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GEOSCIENCES

Use of remotely piloted aircraft systems in monitoring pest and diseases in agricultural crops: global literature review

Fernando Coelho Eugenio[1], Filipe Rocha Louzada Soares[1], Jaine Honorato Oliveira da Silva[1], Régis Ruoso[1] and Roberta Aparecida Fantinel[2*]

[1]Universidade Federal de Santa Maria, Rodovia Taufik Germano, 3013, 96503-205, Passo D'Areia, Cachoeira do Sul, Rio Grande do Sul, Brazil. [2]Universidade Federal de Santa Maria, Camobi, Santa Maria, Rio Grande do Sul, Brazil. *Author for correspondence. E-mail: fantinel.ar@gmail.com

ABSTRACT. The use of Remotely Piloted Aircraft Systems (RPAS) as Remote Sensing platforms has been gaining more and more applicability in various fields of study, one of them being the agricultural sector. The interest in this technology segment is mainly due to its flexibility to acquire high-resolution data quickly. Data that helps, for example, identify and monitor pests and diseases. Therefore, this work aims to develop a systematic analysis at a global level to assess the evolution of publications over the years and the current state of the art in the use of RPAS technology in monitoring pests and diseases in crops. Twenty-nine scientific articles came from the Web of Science, Scopus, and Google Scholar platforms, identifying the places of origin of publications, agricultural species, platforms, and sensors. China and the United States published most of the works. Multirotor platforms have been more used compared to fixed-wing platforms. RGB (Red, Green, and Blue) and Multispectral sensors totaled 25% and 40.44%, respectively. It is expected that technological advances and RPAS improvement increasingly strengthened the control of pests and diseases in crops, contributing to a greater appreciation of the benefits of this system.

Keywords: agriculture; Sensors; Platforms.

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Introduction

Identifying the appearance of pests and diseases early in crops is extremely important so that the producer can take precautions in advance and thus avoid considerable economic losses. Thus, real-time monitoring and identification of pests and diseases in agricultural plantations (PDPA) are the basis for timely prevention and control. Traditionally, land surveys have been the only practical approach to monitoring and discriminating these PDPAs. However, these are often time-consuming and expensive.

Visual assessment of disease severity, for example, is often subject to subjectivity, in addition to being laborious (Bock, Poole, Parker & Gottwald, 2010; El Jarroudi et al., 2014). Therefore, Remote Sensing (SR) has become a viable technology for detecting and evaluating PDPA in recent decades.

The perspective these images provide of the target areas offers an objective assessment and a low-cost method for monitoring large areas compared to land-based exploration (Dash, Watt, Pearse, Heaphy, & Dungey, 2017). Furthermore, these images provide a panoramic view of growing areas, so early detection of pests and diseases in their spatial extent can help contain the spread and reduce production losses. Ahmad, Ordoñez, Cartujo, and Martos (2021) highlight an increase in the application of RPAS in agriculture in recent years along with the development of new strategies and data acquisition and analysis. Thus, images acquired through RPAS are increasingly calling attention to the discrimination of healthy plants from diseased plants, in addition to monitoring the progress of such diseases in the field Dehkordi, El Jarroudi, Kouadio, Meersmans, & Beyer, 2020).

Studies carried out by Roosjen, Kellenberger, Kooistra, Green, and Fahrentrapp (2020) highlighted the potential of RPAS in detecting *Drosophila suzukii* (spotted wing drosophila) in fruits. Song et al. (2020) estimated reed loss caused by the *Locusta migratoria manilensis* (locust) attack using hyperspectral data based on RPAS. Maes and Steppe (2019), Ampatzidis and Partel (2019), Romero, Luo, Su, and Fuentes (2018) used RPAS in precision agriculture to detect weeds, diseases, assessment of vegetation cover, nutritional status, growth vigor, and water stress.

In this context, the use of RPAS to detect PDPA during crop growth stages can help implement effective management plans promptly to avoid or mitigate significant losses in yield and quality. Given the above, the present work aimed to perform a systematic review at a global level to analyze the publications' evolution over the years and state of art on the use of RPAS technology in monitoring pests and diseases in crops.

Material and methods

The research methodology adopted is the systematic and bibliometric review of recent publications in RPAS application. For this purpose, the searches were performed on the scientific information platforms Web of Science, Scopus, and Google Scholar, widely applied in the institutional and scientific scope.

The search configured the descriptors of scientific articles according to the combinations of terms (Table 1). The period considered for the research comprised the year 2000 to 2020 and considered the descriptors in titles, keywords, and abstracts.

Table 1. Descriptors used to search for scientific articles on the Web of Science, Scopus and Capes platforms.

Thematic areas	Descriptive terms
Platform	"RPAS" "UAS" "UAV"
Area	"Agriculture" "Agricultural"
Application	"Pests" "Disease"

Search for scientific articles

The identification phase returned 625 articles. After reading the abstract, 588 articles were excluded in the selection phase as they did not meet the research purpose. The Eligibility phase had 37 articles within the subject under study. However, the publications were grouped regardless of the search platform, excluding two articles repeated between platforms. Thus, in the Inclusion phase, 29 articles were kept for systematic review.

Figure 1 illustrates the flowchart of the PRISMA method (Liberati et al., 2009), describing the four phases applied for the selection of articles.

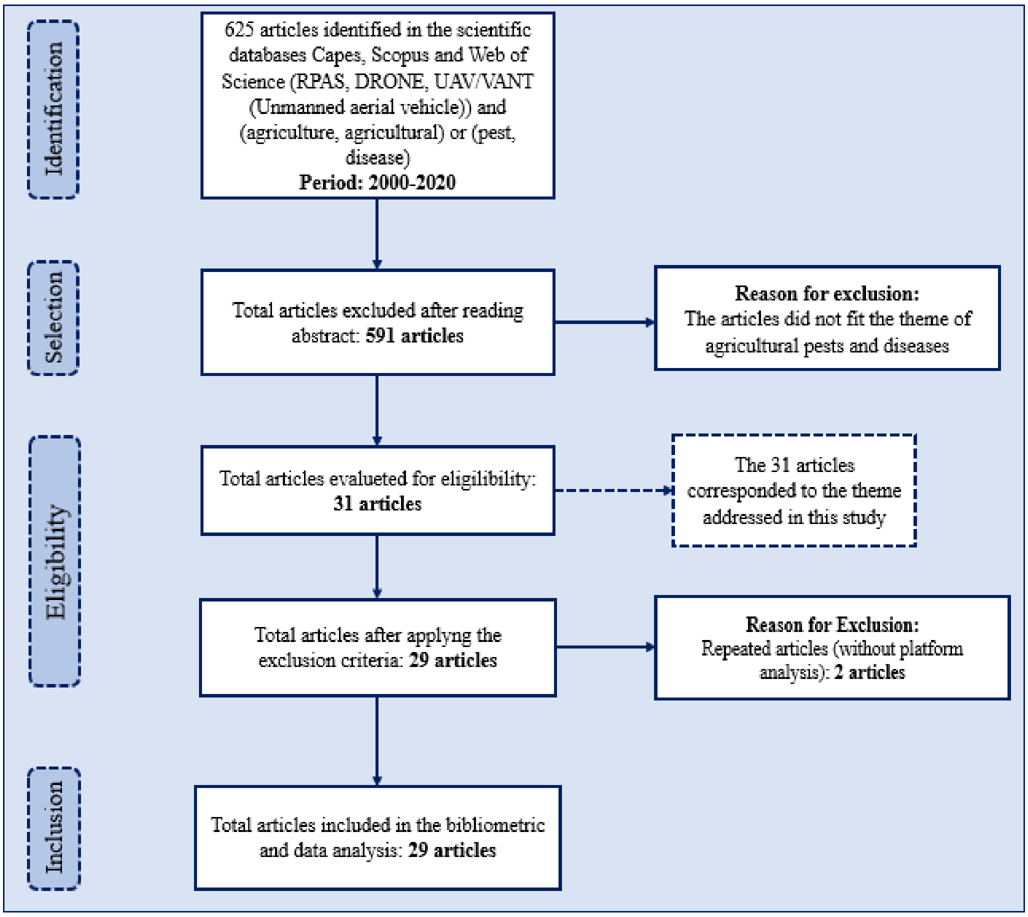

Figure 1. Identification and selection of articles for systematic review on the use of RPAS in monitoring pests and diseases in agriculture.

Data processing and analysis

Microsoft Excel® spreadsheet tabulated the data for analysis and quantification, with the following study variables: article title, journal name, country, author, year of publication, descriptors, thematic axis (pests or diseases), type of platforms, and sensor. Subsequently to the data tabulation, quantitative analyzes were carried out at different levels, enabling a better approach related to trends and contributions to the practical application of RPAS. Finally, it addresses the most recurrent aspects of its application and the important advances, trends, and innovations.

Results and discussion

Use of RPAS applied to pests and diseases in agriculture

Figure 2 shows the number of publications over time, over 20 years. Discussion on the topic of PDPA starts from 2016 onwards, but the evolution in 2018 is notorious. In subsequent years there was a decline in publications. This fact may be related to research that is still not widespread on the application of RPAS in PDPA. However, it is essential to highlight that RPAS positively helps monitor attacks or invasion of pests and diseases and can promote significant gains compared to conventional methods.

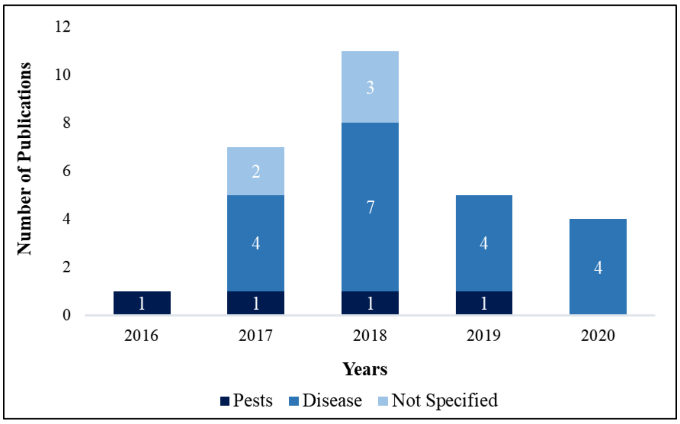

Figure 2. Number of publications related to agricultural pests and diseases over the years.

According to Eugenio and Zago (2019), the use of RPAS is recent in the agricultural sector and, consequently, there is a lack of studies, a fact that may be related to the high cost of sensors coupled to RPAS, lack of qualified professionals and the non-popularization of the technology in the agricultural scope.

RPAS to help monitor PDPA has an evolutionary trend in disseminating scientific production, so that research has been carried out in almost all countries (Figure 3). The most prominent countries in the production of scientific articles were China (27.6%), the United States (USA) (17.24%), followed by Switzerland (7%). Africa, Iran, Brazil, and Germany totaled 6.90% each, while India, Australia, France, Greece, and Japan totaled 3.45% each. Only one article (3.45%) did not inform the research's country.

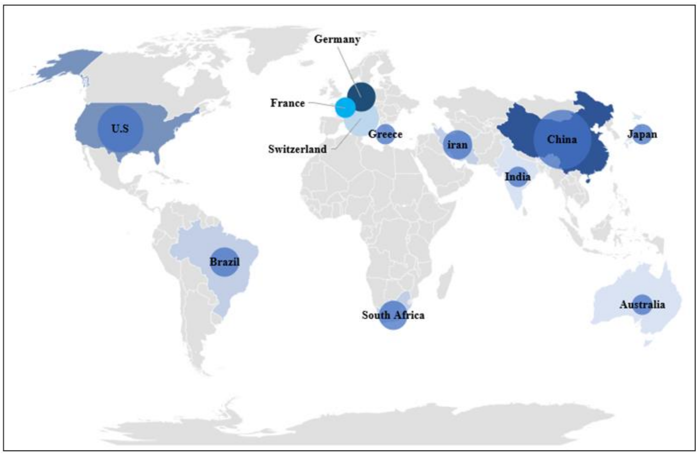

Figure 3. Classification of articles by countries.

The fact that China and the USA have many publications may be related to the concentration of agricultural activities in these countries. For example, according to Leusin Jr. (2017), China is the world's largest producer of rice and tobacco, the second-largest wheat and corn producer, and the fourth-largest soy producer. This fact corroborates Yang, Yang, and Mo (2017), in which they highlight that the main applications of RPAS in China are due to the efficient management of pests and diseases, aiming to increase crop protection. On the other hand, the US produced in 2017-2018 a total of 20.9 million bales of 218 kg cotton, with a production value of $7.2 billion (USD), ranking third after India and China, and is the largest cotton exporting country in the world (USDA, 2017).

Agricultural species

Four groups classify agricultural species: annual, perennial, greenhouse, and uninformed crops (Figure 4). Most studies refer to perennial crops, with *Triticum* sp. (wheat) with 20%, *Zea mays* (corn) (10%), *Pyrus* (pear), *Gossypium* (cotton), and *Solanum lycopersicum* (tomato) totaled 6.67% each. According to Liakos, Busato, Moshou, Pearson, and Bochtis (2018), wheat is one of the most economically influential cultures in the world.

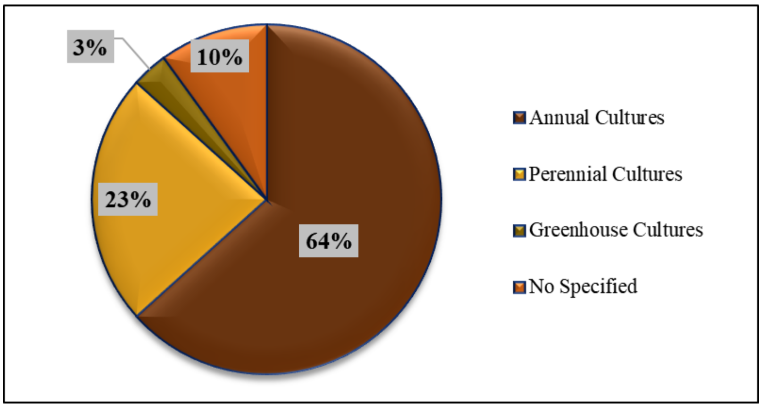

Figure 4. Classification of publications by agricultural crops.

Dehkordi et al. (2020) evaluated, through RGB images obtained from RPAS, healthy plants infected by leaf rust of *Triticum aestivum* L. (wheat), aiming at a system to assist producers in improving the management of this disease. Furthermore, studies carried out by Chivasa, Mutanga, and Biradar (2020) aimed to evaluate the phenotyping efficiency of *Zea mays* L. (maize) crop using RPAS data in response to corn streak virus disease. Finally, Tetila, Machado, Belete, Guimarães, and Pistori (2017) used RPAS images to identify leaf diseases in Glycine max (soybean), indicating the great possibility of using imaging tools to detect leaf anomalies.

Perennial crops represent 23% of the use of images obtained from RPAS for pests and diseases. Bagheri, Mohamadi-Monavar, Azizi, and Ghasemi (2018) evaluated the fire blight in pear orchards at leaf and treetop levels. Abdulridha, Batuman, and Ampatzidis (2019) used RPAS images to detect cancer in *Tangerine sugar* Belle treetops. Studies carried out by Mattupalli, Moffet, Shah, and Young (2018) aimed to develop a workflow to produce maps of Phymatotrichopsis root rot disease that affects the culture of *Medicago sativa* L. (alfalfa), through sets of high-resolution images acquired from two different platforms, as well as evaluating the feasibility of using the maps to monitor disease progression in alfalfa fields. Ye et al. (2020) used multispectral images to identify locations infested or not with Fusarium wilt, a disease that attacks banana plantations. Using RPAS images and a multispectral camera, Heim et al. (2019) could discriminate myrtle rust (*Austropuccinia psidii*) in lemon trees treated and not treated with fungicide at the canopy level. Next, with 10% of publications, greenhouse crops stand out. Attada and Katta (2019) used RPAS images to detect pests in greenhouse crops.

Platforms and Sensors

The most used RPAS platform was the multirotor type, representing 75% of the analyzed articles, and 25% were the fixed-wing ones. Regarding the sensors embedded in the RPAS (Figure 5), 44.44% of the studies used multispectral cameras, mostly coupled to multirotor platforms. On the other hand, RGB and hyperspectral sensors accounted for 25% and 13.89%, respectively, while 16.67% of authors did not inform the type of sensor used.

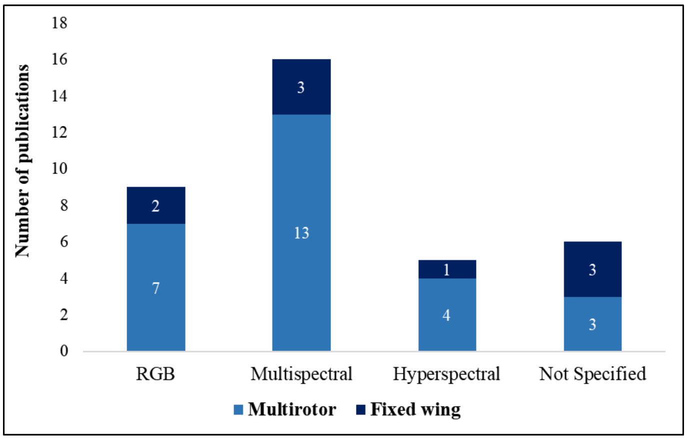

Figure 5. Relationship between sensor type and platform type.

Eugenio et al. (2020) highlighted the combination of different sensors as the current and next step in applications using RPAS, with the integration of artificial intelligence algorithms. Regarding multispectral sensors, their wide use is related to capturing critical information about vegetation (Chianucci et al., 2016). The main advantage of RGB sensors is their high availability, high spatial resolution, and low cost of the cameras, compared to other types of sensors (García-Berná et al., 2020).

It is important to emphasize that all sensors had the preference to use multirotor platforms. One of the features of these platforms is the ability to land and take off vertically and facilitate the assessment of small areas compared to fixed-wing models (Eugenio et al., 2020). Furthermore, according to Del Cerro, Ulloa Barrientos, and De León Rivas (2021), multirotor has become more popular due to their mechanical simplicity.

Conclusion

Scientific publications emphasized the use of RPAS from 2016 onwards, which shows that research related to pests and diseases in crops is recent. However, these techniques have shown promising results in mapping and identifying the damage caused by PDPA. Also, most research using sensors embedded in RPAS focus on diseases. However, there is a greater need for reproducible research and applicable to pests in agricultural species. Concerning the agricultural species analyzed, there is greater interest on the part of researchers in annual crops. Among the articles analyzed, the most frequent platform was the multirotor type. The information obtained by RPAS offers a range of possibilities for monitoring at all stages of the crop cycle. When incorporated with sensors that allow spatial data acquisition, they become an essential tool for real-time visualization. One of the challenges of monitoring pests and diseases through data acquisition with RPAS is developing techniques that recognize anomaly patterns. Another point to be highlighted is acquiring data with RPAS, which requires significant technical knowledge and experience to process them. Finally, it is necessary to highlight that the technological advances and improvement of RPAS have increasingly facilitated the accurate assessment in large areas in a short time and at a lower cost, aiming to improve the quality of information used for decision-making. Likewise, Big Data and deep learning approaches can also be included in the image processing for the stages of detection and identification of pests and diseases, thus aiming to contribute to their control effectively. It is expected that with the advancement of RPAS platform technology, new camera designs, improved image processing techniques, and a more significant number of RPAS-based Remote Sensing studies for pest and disease application in crops will be increasingly strengthened, contributing to a greater appreciation of the benefits of these systems.

References

Abdulridha, J., Batuman, O., & Ampatzidis, Y. (2019). UAV-based remote sensing technique to detect citrus canker disease utilizing hyperspectral imaging and machine learning. *Remote Sensing*, *11*(11), 1-22. DOI: https://doi.org/10.3390/rs11111373

Ahmad, A., Ordoñez, J., Cartujo, P., & Martos, V. (2020). Aeronaves pilotadas remotamente (RPA) na agricultura: uma busca pela sustentabilidade. *Agronomy, 11*(1), 1-25. DOI: https://doi.org/10.3390/agronomy11010007

Ampatzidis, Y., & Partel, V. (2019). High-throughput UAV-based phenotyping in citrus using multispectral imaging and artificial intelligence. *Remote Sensing*, *11*(4), 1-19. DOI: https://doi.org/10.3390/rs11040410

Attada, V., & Katta, S. (2019). Uma Metodologia para Detecção e Classificação Automática de Pragas Utilizando SVM Otimizado em Cultivos de Efeito Estufa. *Jornal Internacional de Engenharia e Tecnologia Avançada, 8*(6), 1485-1491. DOI: https://doi.org/10.35940/ijeat.F8133.088619

Bagheri, N., Mohamadi-Monavar, H., Azizi, A., & Ghasemi, A. (2018). Detection of Fire Blight disease in pear trees by hyperspectral data. *European Journal of Remote Sensing*, *51*(1), 1-10. DOI: http://doi.org/10.1080/22797254.2017.1391054

Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. (2010). Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Critical Reviews in Plant Sciences, 29*(2), 59-107. DOI: http://doi.org/10.1080/07352681003617285

Chianucci, F., Disperati, L., Guzzi, D., Bianchini, D., Nardino, V., Lastri, C., & Corona, P. (2016). Estimation of canopy attributes in beech forests using true colour digital images from a small fixed-wing UAV. *International Journal of Applied Earth Observation and Geoinformation*, *47*, 60-68. DOI: https://doi.org/10.1016/j.jag.2015.12.005

Chivasa, W., Mutanga, O., & Biradar, C. (2020). UAV-Based Multispectral Phenotyping for Disease Resistance to Accelerate Crop Improvement under Changing Climate Conditions. *Remote Sensing, 12*(15), 1-27. DOI: https://doi.org/10.3390/rs12152445

Dash, J. P., Watt, M. S., Pearse, G. D., Heaphy, M., & Dungey, H. S. (2017). Assessing very high resolution UAV imagery for monitoring forest health during a simulated disease outbreak. *ISPRS Journal of Photogrammetry and Remote Sensing*, *131*, 1-14. DOI: https://doi.org/10.1016/j.isprsjprs.2017.07.007

Del Cerro, J., Ulloa, C. C., Barrientos, A., & De León Rivas, J. (2021). Unmanned aerial vehicles in agriculture: A survey. *Agronomy*, *11*(2), 1-19. DOI: https://doi.org/10.3390/agronomy11020203

Dehkordi, R. H., El Jarroudi, M., Kouadio, L., Meersmans, J., & Beyer, M. (2020). Monitoring wheat leaf rust and stripe rust in winter wheat using high-resolution UAV-based red-green-blue imagery. *Remote Sensing*, *12*(22), 3696. DOI: https://doi.org/10.3390/rs12223696

El Jarroudi, M., Kouadio, A. L., Mackels, C., Tychon, B., Delfosse, P., & Bock, C. H. (2014). A comparison between visual estimates and image analysis measurements to determine Septoria leaf blotch severity in winter wheat. *Plant Pathology*, *64*(2), 355-364. DOI: https://doi.org/10.1111/ppa.12252

Eugenio, F. C., Schons, C. T., Mallmann, C. L., Schuh, M. S., Fernandes, P., & Badin, T. L. (2020). Remotely piloted aircraft systems and forests: A global state of the art and future challenges. *Canadian Journal of Forest Research*, *50*(8), 705-716. DOI: 10.1139/cjfr-2019-0375

Eugenio, F. C., & Zago, H. B. (2019). *O livro dos drones: um guia completo para entender todas as partes e funcionamento* (1. ed.). Alegre, ES: CAUFES.

García-Berná, J. A., Ouhbi, S., Benmouna, B., Garcia-Mateos, G., Fernández-Alemán, J. L., & Molina-Martínez, J. M. (2020). Systematic Mapping Study on Remote Sensing in Agriculture. *Applied Sciences*, *10*(10), 1-29. DOI: https://doi.org/10.3390/app10103456

Heim, R. H., Wright, I. J., Scarth, P., Carnegie, A. J., Taylor, D., & Oldeland, J. (2019). Multispectral, aerial disease detection for myrtle rust (*Austropuccinia psidii*) on a lemon myrtle plantation. *Drones, 3*(1), 1-14, DOI: https://doi.org/10.3390/drones3010025

Leusin Jr., S. (2017). China e sua agricultura: desafios e possíveis implicações para o Brasil. *Panorama Internacional, 2*(3), 1-7.

Liakos, K. G. Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 1-29. DOI: https://doi.org/10.3390/s18082674

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P., … Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Journal of Clinical Epidemiology*, *62*(10), 1-34. DOI: https://doi.org/10.1016/j.jclinepi.2009.06.006

Maes, W. H., & Steppe, K. (2019). Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends Plant Sci*ence, *24*(2), 152-164. DOI: https://doi.org/10.1016/j.tplants.2018.11.007

Mattupalli, C., Moffet, C. A., Shah, K. N., & Young, C. A. (2018). Supervised classification of RGB aerial imagery to evaluate the impact of a root rot disease. *Remote Sensing*, *10*(6), 1-17. DOI: https://doi.org/10.3390/rs10060917

Romero, M., Luo, Y., Su, B., & Fuentes, S. (2018). Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management. *Computers and Electronics in Agriculture*, *147*, 109-117. DOI: https://doi.org/10.1016/j.compag.2018.02.013

Roosjen, P. P., Kellenberger, B., Kooistra, L., Green, D. R., & Fahrentrapp, J. (2020). Deep learning for automated detection of Drosophila suzukii: potential for UAV-based monitoring. *Pest Management Science*, *76*(9), 2994-3002. DOI: https://doi.org/10.1002/ps.5845

Song, P., Zheng, X., Li, Y., Zhang, K., Huang, J., Li, H., ... Wang, X. (2020). Estimating reed loss caused by Locusta migratoria manilensis using UAV-based hyperspectral data. *Science of The Total Environment*, *719*, 137519. DOI: https://doi.org/10.1016/j.scitotenv.2020.137519

Tetila, E. C., Machado, B. B., Belete, N. A., Guimarães, D. A., & Pistori, H. (2017). Identification of soybean foliar diseases using unmanned aerial vehicle images. *IEEE Geoscience and Remote Sensing Letters*, *14*(12), 2190-2194. DOI: https://doi.org/10.1109/LGRS.2017.2743715

United States Department of Agriculture [USDA]. (2017). *Census of Agriculture*. Washington, D.C.: USDA.

Yang, S., Yang, X., & Mo, J. (2017). The application of unmanned aircraft systems to plant protection in China. *Precision Agriculture*, *19*(2), 278-292. DOI: https://doi.org/10.1007/s11119-017-9516-7

Ye, H., Huang, W., Huang, S., Cui, B., Dong, Y., Guo, A., ... Jin, Y. (2020). Identification of banana fusarium wilt using supervised classification algorithms with UAV-based multi-spectral imagery. *International Journal of Agricultural and Biological Engineering*, *13*(3), p. 136-142. DOI: https://doi.org/10.25165/j.ijabe.20201303.5524