; methodology, R.D. and F.S.; software, F.S.; validation, R.D.; formal analysis, F.S.; investigation, R.D.; data curation, F.S.; writing—original draft preparation, R.D. and F.S.; writing—review and editing, R.D. and F.S.; visualization, R.D. and F.S.; supervision, R.D. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Twitter data can be downloaded from the following link (https://drive.google.com/file/d/1sM4HYLwZD_WC5jYn80M6t-qugsPXU5iv/view?usp=sharing (accessed on 27 November 2022)) as the list of the tweet ids used in the analysis, in agreement with the Twitter policy. (<https://developer.twitter.com/en/developer-terms/more-on-restricted-use-cases> (accessed on 27 November 2022)). Web of Science data are proprietary and cannot be shared without the permission of WoS.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Top20 countries in terms of publications

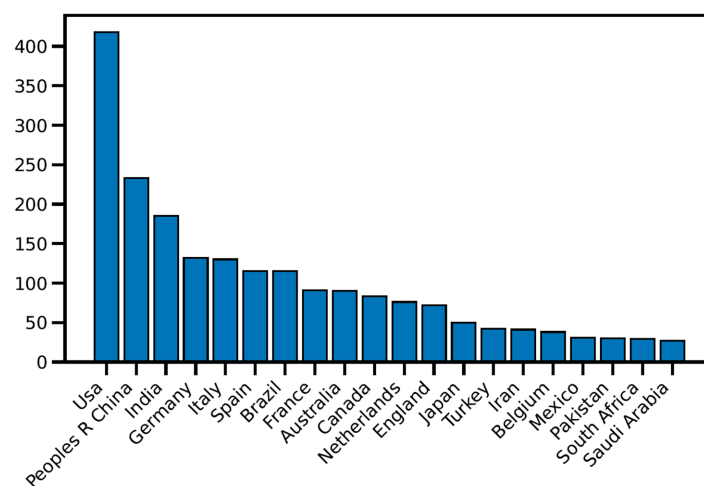


Figure A1. Top 20 countries in terms of publication (1977–mid2022).

Top20 countries in terms of researchers

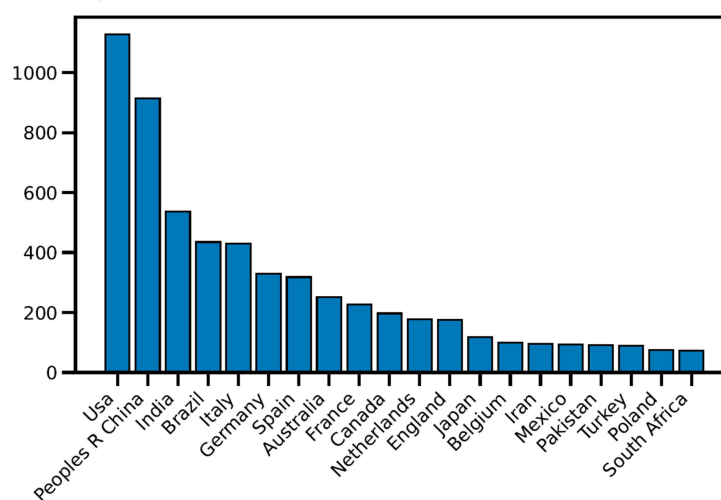


Figure A2. Top 20 countries in terms of researchers (1977–mid2022).

Table A1. Driving list of relevant keywords categorised into groups and used for agricultural keywords selection.

SATELLITE PLATFORM/INSTRUMENT	SENSOR TYPE	ELECTROMAGNETIC SPECTRUM	VEGETATION INDEX	IMAGERY FEATURES	IMAGE PROCESSING	CROP TYPE	CROP MANAGEMENT
ALOS Aqua Gaofen Landsat PlanetScope Pleiades Prisma QuickBird RadarSAT RapidEye Sentinel Terra MODIS *	Hyperspectral Multispectral Radar RGB Thermal	NIR SWIR TIR VIS	EVI GCI GNDVI LAI MSAVI NDRE NDVI NDWI RECI SAVI VARI	Multitemporal Resolution Revisit time	+ AI Classification Fusion + DL Interoperability + ML Recognition	Cereals Barley Corn Maize Rice Wheat Banana Oil palm Soybean Sugarcane Potato Tomato Orchards Olive Vineyard	Disease Fertilisation Harvest Pest Phenology Pruning Tillage Sowing Weed Yield

* instrument. + AI = Artificial intelligence; DL = Deep learning; ML = Machine learning.

Table A2. Stem, frequency and ranking of agricultural keywords selected through the driving list.

Research Field	Keyword	Stem	Frequency	Ranking
imagery_features	resolution	resolut	518	34
crop_management	yield	yield	380	65
satellites	landsat	landsat	290	107
vegetation_index	ndvi	ndvi	288	108
image_processing	classification	classifi	220	156
crop_type	wheat	wheat	178	217
satellites	modis	modi	155	268
sensors	radar	radar	134	312
sensors	multispectral	multispectr	128	329
crop_management	harvest	harvest	119	353
vegetation_index	vari	vari	115	363
crop_type	rice	rice	109	380
crop_management	phenology	phenolog	103	416
crop_type	maize	maiz	94	451
vegetation_index	lai	lai	82	506
sensors	hyperspectral	hyperspectr	79	529
sensors	thermal	thermal	72	576
crop_type	corn	corn	70	591
vegetation_index	evi	evi	58	672
crop_type	soybean	soybean	58	674
image_processing	fusion	fusion	49	764
crop_management	disease	diseas	46	794
imagery_features	multitemporal	multitempor	42	866
crop_management	weed	weed	42	867
satellites	sentinel	sentinel	39	891
em_spectrum	vis	vis	39	905
crop_type	cereals	cereal	36	950
crop_type	potato	potato	33	989
crop_management	pest	pest	32	1017
em_spectrum	nir	nir	30	1064
crop_type	barley	barley	30	1057
crop_type	sugarcane	sugarcan	30	1076
crop_management	sowing	sow	30	1060
crop_management	tillage	tillag	27	1135
satellites	quickbird	quickbird	26	1164
satellites	rapideye	rapidey	26	1169
imagery_features	revisit time	revisit	23	1271
crop_type	orchards	orchard	23	1242
vegetation_index	ndwi	ndwi	22	1307
satellites	terra	terra	22	1300
vegetation_index	savi	savi	21	1337
image_processing	ml	ml	19	1444
image_processing	recognition	recognit	19	1428
sensors	rgb	rgb	18	1470
crop_type	olive	oliv	17	1526
crop_type	vineyard	vineyard	17	1517
crop_type	oil palm	palm	16	1594
satellites	alos	alo	15	1612
em_spectrum	tir	tir	14	1686
vegetation_index	gndvi	gndvi	13	1780
satellites	aqua	aqua	12	1841
vegetation_index	ndre	ndre	11	1986
satellites	radarsat	radarsat	9	2164
em_spectrum	swir	swir	9	2171
satellites	planetscope	planetscop	8	2350
crop_type	tomato	tomato	8	2319
vegetation_index	msavi	msavi	5	2944
image_processing	interoperability	interoper	5	2869
image_processing	dl	dl	4	3368
crop_type	banana	banana	4	3451
image_processing	ai	ai	3	4021
satellites	gaofen	gaofen	2	4403
satellites	prisma	prism	2	5033
vegetation_index	gci	gci	1	13,093
vegetation_index	reci	reci	1	8925
satellites	pleiades	pleiad	1	6140

Table A3. Overview of the community features: label, number of nodes and stems with frequency.

COMMUNITY LABEL	AGRO-METEOROLOGY	STATISTICAL ANALYSIS	RADAR	SOIL PROPERTIES	LAND USE CLASSIFICATION	GEOLOCATION AND NAVIGATION	UNMANNED AERIAL VEHICLE	AI ALGORITHMS	SPECTRAL REGIONS	VEGETATION INDEXES	PLANT GREENNESS
NUMBER OF NODES COMMUNITY COLOR	47	37	33	31	31	30	30	27	24	22	22
STEMS AND FREQUENCY	evapotranspir 14	rmse 12	radar 17	carbon 6	classif 13	navig 23	unman 13	machin 9	band 8	index 11	leaf 10
	temperature 10	coeffici 15	apertur 15	organ 6	classifi 8	gnss 11	aerial 9	vector 8	red 8	modi 9	nitrogen 9
	water 8	regress 13	sar 13	soil 6	lulc 8	posit 9	uav 9	learn 8	reflect 8	veget 7	chlorophyl 9
	precipit8 8	squar 9	backscatt 13	electr 5	likelihood 7	kinemat 8	vehicl 9	random 7	infrar 7	ndvi 7	n 6
	thermal 7	moistur 8	synthet 12	clay 4	kappa 7	receiv 5	precis 6	rf 6	hyperspectr 7	evi 6	content 5
	balance 7	correl 7	polar 11	induct 3	accuraci 6	rtk 5	flight 4	svm 6	nm 4	spectroradiomet 5	-1 4
	surface 7	error 11	vv 11	salin 3	urban 6	real-tim 4	platform 4	neural 6	nir 4	resolut 5	solar-induc 4
	drought 7	predict 6	hh 7	ec 3	chang 5	system 4	camera 4	network 5	near-infrar 4	normal 4	kg 4
	et 6	root 5	c-band 7	eca 3	class 5	global 4	dem 3	convolut 5	spectral 3	moder 4	canopi 3
	energi 6	mean 5	l-band 7	matter 3	cover 5	signal 3	digit 3	deep 5	spectra 3	differ 3	fertil 3
	rainfall 5	least 5	radarsat-2 6	soc 2	overal 4	speed 3	elev 3	forest 5	green 2	spatial 3	fluoresc 3
	trmm 4	plsr 4	microwav 6	phosphorus 2	maximum 4	geograph 3	uav-bas 3	decis 2	visibl 2	indic 3	lai 3
	meteorology 4	absolut 4	optic 5	ph 2	built-up 3	gis 2	height 3	support 4	tir 2	terra 2	sif 2
	lst 4	r-2 4	palsar 5	appar 2	supervis 3	path 2	rgb 3	artifici 4	blue 2	imag 2	rate 2
	emiss 4	retriev 3	sentinel-1 5	eddi 2	bodi 3	dgps 2	topographi 2	tropic 3	red-edg 2	high 2	nutrient 2
	actual 3	passiv 3	polarimetr 5	ecosystem 2	land 3	real 2	srtm 2	ann 3	hyperion 2	savi 2	ha 2
	sebal 3	ordinary 3	vh 3	depth 2	sprawl 2	autonom 2	man 2	train 2	shortwav 2	low 1	biomass 2
	vci 3	partial 3	alo 3	fao 1	mlc 2	steer 1	altitud 2	algorithm 2	swir 1	ndwi 2	biophys 2
	climat 3	valid 3	angl 3	cm 1	use/land 2	rs 1	lidar 2	deforest 1	airborn 1	distribut 1	photosynthesi 1
	gaug 3	model 2	s2 2	servic 1	increas 2	robot 1	farmer 2	cnn 2	multispectr 1	aqua 1	absorpt 1

The first 20 stems per community are reported. Colors represent communities plotted in the WoS dataset semantic network (see also Figure 8).

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