

Innovations in Agriculture for Sustainable Agro-Systems

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1. Context

Agriculture has changed dramatically and has been improved due to new technologies. Smart technologies, such as artificial intelligence, robotics, and the Internet of Things, play an important role in achieving enhanced productivity. However, their implications on the ecosystem are unknown or underestimated.

In addition to favoring production, innovations in agriculture may have many positive environmental impacts such as reductions in agrochemicals application, saving water and energy, waste reduction, and prevention of water, soil, and air pollution.

Undoubtedly, there are no shortage of uses for these technologies; multispectral cameras, sensors, and drones are combined with appropriate software and robotic or conventional systems to remove weeds or for the precise application of herbicides and fertilizers. Smart agriculture approaches already include disease prediction models to adjust the greenhouse environment or reduce infections to aid growers in early disease detection.

However, some of the smart technologies that are already in use may have undesirable impacts on the environment, as well as on wider society. For this, a responsible innovation should be further developed in order to provide the most benefits in agriculture, while at the same time, it should be environmentally friendly. In light of this method of development, the possibilities and limitations of innovations should be explored.

This Special Issue, entitled “Innovations in Agriculture for Sustainable Agro-Systems”, aims to highlight responsible innovation and contribute to the further development of new ideas for establishing sustainable agro-systems. Smart technologies certainly have the potential to solve many problems in the agricultural sector and meet the challenges of modern agricultural production, increase farmers’ capacity for action, and improve agricultural ecosystems. However, digital technology brings changes in society that are often accompanied by inherent risks. The agricultural sector is no exception. Many questions, therefore, are being raised about whether innovations in agriculture can meet expectations, which of them can be applied on a practical level, what difficulties may be encountered, what vulnerabilities they could raise, and finally, what is the implementation cost and financial benefit [1]. In this sense, new technologies, which are often proposed as solutions to overcome problems that pose barriers to agricultural production, still have many technical and governance issues. In addition, the application of the new technology also requires the building of knowledge and skills about these new, different, and complex systems, as well as the establishment of necessary infrastructures by producers and the state. Technology and equipment must be used to improve agricultural production such as 3D, infrared, multispectral, hyperspectral, and satellite image processing [2], identification and geolocation using RFID or GPS [3], ultrasonic and biochemical measurements on fluids, weighing scales, water meters, use of robots, etc. [4,5], has been the subject of numerous studies in recent decades [1]. For this reason, a literature review is necessary to identify what is considered a realistic application of technology in the agricultural sector.

Based on that, we used the Scopus database to drive future scientific research and technology development efforts with “Innovations in Agriculture for Sustainable Agro-Systems”. Scientific issues such as “Smart technologies”, “Artificial intelligence”, “Robotics”,



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and “The Internet of Things” were further investigated using the VOSviewer mapping software [6–9].

2. Why Is This Special Issue Important in Agriculture?

To evaluate the intensity of the introduction of innovations in agriculture, the Scopus database was accessed on 7 August 2023. Though the term “innovation in the agricultural sector” is a broad subject and includes all new ideas and technologies that prove successful in practice, the initial search in the Scopus database for the needs of this Special Issue, performed with keywords “Agriculture” AND “Sustainable”, filtering the search results to keywords up to “Smart technologies” or “Artificial intelligence” or “Robotics” or “Internet of Things”.

The Scopus bibliographic database yielded a total of 443.601 and 14.087 documents based on the search strategy criteria “Agriculture” and “Sustainable”, and 16.217, 6.861, 3.114, and 4.898 documents based on the search strategy criteria “Smart technologies” or “Artificial intelligence” or “Robotics” or “Internet of Things”, respectively. The results are presented as graph-based maps by creating a map based on bibliographic data as distance-based maps to reflect the strength of the relation between the items [9]. All distance-based and graph-based maps were analyzed using the following methods of analysis (i) the type of analysis: co-occurrence; (ii) the unit of analysis: all keywords; and (iii) the counting method: full counting.

Figures 1–4 show the co-keyword network of the keywords visualized using the bibliometric analysis software VOSviewer. In detail, the co-keyword network visualization was: “Agriculture” AND “Sustainable” AND “Smart technologies” (Figure 1), “Agriculture” AND “Sustainable” AND “Artificial intelligence” (Figure 2), “Agriculture” AND “Sustainable” AND “Robotics” (Figure 3), and “Agriculture” AND “Sustainable” AND “Internet of Things” (Figure 4). The size of a keyword node represents the keyword occurrence frequency. A link between two nodes represents a co-occurrence relationship, with the thickness indicating the length strength.

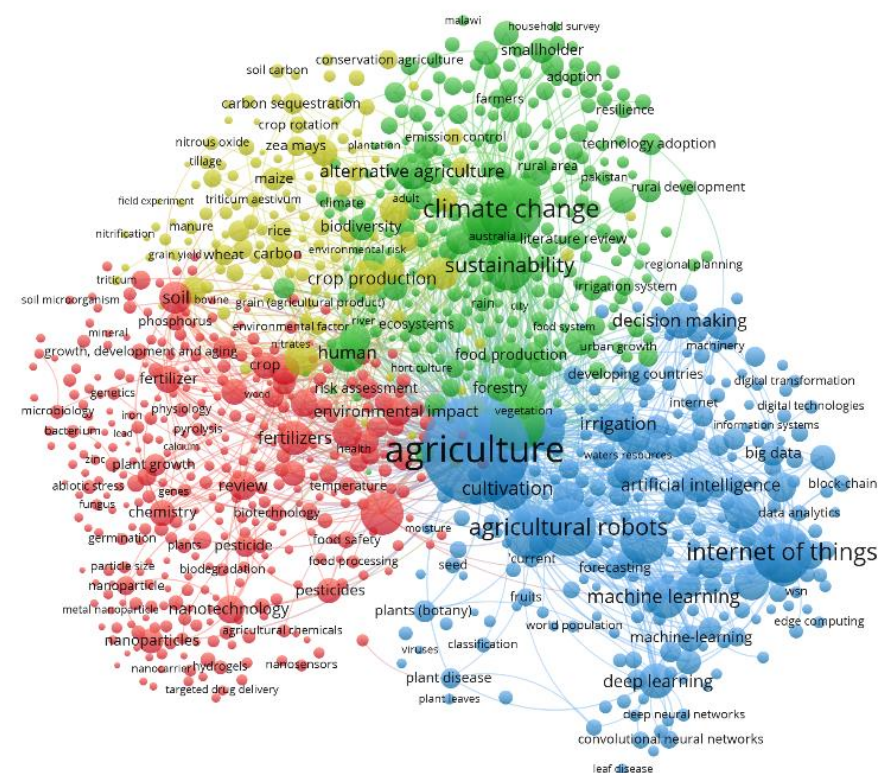
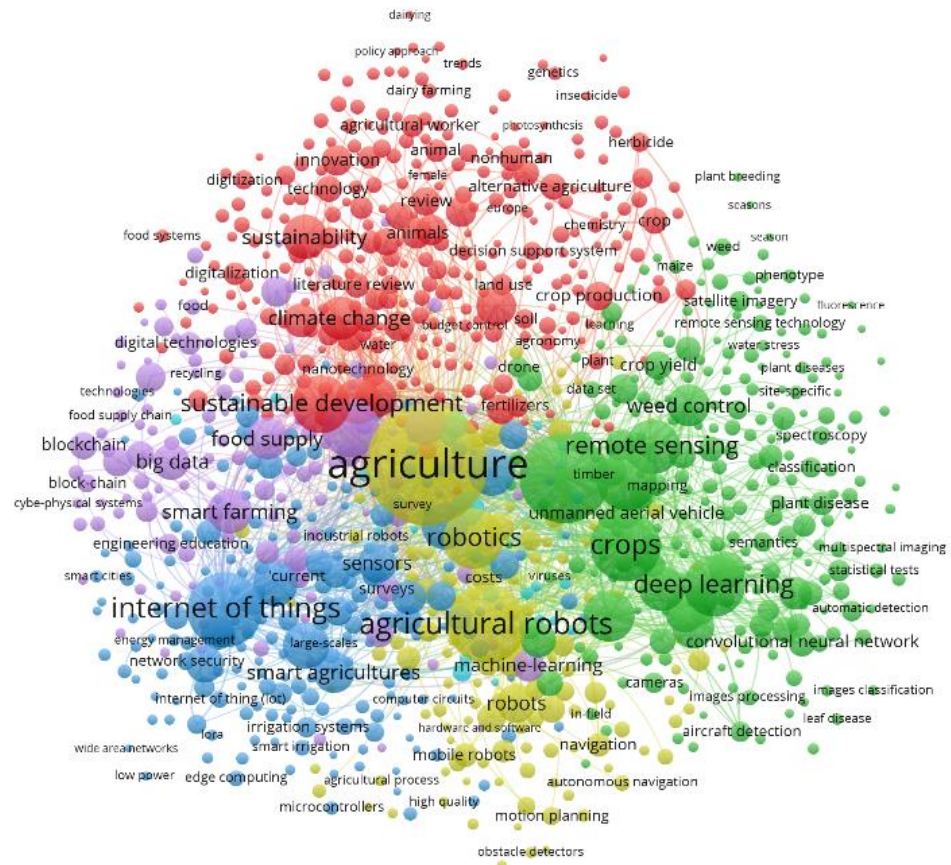
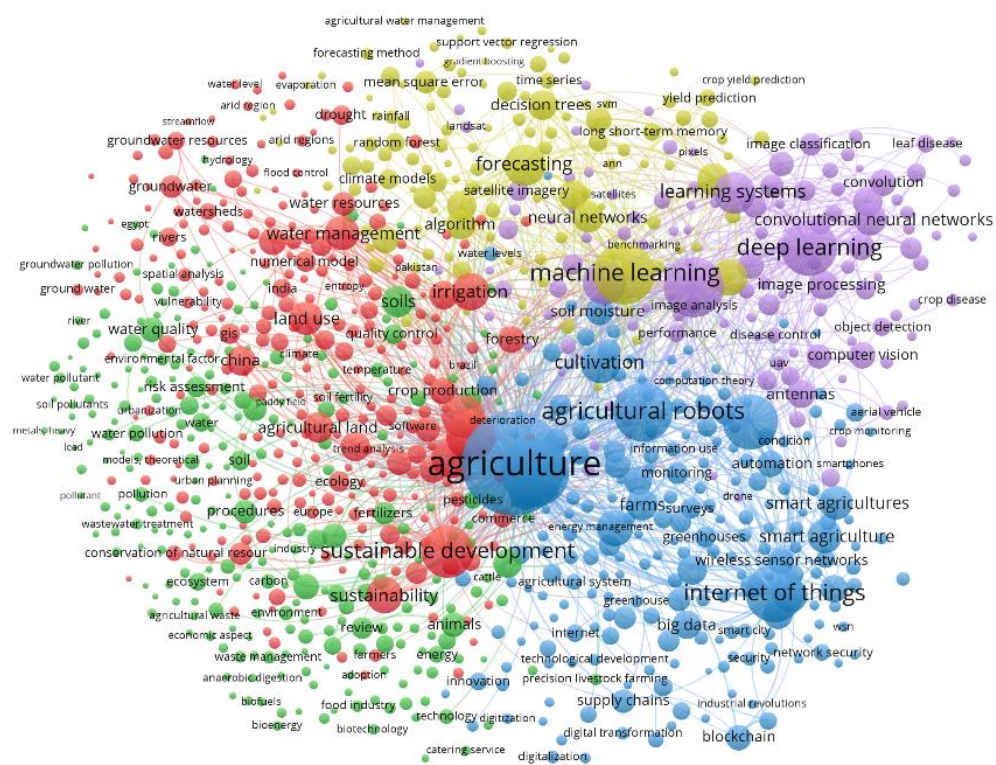


Figure 1. Co-keyword network visualization based on “Agriculture” AND “Sustainable” AND “Smart technologies”.



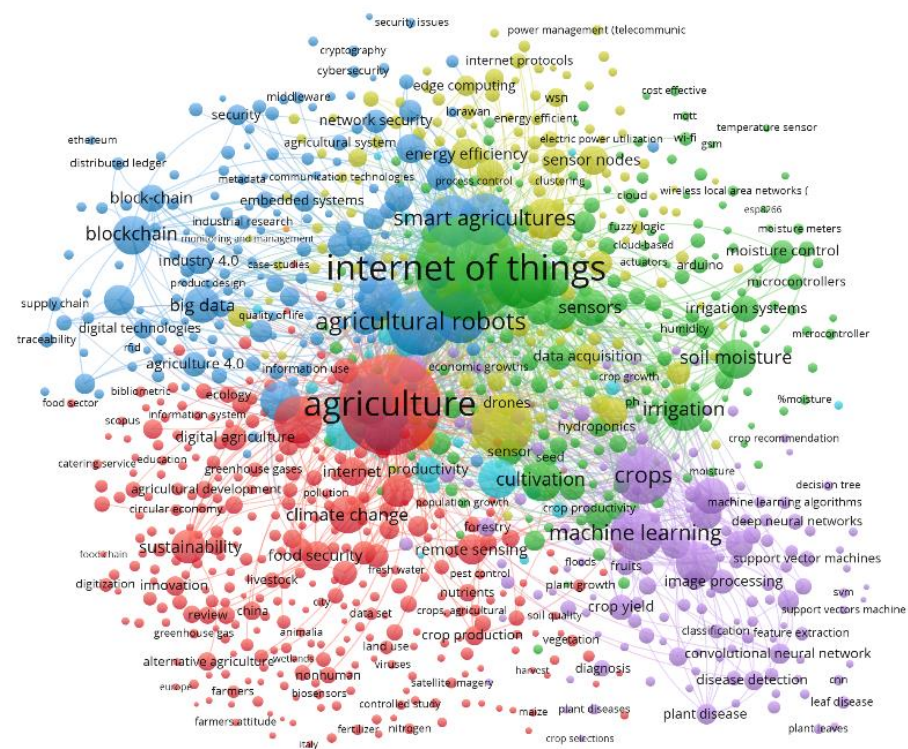


Figure 4. Co-keyword network visualization based on “Agriculture” AND “Sustainable” AND “Internet of Things”.

The keywords for “Agriculture”, “Sustainable” AND “Smart technologies” were presented as four clusters defined by 997 keywords (items), which contributed a Total Link Strength (TLS) of 787.086 or 100%, as presented in Figure 1. Cluster 1 (red circles) is defined by 353 keywords, with keywords including “soil”, which contributed 9.951 TLS or 1.26%, “fertilizers”, which contributed 9.100 TLS or 1.16%, “sustainable agriculture”, which contributed 8.726 TLS or 1.11%, and “nanotechnology” contributed 4.402 TLS or 0.56%. Cluster 2 (green circles) is defined by 272 keywords, with keywords including “climate change” contributed 20.652 TLS or 2.63%, “sustainable development” contributed 16.656 TLS or 2.12%, “sustainability” contributed 10.588 TLS or 1.34%, “alternative agriculture” contributed 7.274 TLS or 0.92%, and “biodiversity” contributed 4.615 TLS or 0.59%. Cluster 3 (blue circles) is defined by 245 keywords, with keywords including “agriculture” contributing 54.622 TLS or 6.94%, “agricultural robots” contributed 15.118 TLS or 1.92%, “Internet of Things” contributed 13.997 TLS or 1.78%, “machine learning” contributed 7.175 TLS or 0.92%, and “decision making” contributed 6.642 or 0.84%. Cluster 4 (mustard color circles) is defined by 127 keywords, with keywords including “soils” contributing 9.086 TLS or 1.15%, “greenhouse gases” contributing 7.093 TLS or 0.90%, “crop production” contributing 8.743 TLS or 1.11%, “nitrogen” contributing 6.402 TLS or 0.81%, and “fertilizer application” contributing 3.851 TLS or 0.49%.

The keywords for “Agriculture”, “Sustainable” AND “Artificial intelligence” were presented as five clusters defined by 996 keywords (items), which contributed a Total Link Strength (TLS) of 395.295 or 100%, as presented in Figure 2. Cluster 1 (red circles) is defined by 273 keywords, with keywords including “sustainable development” contributing 8.019 TLS or 2.03%, “decision making” contributing 7.666 TLS or 1.94%, “decision support systems” contributing 6.118 TLS or 1.55%, “climate change” contributing 5.261 TLS or 1.33%, and “water management” contributing 4.840 TLS or 1.22%. Cluster 2 (green circles) is defined by 265 keywords, with keywords including “environmental monitoring”, which contributed 2.847 TLS or 0.72%, “water quality”, which contributed 2.746 TLS or 0.69%, “environmental impact”, which contributed 2.498 TLS or 0.63%, “ecosystem” contributed 1.404 TLS or 0.35%, and “water pollution” contributed 1.296 TLS or 0.33%. Cluster 3 (blue

circles) is defined by 213 keywords, with keywords including “agriculture” contributing 27.225 TLS or 6.89%, “artificial intelligence” contributing 12.658 TLS or 3.02%, “agricultural robots” contributing 8.964 TLS or 2.27%, “Internet of Things” contributing 7.893 TLS or 1.20%, and “precision agriculture” contributing 6.743 TLS or 1.71%. Cluster 4 (mustard color circles) is defined by 123 keywords, with keywords including “machine learning”, which contributed 10.567 TLS or 2.67%, “forecasting”, which contributed 5.666 TLS or 1.43%, “learning algorithms”, which contributed 3.580 TLS or 0.91%, “decision tree” contributed 3.368 TLS or 0.85%, and “artificial neural network” contributed 3.208 TLS or 0.81%. Cluster 5 (purple circles) is defined by 122 keywords, with keywords including “crops” contributing 11.484 TLS or 2.90%, “deep learning” contributing 7.858 TLS or 1.99%, “learning systems” contributing 5.838 TLS or 1.48%, “convolutional neural networks” contributing 3.092 TLS or 0.78%, and “convolutional neural network” contributing 2.592 TLS or 0.66%.

The keywords for “Agriculture”, “Sustainable” AND “Robotics” were presented as six clusters defined by 99 keywords (items), which contributed a Total Link Strength (TLS) of 69.181 or 100%, as presented in Figure 3. Cluster 1 (red circles) is defined by 273 keywords, with keywords including “sustainable development”, which contributed 2.848 TLS or 4.12%, “agricultural technology”, which contributed 1.838 TLS or 2.66%, “climate change”, which contributed 1.720 TLS or 2.49%, “sustainability” contributed 1.278 TLS or 1.85%, and “sustainable agriculture” contributed 1.080 TLS or 1.56%. Cluster 2 (green circles) is defined by 240 keywords, with keywords including “precision agriculture”, which contributed 5.502 TLS or 7.95%, “crops”, which contributed 4.844 TLS or 7.00%, “deep learning”, which contributed 3.094 TLS or 4.47%, “remote sensing” contributed 2.474 TLS or 3.58%, and “weed control” contributed 1.589 TLS or 2.30%. Cluster 3 (blue circles) is defined by 193 keywords, with keywords including “Internet of Things” contributing 4.416 TLS or 6.39%, “smart agricultures” contributing 1.542 TLS or 2.23%, “smart agriculture” contributing 1.465 TLS or 2.12%, “IoT” contributing 1.441 TLS or 2.09%, and “Internet of Things (IoT)” contributing 1.163 TLS or 1.68%. Cluster 4 (mustard color circles) is defined by 134 keywords, with keywords including “agriculture” contributing 9.697 TLS or 14.03%, “agricultural robots” contributing 4.692 TLS or 6.79%, “robotics” contributing 2.578 TLS or 3.73%, “automation” contributing 1.489 TLS or 2.15%, and “robots” contributing 1.012 TLS or 1.46%. Cluster 5 (purple circles) is defined by 116 keywords, with keywords including “artificial intelligence”, which contributed 2.448 TLS or 3.54%, “agricultural technology”, which contributed 1.836 TLS or 2.66%, “food supply”, which contributed 1.657 TLS or 2.40%, “smart farming” contributed 1.201 TLS or 1.74%, and “big data” contributed 901 TLS or 1.30%. Cluster 6 (light blue circles) is defined by 29 keywords, with keywords including “precision farming”, which contributed 891 TLS or 1.29%, “decision support systems”, which contributed 754 TLS or 1.09%, “fuzzy logic”, which contributed 266 TLS, or 0.38%, “genetic algorithms” contributed 266 TLS or 0.38%, and “fuzzy inference” contributed 157 TLS or 0.23%.

The keywords for “Agriculture”, “Sustainable” AND “Internet of Things” were presented as six clusters defined by 998 keywords (items), which contributed a Total Link Strength (TLS) of 233.099 or 100%, as presented in Figure 4. Cluster 1 (red circles) is defined by 301 keywords, with keywords including “agriculture” contributing 16.710 TLS or 7.17%, “sustainable development” contributing 4.312 TLS or 1.85%, “climate change” contributing 2.869 TLS or 1.23%, “sustainability” contributing 1.799 TLS or 0.77%, and “food security” contributing 1.424 TLS or 0.61%. Cluster 2 (green circles) is defined by 216 keywords, with keywords including “Internet of Things”, which contributed 19.747 TLS or 8.47%, “IoT”, which contributed 6.278 TLS or 2.69%, “irrigation”, which contributed 3.982 TLS or 1.71%, “soil moisture” contributed 3.648 TLS or 1.57%, and “sensors” contributed 2.458 TLS or 1.05%. Cluster 3 (blue circles) is defined by 198 keywords, with keywords including “agricultural robots”, which contributed 7.713 TLS or 3.31%, “smart agriculture”, which contributed 5.223 TLS or 2.24%, “Internet of Things (IoT)”, which contributed 4.841 TLS or 2.08%, “smart agriculture” contributed 4.179 TLS or 1.79%, and “artificial intelligence” contributed 4.082 TLS or 1.75%. Cluster 4 (mustard color circles)

is defined by 142 keywords, with keywords including “crops” contributing 7.375 TLS or 3.16%, “machine learning” contributed 5.278 TLS or 2.26%, “deep learning” contributed 3.115 TLS or 1.34%, “learning systems” contributed 2.394 TLS or 1.03%, and “image processing” contributed 1.147 TLS or 0.49%. Cluster 5 (purple circles) is defined by 132 keywords, with keywords including “precision agriculture”, which contributed 6.296 TLS or 2.70%, “wireless sensor networks”, which contributed 3.390 TLS or 1.45%, “antennas”, which contributed 1.970 TLS or 0.85%, “sensor nodes” contributed 1.749 TLS or 0.75%, and “energy utilization” contributed 1.484 TLS or 0.64%. Cluster 6 (light blue circles) is defined by 9 keywords, with keywords including “agricultural productivity”, which contributed 512 TLS or 0.22%, “artificial intelligence (ai)”, which contributed 298 TLS or 0.13%, “machine learning” contributed 149 TLS or 0.06%, and “agricultural sustainability” contributed 120 TLS or 0.05%.

Though the use of this technology in agriculture has been predicted almost fifty years ago, relatively leap progress in sensor technology, computer vision, cost-effective computing power, and artificial intelligence facilitated the considerable progress we see today in the agricultural sector. Global expenditure on agricultural R&D increased by an average of 3.1 percent a year during the period 2000–2009 [10,11]. However, in the past ten years, investment in agricultural innovation has been fueled by an unprecedented convergence of advances in digitization and robotics. These technologies, which are often referred to as “digital agriculture” or “precision-smart farming”, are the foundation for a new, more productive, and sustainable agriculture. In addition, according to the results from similar elaboration using the Scopus tool [12] the year 2022 had more than three times higher the number of documents published concerning innovations in agriculture compared to 2012. The above-mentioned are in agreement with the results of the present research, where it was revealed that the literature review with keywords “Internet of Things”, “smart technologies”, “robotics” and “artificial intelligence” for the period 2012–2022 showed that the largest percentage of works (more than 80%) were published in the periods 2018–2022, 2016–2022, 2018–2021 and 2018–2021, respectively.

3. Conclusions

The above research results present the basic and essential information to allow scientists and students to identify the broad categories of interest in this Special Issue, entitled “Innovations in Agriculture for Sustainable Agro-Systems”. In our view, while many of the searched articles and book chapters have a scope that includes coverage of this field of research, the number of papers on the topics concerning “Smart technologies”, “Artificial intelligence”, “Robotics”, “Internet of Things”, or other important topics such as “sustainability”, “climate change”, “artificial intelligence”, “decision support systems”, “precision agriculture”, or “artificial neural network” are more limited.

As mentioned above, these technologies, which are often referred to as “digital agriculture” or “precision-smart farming” are the foundation for a new, more productive, and sustainable agriculture. So, the purpose of the mapping exercise presented here was to facilitate a description of the evidence base so that a subset of keywords from the maps of Figures 1–4 could be identified in the following contributed papers [13–15].

Keeping the above-mentioned facts in view, scientists were invited to submit research papers related to this Special Issue, entitled “Innovations in Agriculture for Sustainable Agro-Systems”. Three researchers contributed in this regard. In the first contribution, Shah et al. [13] contributed an article entitled “Application of Drone Surveillance for Advance Agriculture Monitoring by Android Application Using Convolution Neural Network”. The authors highlighted important issues where the use of deep learning techniques in the field of agriculture has shown great potential in automatically detecting and classifying plant diseases from leaf images. The authors concluded that the trained model EfficientNet-B3 was used, and an Android application and website were developed, which allowed farmers and users to easily detect diseases from the leaves. In the second contribution, Weigel et al. [14] presented a research article entitled “Monitoring Patch Expansion

Amends to Evaluate the Effects of Non-Chemical Control on the Creeping Perennial *Cirsium arvense* (L.) Scop. in a Spring Wheat Crop". In this research, authors monitored UAV technologies such as UAV cameras for patchy creeping perennial weeds in field experiments and concluded that future improvements in UAV-based camera technologies could monitor important weeds in the field and effectively control them. In the third article, Ramirez-Guerrero et al. [15] reported that emerging technologies in agriculture such as 4IR technologies could help farmers to detect pests and diseases. Moreover, the author's primary focus was emerging technologies for avocado crops such as data collection techniques and image devices.

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References

1. Foubert, B.; Mitton, N. Autonomous Collaborative Wireless Weather Stations: A Helping Hand for Farmers. *ERCIM News* **2019**, *119*, 37–38.
2. Veys, C.; Chatziavgerinos, F.; AlSuwaidi, A.; Hibbert, J.; Hansen, M.; Bernotas, G.; Smith, M.; Yin, H.; Rolfe, S.; Grieve, B. Multispectral imaging for presymptomatic analysis of light leaf spot in oilseed rape. *Plant Methods* **2019**, *15*, 4. [[CrossRef](#)] [[PubMed](#)]
3. Ruiz-Garcia, L.; Lunadei, L. The role of RFID in agriculture: Applications, limitations and challenges. *Comput. Electron. Agric.* **2011**, *79*, 42–50. [[CrossRef](#)]
4. Chastant-Maillard, S.; Saint-Dizier, M. Élevage de précision. *Édit. Fr. Agric.* **2016**, 270.
5. Halachmi, I.; Guarino, M.; Bewley, J.; Pastell, M. Smart Animal Agriculture: Application of real-time sensors to improve animal well-being and production. *Annu. Rev. Anim. Biosci.* **2019**, *7*, 403–425. [[CrossRef](#)] [[PubMed](#)]
6. Eck, N.J.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2009**, *84*, 523–538. [[CrossRef](#)] [[PubMed](#)]
7. Orduña-Malea, E.; Costas, R. Link-based approach to study scientific software usage: The case of VOSviewer. *Scientometrics* **2021**, *126*, 8153–8186. [[CrossRef](#)]
8. Arruda, H.; Silva, É.R.; Lessa, M.; Proença, D.; Bartholo, R. VOSviewer and Bibliometrix. *J. Med. Libr. Assoc. JMLA* **2022**, *110*, 392–395. [[CrossRef](#)] [[PubMed](#)]
9. Vagelas, I.; Leontopoulos, S. A Bibliometric Analysis and a Citation Mapping Process for the Role of Soil Recycled Organic Matter and Microbe Interaction due to Climate Change Using Scopus Database. *Agric. Eng.* **2023**, *5*, 581–610. [[CrossRef](#)]
10. FAO. *The Future of Food and Agriculture—Trends and Challenges*; FAO: Rome, Italy, 2017.
11. Khan, N.; Ray, R.; Sargani, G.R.; Ihtisham, M.; Khayyam, M.; Ismail, S. Current Progress and Future Prospects of Agriculture Technology: Gateway to Sustainable Agriculture. *Sustainability* **2021**, *13*, 4883. [[CrossRef](#)]
12. Gutiérrez Cano, L.F.; Zartha Sossa, J.W.; Orozco Mendoza, G.L.; Suárez Guzmán, L.M.; Agudelo Tapasco, D.A.; Quintero Saavedra, J.I. Agricultural innovation system: Analysis from the subsystems of R&D, training, extension, and sustainability. *Front. Sustain. Food Syst.* **2023**, *7*, 1176366. [[CrossRef](#)]
13. Shah, S.A.; Lakho, G.M.; Keerio, H.A.; Sattar, M.N.; Hussain, G.; Mehdi, M.; Vistro, R.B.; Mahmoud, E.A.; Elansary, H.O. Application of Drone Surveillance for Advance Agriculture Monitoring by Android Application Using Convolution Neural Network. *Agriculture* **2023**, *13*, 1764. [[CrossRef](#)]
14. Weigel, M.M.; Andert, S.; Gerowitt, B. Monitoring Patch Expansion Amends to Evaluate the Effects of Non-Chemical Control on the Creeping Perennial *Cirsium arvense* (L.) Scop. in a Spring Wheat Crop. *Agriculture* **2023**, *13*, 1474. [[CrossRef](#)]
15. Ramirez-Guerrero, T.; Hernández-Pérez, M.; Tabares, M.S.; Marulanda-Tobón, A.; Villanueva, E.; Peña, A. Agroclimatic and Phytosanitary Events and Emerging Technologies for Their Identification in Avocado Crops: A Systematic Literature Review. *Agriculture* **2023**, *13*, 1976. [[CrossRef](#)]

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