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# UAV applications in wheat crop: a bibliometric approach to the literature[1]

## Aplicações de VANT na cultura de trigo: uma abordagem bibliométrica da literatura

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**ABSTRACT -** The main objective of this study was to carry out a bibliometric search in the literature on the use of UAVs in the wheat crop. For this purpose, a search of all scientific articles published until 2021 was carried out in the Web of Science database. Subsequently, bibliometric literature analysis techniques were applied using the software VOSviewer, which allowed evaluating the co-authorships between countries and institutions and the co-occurrences of words between studies. The journals and authors that publish the most on this topic were verified. The results indicate a growing trend of publications on UAV applications in the last 7 years, with China, the United States, and the United Kingdom being the main researchers on this topic. However, China stands out with approximately 40% of the publications. This analysis reveals the main current issues and the most influential institutions around the world that have carried out relevant research in scientific publications, showing the journals that include more publications and the collaborative patterns related to the use of UAVs in the wheat crop. Multi-rotor platforms with embedded multispectral cameras are the most used for this purpose. About 27.8% of the publications are from the topic related to the monitoring of productivity/phenotyping. Therefore, this application is in evidence, but further studies on the use of drones in regions with high wheat production, such as South American countries, are needed.

**Key words:** Trends. Wheat Production. VOSviewer.

**RESUMO -** O presente trabalho tem como objetivo principal realizar uma pesquisa bibliométrica de literatura sobre o uso de VANTs na cultura de trigo. Para tanto, foi realizada uma pesquisa na base de dados da Web of Science, de todos os artigos científicos publicados até o ano de 2021. Posteriormente foram aplicadas técnicas de análise bibliométrica de literatura através do software VOSviewer, no qual avaliou-se as coautorias entre países e instituições, bem como as coocorrências de palavras entre as obras. Foram verificados os periódicos que mais publicam sobre esta temática e os autores que mais publicam. Os resultados indicam uma tendência crescente de publicações com essa aplicação de VANTs nos últimos 7 anos, e que a China, Estados Unidos da América e Reino Unido são os maiores pesquisadores desse tema, porém a china se destaca com aproximadamente 40% das publicações. Esta análise revela os principais assuntos atuais, e as instituições mais influentes em todo o mundo que realizaram pesquisas relevantes em publicações científicas; este estudo expõe os periódicos que incluem mais publicações e os padrões colaborativos relacionados ao uso de VANTs na cultura do trigo. As plataformas mais utilizadas para essa finalidade são do tipo multirotor, embarcados com câmeras multiespectrais. Cerca de 27,8% das publicações são do eixo temático ligado ao monitoramento da produtividade/fenotipagem. Conclui-se que esta aplicação está em bastante evidência, porém são necessários mais estudos com emprego de drones em regiões com alta produção tritícola como países da América do Sul.

**Palavras-chave:** Tendências. Produção Tritícola. VOSviewer.

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## INTRODUCTION

Wheat (Triticum aestivum L.) is one of the most produced cereals in the world and has a wide adaptation to the most diverse biomes and climate conditions across the globe due to its genetic improvement. China, European Union, India, Russia, the USA, Canada, Australia, Ukraine, Pakistan, and Turkey stand out among the world's largest producers. Brazil ranks 16th in world wheat production, with approximately 6.3 million tons (SOUZA, 2018).

Optimal agronomic management according to wheat development stages is essential to optimize wheat yield and grain quality, especially in terms of protein content, as it varies significantly depending on different agricultural practices. Therefore, it requires farmers to have a detailed understanding of the growth status of wheat during each specific development stage in wheat cultivation (WU *et al*., 2016), indicating that periodic monitoring through remote sensing techniques would become an interesting alternative in decision-making.

The use of remote sensing by unmanned aerial vehicles (UAVs) in agriculture has been an effective and practical way of obtaining field information (DU; NOGUCHI, 2017), as the applications of fixed-wing or multi-rotor UAVs, with visible, infrared, and even thermal spectrum sensors are important tools in monitoring the wheat crop. Studies have shown that this technology is playing a key role in monitoring due to its high resource efficiency, low operating cost, low risk, among other technical characteristics (SANKARAN; KHOT; CARTER, 2015; SENTHILNATH *et al*., 2016; VEGA *et al*., 2015).

Applications in wheat are recurrent in the indirect estimation of agronomic parameters such as yield components, nutritional status, nitrogen fertilization, biomass, chlorophyll content, diseases such as yellow rust, plant density, and emergence through indirect determinations of height, vegetation indices, and leaf area index (FU, Z. *et al*., 2020; WAN *et al*., 2018; YAO *et al*., 2017; YUE *et al*., 2018).

Consulting the literature through a bibliometric analysis is essential to measure the current level of technological and scientific development on the use of UAVs applied to wheat. Recently, several investigations have been carried out on the potential of sub-orbital remote sensing platforms, especially UAVs, in precision agriculture, listing the advantages and limitations of this remote sensing equipment as an alternative to traditional platforms such as aircraft and satellites (YAO *et al*., 2017).

According to Brizola and Fantin (2016), the formulation of a research problem is only relevant when researchers can identify gaps, consensuses, and controversies after a critical analysis of the current stage of scientific production on the subject and the insertion of their objective of research on a path not yet taken by other researchers. In this sense, the concept of bibliometric analysis is linked to a quantitative and statistical technique for measuring scientific production indices based on a set of laws and empirical principles for the establishment of theoretical foundations (FERREIRA, 2010).

This research aims to obtain an overview of the studies that relate UAVs applied to the agricultural monitoring of the wheat crop through a bibliometric analysis of the literature. Specifically, the objectives are to (1) select and characterize the studies consulted in the database regarding the year of publication, countries, institutions, journals, and authors, (2) analyze the main terms (keywords) used over the years, as well as the types of platforms and sensors used, and (3) identify key research topics common to UAV use in wheat.

## MATERIAL AND METHODS

All types of documents were searched, but only scientific articles in the field of agriculture/remote sensing published in their final stage, in full, and peer-reviewed were considered. The search engines of the scientific database Web of Science – WOS were used for data collection as proposed by Duan, Wang and Yin (2020) and Wang *et al*. (2019).

The articles were selected from the Social Science Citation Index (SSCI) and the Science Citation Index Expanded (SCI-Expanded), which has a wide range of multidisciplinary data from TM – Thomson Reiters (BIRCH; REYES, 2018). Productions before June 2021 were searched to reach a higher number of works related to the theme, seeking the combination of the highest number of keywords and using Boolean logic in titles, abstracts, and keywords through the association of the following criteria: TS=((“UAV” OR “VANT” OR “DRONE*” OR “RPA” OR “unmanned aerial vehicle” OR “remotely piloted aircraft”) AND (“RGB*” OR “RGB-image” OR “multispectral*” OR “hyperspectral*”) AND (“wheat*” OR “wheat culture” OR “wheat cereal” OR “winter wheat” OR “productivity*” OR “grain yield” OR “precision agriculture” OR “productivity estimate”). Numerous words that have no relation to the study were disregarded as a selection criterion, using the “NOT” operator.

Access to the Web of Science database was carried out through the Coordination for the Improvement of Higher Education Personnel (CAPES) research portal of the Ministry of Education (MEC), which allows access to the production of various scientific bases. The Federated Academic Community (CAFe) platform, which allows remote access to the content of CAPES portal of journals, available through the National Education and Research Network (RNP), was used.

The bibliometric analysis was developed using the free software VOSviewer version 1.6.16, based on the Java® language (VAN ECK; WALTMAN, 2013), which is a tool to create, visualize, explore, and filter concept maps from a database. The analyses are limited only to co-authors (relationship between authors) and co-occurrence (most frequent words) when integrating more than one database in VOSviewer, which is the reason why we chose to use only the Web of Science database. This review was based on a survey and analysis of scientific publications overtime related to the use of UAVs in wheat.

The types of biometric analysis performed were citation, with information of year and local the topic is being researched (general characteristics); bibliographic coupling, which identified the institutions and journals that publish on the subject; co-authorship, which listed the main authors (social structure of research), highlighting those who work together; and co-occurrence, which identified which words have been most used in each period. Analyses about the type of platform and sensors and variables researched (state of the art) were performed through the individual reading of documents, with subsequent tabulation in an electronic spreadsheet.

Concept maps constructed from VOSviewer are created in three steps, according to Van Eck and Waltman (2013). The first step (OLCZYK, 2016) occurs firstly from the construction of the similarity matrix so that the elements are given by Equation (1):

$$As_{ij} = \frac{C_{ij}}{c_i c_j} \qquad (1)$$

where denotes the searched criteria (e.g., co-occurrences) of elements i and j, denote the total occurrences of i and j. Thus, the next step is the construction of the network based on the matrix elements defined above. Very similar elements must be located close to each other, while not very similar elements must remain further apart. For this, the location function to be minimized is given by Equation (2):

$$V = (X_i, \ldots, X_n) = \sum_{i<j}^{n} sij \left\| X_i - X_j \right\|^2 \qquad (2)$$

where denotes the location of element i, and ||-|| denotes the norm of the difference between the i and j positions. The authors also impose the condition that the average distance between two items is equal to 1, according to Equation (3):

$$\frac{2}{n(n-1)} \sum_{i<j}^{n} \left\| X_i - X_j \right\| = 1 \qquad (3)$$

where n is the number of publications, $S_{ij}$ is the similarity already defined between i and j, is a parameter for solving the equation, and $C_i$ is the cluster to which unit i is assigned. δ $(X_i, X_n)$ is equal to 1 if j and i are equal or 0 otherwise.

Finally, the degree of relationship between clusters and statistics generated by the software was discussed after the concept maps were generated.

## RESULTS AND DISCUSSION

The generic search found 297 scientific publications, 134 of which in the form of peer-reviewed scientific articles published in the area of agriculture/remote sensing. The final sample of 72 documents was defined after this initial filtering and discarding duplicate articles in the WOS database.

Figure 1 shows the frequency of publications overtime per year, with the first record in 2008 and an average of less than 1 article per year between 2008 and 2014. The year with the most publications was 2019. No records were found in 2009, 2011, 2012, and 2013. A significant increase in the number of studies related to this topic could be observed from 2015, which demonstrates a high popularization of the use of UAVs in studies with wheat only in the last 6 years (Figure 1).

The countries that published the most on this topic were China, with approximately 40% of the publications, followed by the United States, with 9.6%, the United Kingdom, with 9%, and France, with 5% (Figure 2). Brazil ranked the last positions, with only 1 article recently published (VOLPATO *et al*., 2021), a fact that demonstrates a lack of high-impact articles in this application. It is noteworthy the fact of having co-authors of other nationalities in the same article, causing the same publication to appear more than once in the count and different nationalities.

According to the results, about 132 institutions contributed to the analyzed publications in co-authorship. Figure 3 shows a network of cooperation between these institutions, with five clusters with at least two documents each. Colors represent clusters of institutions, sizes represent the number of published articles, and lines represent the cooperation strength. All clusters in the network have at least one Chinese institution carrying out research.

The largest cluster (red) contains 14 institutions, with Nanjing Agricultural University from China standing out for the number of publications and citations (9 and 127, respectively). In this context, China is the most representative country in this cluster. International technical collaboration is evident in this cluster, given the participation of the International Maize and Wheat Improvement Center – CIMMYT in Mexico, the Universities of Nebraska, Minnesota, and Washington in the United States, Rothamsted Research

**Figure 1** - Quantity; Year of publication

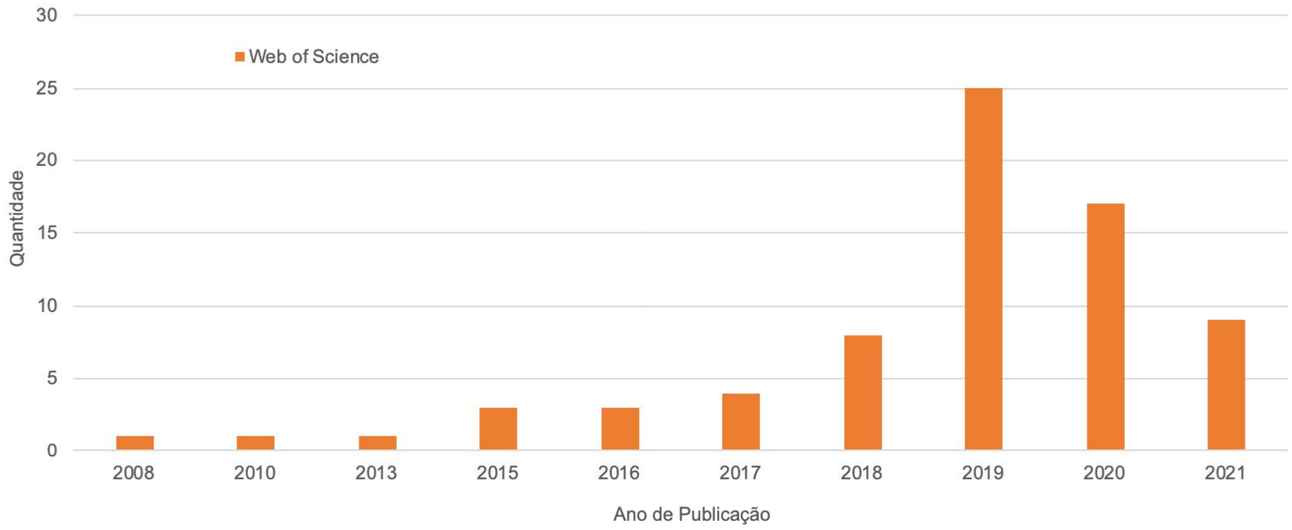
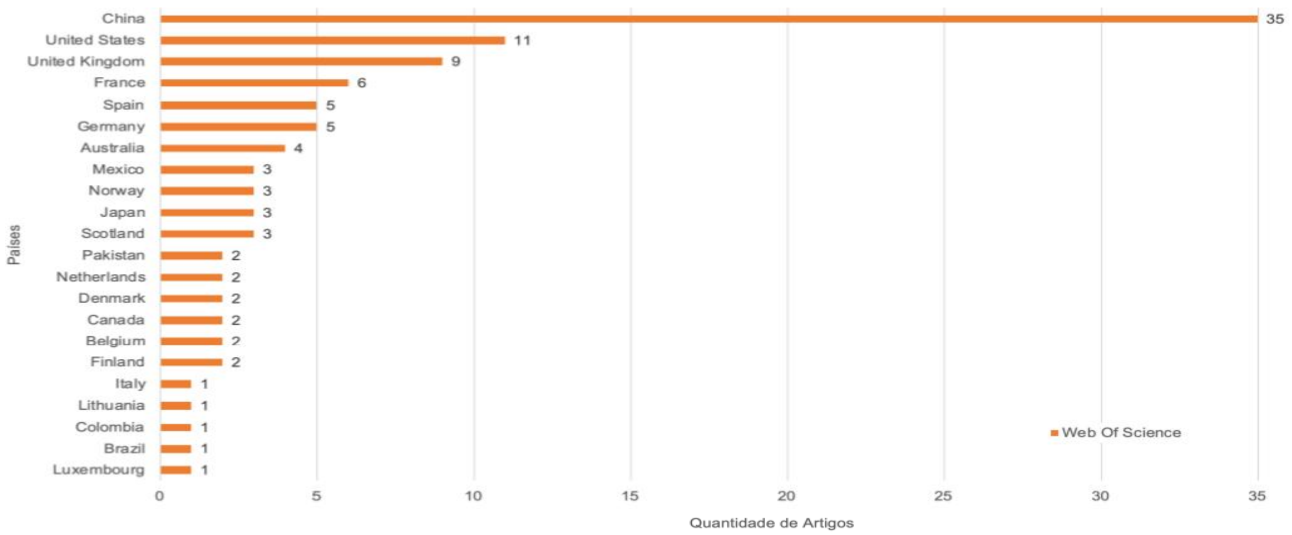



**Figure 2** - Countries; Number of articles




Center in the United Kingdom, Norwegian University of Life Sciences in Norway, Agriculture and Agri-Food of Canada, Institut National de la Recherche Agronomique – INRA of France.

The second cluster (green) is formed by five institutions: Beijing Research Center for Information Technology in Agriculture (China), National Engineering Research Center for Information Technology in Agriculture Beijing (China), Beijing Academy of Agriculture and Forestry Sciences (BAAFS) (China), Shandong Agricultural University (China), and Newcastle University (United Kingdom). The main characteristic of this cluster is the connection with the information technology area, bringing applications such as artificial intelligence.

The blue cluster is also formed by five institutions, most of which are from the United Kingdom, but with ties to China: Loughborough University (United Kingdom), University of Essex (United Kingdom), Beihang University (China), NIAB EMR: Horticultural Research at East Malling (UK), and Northwest A&F University (China).

The yellow cluster is the penultimate considering the number of documents and citations, with the Chinese Academy of Sciences (China), Universität Bonn (Germany), Manchester Metropolitan University (USA), and Guangzhou Geography Institute (China). The last cluster (purple) is formed by Scotland's Rural College (Scotland), University of Edinburgh (United Kingdom), Finnish Geodetic Institute (Finland), and Shandong University of Science and Technology (China).

Table 1 shows the scenario of the number of articles published in each journal and the number of citations, which was used as a criterion for ranking with its respective percentage. The journal Remote Sensing was ranked first, with a total of 27 articles published and approximately 40% of citations, being considered the most popular journal considering this subject. Sensors were ranked second, with approximately 15% of citations and six articles, followed by Computers and Electronics in Agriculture and Plant Methods, with approximately 13.9% and 8.13% of citations and eight and three articles, respectively (third and fourth place).

**Figure 3 -** Cooperation regarding co-authorship between institutions

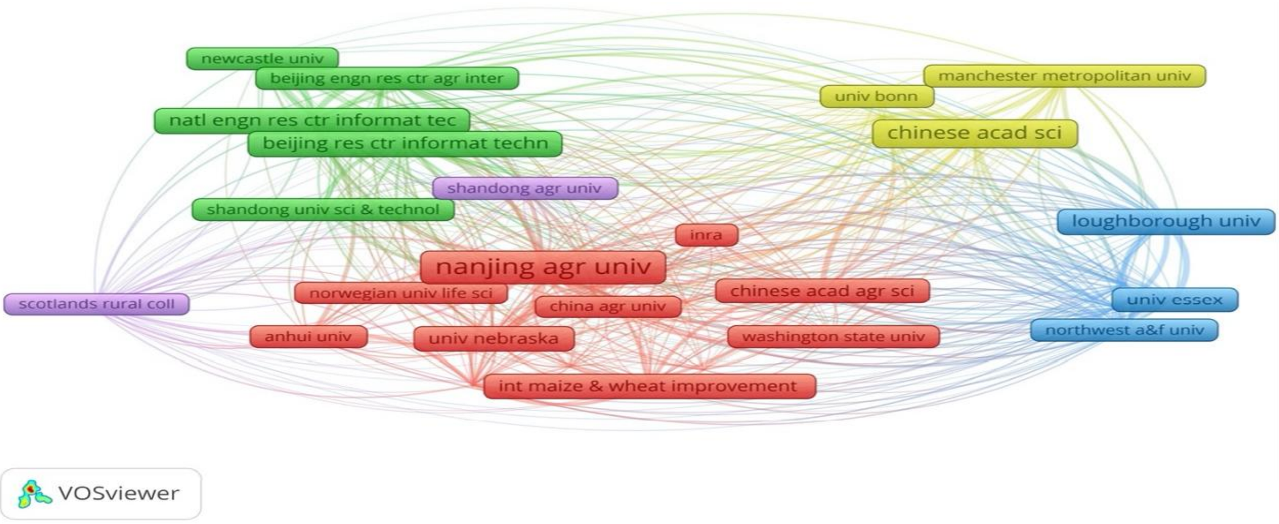



**Table 1 -** Ranking of journals according to the number of citations

| Ranking | Journal | % | Article | Citation |
|---|---|---|---|---|
| 1 | Remote Sensing | 40.05 | 27 | 650 |
| 2 | Sensors | 15.10 | 6 | 245 |
| 3 | Computers and Electronics in Agriculture | 13.92 | 8 | 226 |
| 4 | Plant Methods | 8.13 | 3 | 132 |
| 5 | Remote Sensing of Environment | 8.13 | 1 | 132 |
| 6 | Plant Science | 2.90 | 1 | 47 |
| 7 | Agricultural and Forest Meteorology | 2.22 | 1 | 36 |
| 8 | Frontiers in Plant Science | 2.03 | 5 | 33 |
| 9 | ISPRS Journal of P. and Remote Sensing | 1.97 | 1 | 32 |
| 10 | Precision Agriculture | 1.36 | 2 | 22 |
| 11 | Journal of Near Infrared Spectroscopy | 1.29 | 1 | 21 |
| 12 | International Journal of Remote Sensing | 0.80 | 2 | 13 |
| 13 | Applied Optics | 0.43 | 2 | 7 |
| 14 | International J. of Agricultural and Bio. Eng. | 0.43 | 1 | 7 |
| 15 | Agronomy-Basel | 0.31 | 2 | 5 |
| 16 | Plant Production Science | 0.25 | 1 | 4 |
| 17 | Transactions on Industrial Informatics | 0.18 | 1 | 3 |
| 18 | J. of Selected Topics in Applied Earth O. and R. | 0.12 | 1 | 2 |
| 19 | Pakistan Journal of Agricultural Sciences | 0.12 | 1 | 2 |

*Continuation Table 1*

| | | | | |
|---|---|---|---|---|
| 20 | Spectroscopy and Spectral Analysis | 0.12 | 1 | 2 |
| 21 | Plant Journal | 0.06 | 1 | 1 |
| 22 | Sustainability | 0.06 | 1 | 1 |
| 23 | Agriculture-Basel | 0.00 | 1 | 0 |
| 24 | Functional Plant Biology | 0.00 | 1 | 0 |

In terms of authors, Table 2 shows the ranking of the seven main authors who published the most on the subject in order of citations with their respective percentages. Importantly, the software VOSviewer separates the authors from a document, that is, the same article with three co-authors is counted for each of them, for example.

The author with the highest number of publications was researcher Zhu Yan from Nanjing Agricultural University – China, with the first study as a co-author being published in 2017 (YAO *et al*., 2017), which estimated the leaf area index of wheat using UAVs. The last out of nine studies in which this author appears is from 2020 (FU, Z. *et al*., 2020) and is related to the monitoring of wheat growth and yield estimation using UAVs. Ranked second is the researcher Yongchao Tian, with eight articles, followed by Weixing Cao and Guijun, with seven articles each. Again, all of the top places in the ranking are of Chinese origin.

Regarding the number of citations, the most cited author is Frederic Baret from France (INRA – Institut National de la Recherche Agronomique), with 390 citations and only four publications found in the WOS database (FU *et al*., 2019; LELONG *et al*., 2008; LU *et al*., 2019b; MADEC *et al*., 2019). The first study of this author cataloged here has this researcher as a co-author (LELONG *et al*., 2008), and quantitative monitoring of small wheat plots was conducted using a drone. Finnish researcher Eija Honkavaara was ranked second, with 270 citations and two studies, dealing with processing and radiometric correction of images applied to wheat (HONKAVAARA *et al*., 2013; HONKAVAARA; KHORAMSHAHI, 2018).

Figure 4 shows the production of the main authors with co-citations as a criterion, in which the point size represents the number of publications and the number of lines the number of citations of the publications. They are grouped in the composition of the concept map, bringing it closer to an author (or group of authors) whose texts, also grouped, appear cited together. Thus, researchers who work together and the social structure of the research on UAVs applied to wheat are evidenced. Thus, Figure 4 shows the structure of seven groups of researchers (some may be hidden in the image due to scale) that work together, with at least two documents.

There are two primary groups, one (larger) on the left with five clusters (green, blue, yellow, purple, and orange), in which the most cited authors are Zhu Yan, Tian Yongchao, and Cheng Tao. The group on the right is the smallest (red and brown) and has authors frequently cited, such as Frederic Baret, but more distant from the others. The latter is characterized by being a more heterogeneous group of researchers (according to nationality) and has a very cohesive and emerging cluster in the context of publications (brown). Moreover, the strong collaboration between Chinese researchers is highlighted once again.

The keyword criterion is considered a central element of articles, as it provides a highly summarized form of an article’s content. Keyword selection in relevant studies needs to be systematically analyzed to understand the focus areas and development trends of a field (LIU *et al*., 2016).

Figure 5 shows the main keywords found in the studied articles, considering the co-occurrence of at least two words and the seven clusters of words in order of size: red, green, blue, yellow, purple, gray, and orange. Naturally, words related to UAVs and wheat are present in all groups, with their acronyms and synonyms.

However, some words related to the agronomic parameters of the crop need to be highlighted, such as field phenotyping, height, biomass, leaf area index, nitrogen nutrition index, grain yield, vegetation index, density, canopy reflectance, chlorophyll content, and yellow rust. These words remind us of the capillarity of using drones in the indirect determination of the most diverse parameters. Likewise, there is a significant presence of words related to the use of computer algorithms for machine learning and statistical modeling, such as machine learning, deep learning, prediction, models, segmentation, and gaussian processes regression.

Figure 6 shows the year of emergence/predominance of these terms in the articles, with techniques that relate to the use of red-edge and RGB camera bands being relatively new in this application. Similarly, words related to artificial intelligence are slightly contemporary with the others, with appearance between 2019 and 2020.

**Table 2 -** Ranking of the 26 authors who publish the most and are most frequently cited

| Ranking | Author | Article | % Articles | Citation | % Citations |
|---|---|---|---|---|---|
| 1 | Baret, Frederic | 3 | 0.66 | 390 | 3.76 |
| 2 | Honkavaara, Eija | 2 | 0.44 | 270 | 2.60 |
| 3 | Hakala, Teemu | 1 | 0.22 | 246 | 2.37 |
| 4 | Kaivosoja, Jere | 1 | 0.22 | 246 | 2.37 |
| 5 | Litkey, Paula | 1 | 0.22 | 246 | 2.37 |
| 6 | Makynen, Jussi | 1 | 0.22 | 246 | 2.37 |
| 7 | Pesonen, Liisa | 1 | 0.22 | 246 | 2.37 |
| 8 | Polonen, Ilkka | 1 | 0.22 | 246 | 2.37 |
| 9 | Saari, Heikki | 1 | 0.22 | 246 | 2.37 |
| 10 | Burger, Philippe | 1 | 0.22 | 222 | 2.14 |
| 11 | Jubelin, Guillaume | 1 | 0.22 | 222 | 2.14 |
| 12 | Labbe, Sylvain | 1 | 0.22 | 222 | 2.14 |
| 13 | Lelong, C. C. D. | 1 | 0.22 | 222 | 2.14 |
| 14 | Roux, Bruno | 1 | 0.22 | 222 | 2.14 |
| 15 | Jin, Xiuliang | 3 | 0.66 | 179 | 1.73 |
| 16 | Liu, Shouyang | 3 | 0.66 | 176 | 1.70 |
| 17 | Lopez-Granados, F. | 1 | 0.22 | 135 | 1.30 |
| 18 | Pena, J. M. | 1 | 0.22 | 135 | 1.30 |
| 19 | Torres-Sanchez, J. | 1 | 0.22 | 135 | 1.30 |
| 20 | Comar, Alexis | 1 | 0.22 | 132 | 1.27 |
| 21 | Aemerle, Matthieu | 1 | 0.22 | 132 | 1.27 |
| 22 | Zhu, Yan | 9 | 1.99 | 127 | 1.22 |
| 23 | Tian, Yongchao | 8 | 1.77 | 123 | 1.19 |
| 24 | Cheng, Tao | 6 | 1.33 | 111 | 1.07 |
| 25 | Yao, Xia | 6 | 1.33 | 111 | 1.07 |
| 26 | Yang, Guijun | 7 | 1.55 | 98 | 0.94 |

**Figure 4 -** Relationship between co-authors and citations

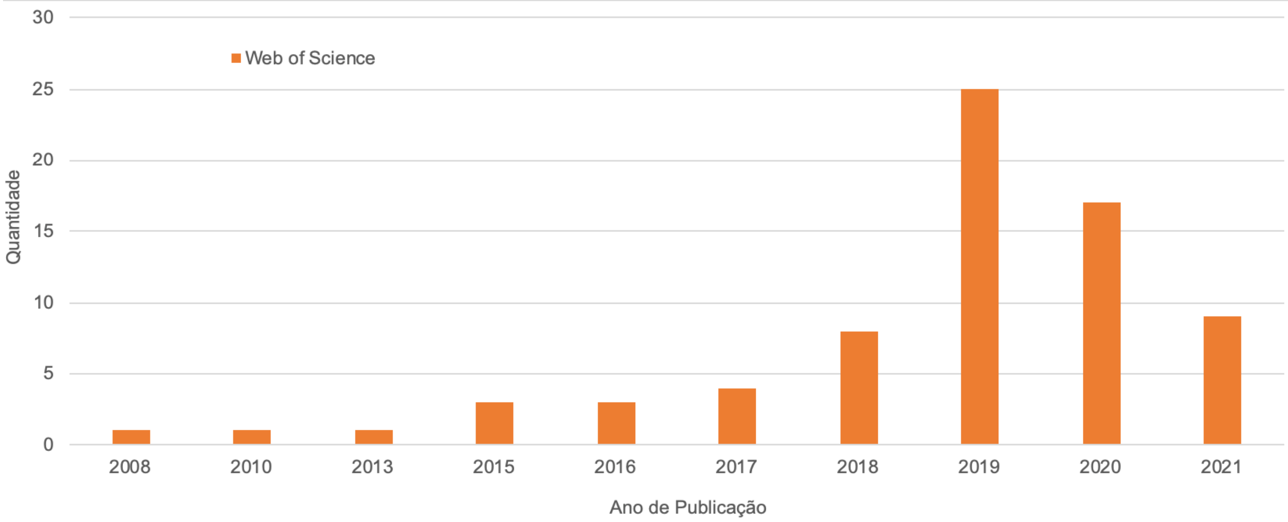
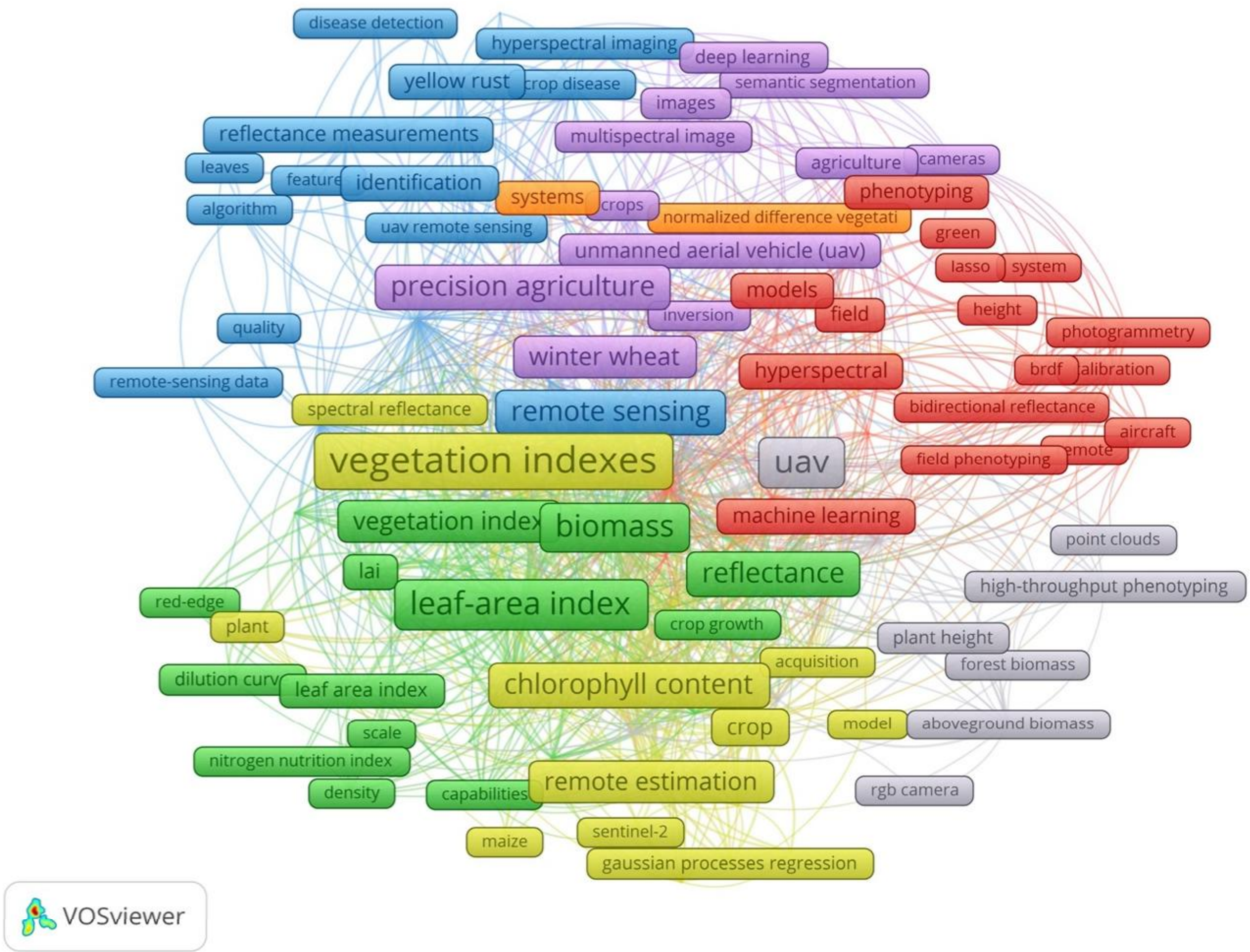


**Figure 5 -** Keywords, where colors represent the groups and size represents the frequency of occurrence




The more “classic” words are those that have emerged more frequently from 2017 onwards, standing out precision agriculture, nitrogen status, index area, and hyperspectral (refers to the use of hyperspectral sensors), among others (Figure 6).

The most used mapping platforms (UAVs) in wheat are shown in Figure 7. There is a predominance of multi-rotor drones, which are the platform used in approximately 95% of the studies. The most used equipment consists of the models Phantom 4 (standard, advanced, and professional), S1000, and Matrice 600 from the Chinese manufacturer DJI. The most used fixed-wing equipment was the e-Bee from Sensefly. Importantly, most of the studies used more than one platform or the same one with different sensors. Only those used in at least two studies were considered, and those with one study were only classified as others, representing 16 articles.

Chinese-made platforms are predominant, especially DJI. However, the German model Microcopter, from the manufacturer MK EASY, is also widely used. The United States is represented by the multi-rotors 3DR model Solo and Topcon model Falcon 8. The use of the model Phantom 4 Multispectral was not observed despite the predominance of DJI platforms. This model is originally manufactured with a 6-band multispectral sensor (RGB, red, green, blue, red edge, and near-infrared).

Remote sensors used in the cataloged studies are attached onboard remotely piloted aircraft. The three types used in wheat are multispectral (45.8%), RGB (36.1%), and hyperspectral (26.4%). We observed that more than one coupled sensor was used simultaneously in part of the studies. Furthermore, this study reveals that the most popular embedded sensors are not Chinese despite the predominance of Chinese platforms in this application.

Twenty out of the 33 studies used multispectral sensors from the French manufacturer Micasense (models 4-band Parrot Sequoia and 5-band RedEdge). Seven studies used the Tetracam sensor (USA). Another less frequent sensor was the Italian MAIA SAL, used in the studies by Fiorentini, Zenobi and Orsini (2021).

**Figure 6 -** Keywords by year of occurrence, where color represents the year and size represents the frequency

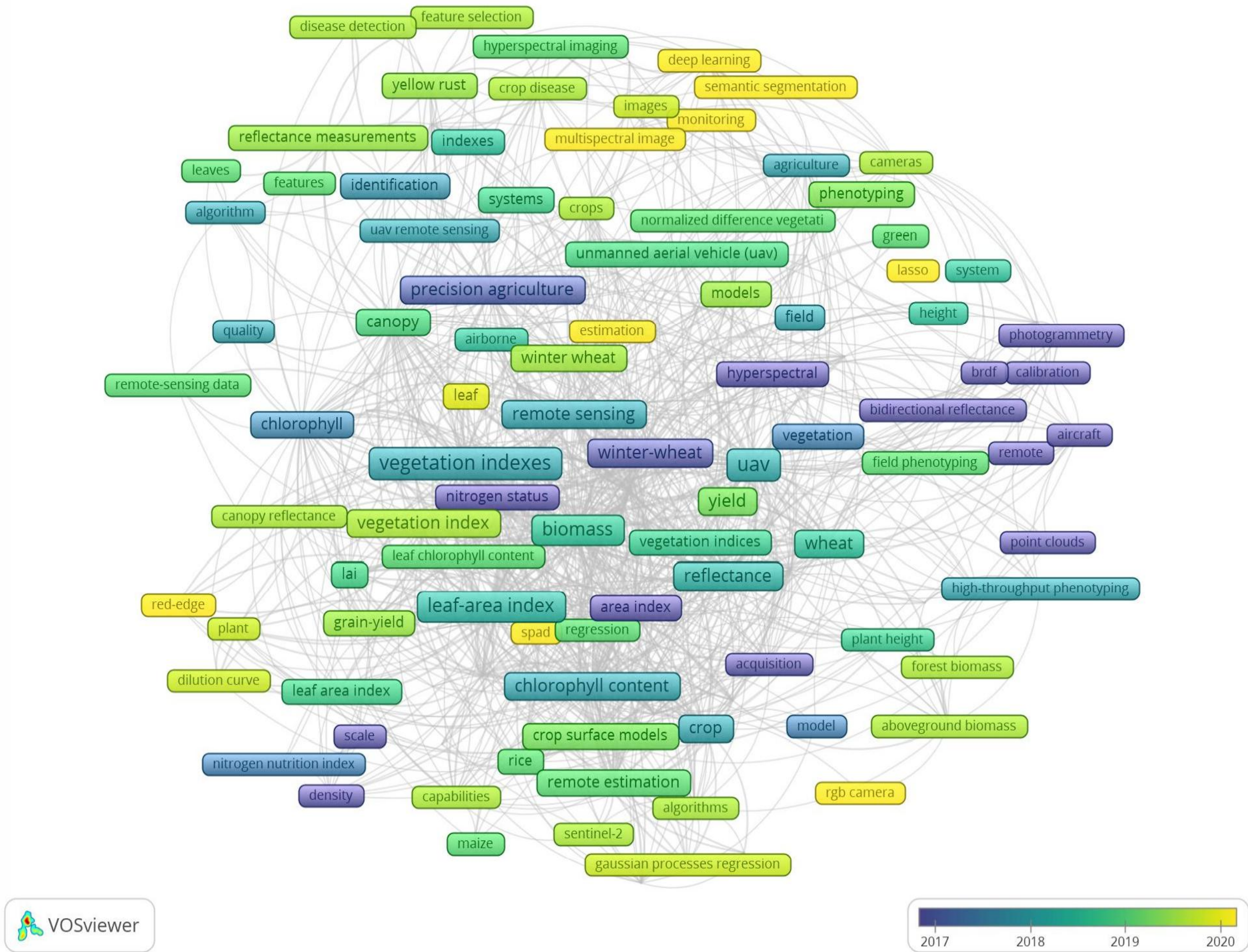
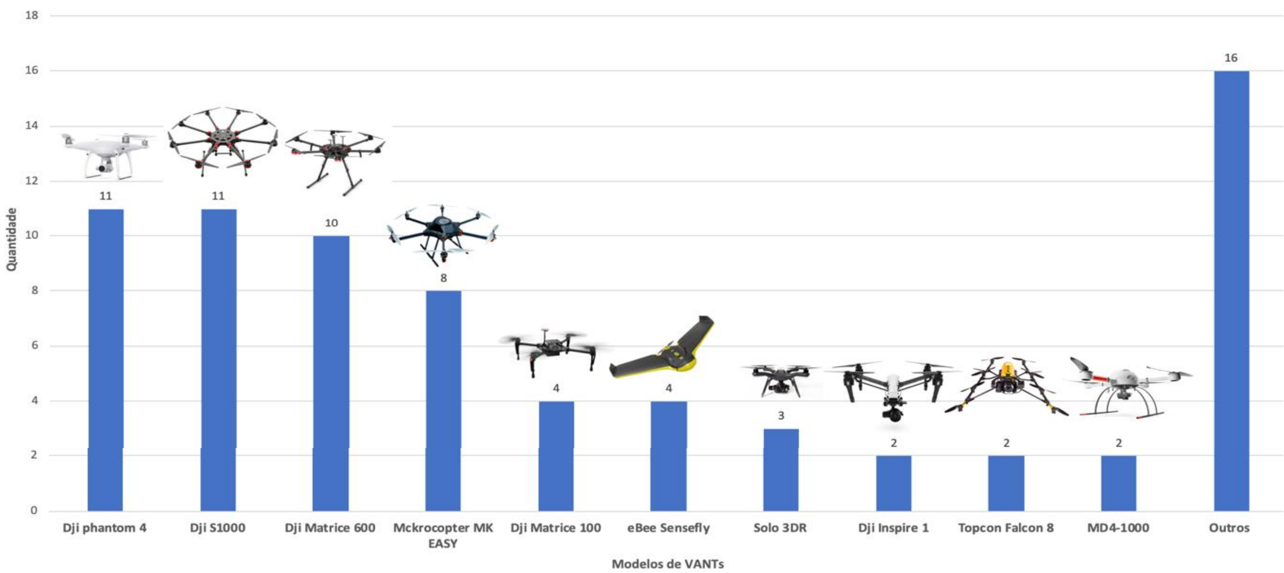



**Figure 7 -** Quantity; UAV models; Others



Studies that used the visible spectrum band (RGB) had a predominance of Chinese sensors (models coupled to Phantom 4), although many studies used Japanese sensors such as Sony and Canon. Hyperspectral sensors were used not only coupled to flying platforms but also as in situ proximal sensors for calibration and validation of aerial sensors.

The latter stood out with the spectroradiometer FieldEspec from the manufacturer ASD (USA), among other various proximal sensors of different wavelengths. The use of orbital sensors associated with drones in the studies of this crop was also found. The products of the Sentinel-2 orbital sensor from the European Space Agency are used in at least three studies (REVILL *et al*., 2019, 2020; ZHANG, S. *et al*., 2019).

Table 3 shows the studied agronomic variables separated into six main thematic axes. Most of the studies (27.8%) focus on the investigation of the existing relationships between the yield components of wheat and its correlation with vegetation indices. Plant genetic improvement (phenotyping) studies are also included in this topic, and the selection and productivity analyses are carried out.

The second cluster (19.4%) is dedicated to studies related to the nutritional status of the crop, especially trials with the application of different nitrogen doses. In equal proportion, the third cluster presents studies related to the spectral-temporal monitoring of the wheat crop, all of them with periodic flights and field evaluations of the vegetative crop stage and agronomic parameters (Table 3).

The highlight of the fourth cluster (16.7%) is the indirect determination of the leaf area index (LAI). These studies are also applied in the determination of chlorophyll content, dry matter, and biomass. Yellow rust is the most investigated wheat disease through UAVs, which, together with other diseases and pests, account for 15.4% of the studies in the fifth cluster.

**Table 3** - Thematic axes of UAV applications in wheat

| Type of study | Proportion | Authors |
|---|---|---|
| - Grain yield – Productivity - Phenotyping | 27.8% | Shafiee *et al*. (2021), Volpato *et al.* (2021), Zhou *et al.* (2021), Fernandez-Gallego *et al.* (2020), Moghimi, Yang and Anderson (2020), Bukowiecki *et al*. (2020), Z. Fu *et al.* ( ), J. Jiang *et al.* ( ), Ma *et al.* (2020), Li *et al.* (2019), Sadeghi-Tehran *et al.* (2019), Ostos-Garrido *et al.* (2019), Holman *et al*. (2019), Hassan *et al.* (2019), Madec *et al*. (2019), Guan *et al.* (2019), Kanning *et al.* (2018), Z. Fu *et al.* ( ), J. J. Jiang *et al.* ( ); Haghighattalab *et al.* (2016), Sankaran, Khot and Carter (2015) and Overgaard *et al.* (2010). |
| - Nutritional status - Nitrogen fertilization | 19.4% | Fiorentini, Zenobi and Orsini (2021), Jie Jiang *et al.* (2020), Y. Fu ( ), G. Yang *et al*. ( ), H. Liu *et al*. (2020), Lu ( ), Wang *et al*. (2019), Jiale Jiang ( ), Cai *et al.* ( ), Dong *et al*. (2019), Chen *et al*. (2019), H. Zhao *et al*. (2019), L. Yao *et al.* (2019), H. Zheng *et al.* (2018), Zhu *et al.* (2018), Latif *et al.* (2018). |
| - Monitoring - Spectro-temporal | 19.4% | T. Zhang *et al*. (2021), Z. Fu *et al*. ( ), J. Jiang *et al*. (); Revill *et al*. ( ), S. Zhang *et al*. (2019), Jiale Jiang (), Zheng *et al*. ( ), J. Zhao *et al*. (2018), Honkavaara and Khoramshahi (2018), X. Yao *et al*. (2017), Mengmeng *et al*. (2017), Roosjen *et al*. (2016), Schirrmann *et al*. (2016), Burkart *et al*. (2015), Honkavaara *et al*. (2013), Lelong *et al*. (2008). |
| - Biomass - Leaf area index - Chlorophyll | 16.7% | Khadka *et al*. (2021), Y. Fu ( ), G. Yang *et al*. ( ), Banerjee, Spangenberg and Kant (2020), Revill ( ), Tao *et al.* (2020), Hasan *et al*. (2019), Yue *et al.* ( ), Lu ( ), Zhou *et al*. (2021), Kanning *et al*. (2018), Mozgeris *et al*. (2018), X. Yao *et al*. (2017). |
| - Diseases - Pests | 15.4% | Su ( ), Yi *et al.* ( ), Guo *et al.* (2021), Heidarian Dehkordi *et al.* (2020), L. Liu *et al*. (2020), Q. Zheng *et al*. (2020), Bhandari *et al*. (2020), Su ( ), Liu *et al*. ( ), Bohnenkamp, Behmann and Mahlein (2019), Rasmussen *et al.* (2019), Mateen and Zhu (2019), X. Zhang *et al*. (2019), Torres-Sanchez, Lopez-Granados and Pena (2015). |
| - Population - Uniformity | 6.9% | T. Liu *et al*. (2017), Hu, Chapman and Zheng (2021), Jin *et al*. (2017), Schirrmann *et al.* (2016) and Sankaran, Khot and Carter (2015). |

The least researched topic (6.9%) concerns experiments at initial plant stages, in which plant densities per square meter, planting uniformity, emergence rate, among others, are commonly evaluated. This result is attributed to the fact that wheat is grass with high complexity in the application of image classification techniques and plant counting algorithms in its initial stage despite the high spatial resolutions provided by sensors embedded on drones. About 8% of the studies fit into more than one thematic axis established by this scientific research.

## CONCLUSIONS

1. The year 2019 presented the highest number of publications and China was the country with the highest number of publications and, consequently, the highest number of authors. The decrease in the average number of publications in 2020 june be related to the Covid-19 pandemic. Nanjing Agricultural University is the institution with the highest number of publications and Remote Sensing is the journal that publishes the most. The most influential author (most-cited) is Frederic Baret (France) from INRA – Institut National de la Agronomique, with 390 citations;
2. A contemporary trend was observed in the use of machine learning techniques, especially statistical analyses. However, further studies are suggested in South American countries, where there is an expressive wheat production;
3. Multi-rotors and multispectral sensors comprise most platforms and sensors used in the studies, with the main line of investigation being aspects related to crop yield components. The use of this type of UAV in most studies is attributed to the fact that Asia (most studies) has a predominance of small areas, in which the use of multi-rotors is ideal;
4. The studies presented in this research are considered sufficient from the point of view of bibliometric analysis of the Web of Science database to have a global panorama of the use of drones as a platform for mapping the wheat crop. Furthermore, the main agronomic characters investigated through this Remote Sensing technology could be observed.

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