Article

Machine Learning and Food Security: Insights for Agricultural Spatial Planning in the Context of Agriculture 4.0

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Abstract: Climate change and global warming interconnected with the new contexts created by the COVID-19 pandemic and the Russia-Ukraine conflict have brought serious challenges to national and international organizations, especially in terms of food security and agricultural planning. These circumstances are of particular concern due to the impacts on food chains and the resulting disruptions in supply and price changes. The digital agricultural transition in Era 4.0 can play a decisive role in dealing with these new agendas, where drones and sensors, big data, the internet of things and machine learning all have their inputs. In this context, the main objective of this study is to highlight insights from the literature on the relationships between machine learning and food security and their contributions to agricultural planning in the context of Agriculture 4.0. For this, a systematic review was carried out based on information from text and bibliographic data. The proposed objectives and methodologies represent an innovative approach, namely, the consideration of bibliometric evaluation as a support for a focused literature review related to the topics addressed here. The results of this research show the importance of the digital transition in agriculture to support better policy and planning design and address imbalances in food chains and agricultural markets. New technologies in Era 4.0 and their application through Climate-Smart Agriculture approaches are crucial for sustainable businesses (economically, socially and environmentally) and the food supply. Furthermore, for the interrelationships between machine learning and food security, the literature highlights the relevance of platforms and methods, such as, for example, Google Earth Engine and Random Forest. These and other approaches have been considered to predict crop yield (wheat, barley, rice, maize and soybean), abiotic stress, field biomass and crop mapping with high accuracy ($R2 \approx 0.99$ and $RMSE \approx 1\%$).

Keywords: literature review; bibliometric analysis; Food 4.0; Industry 4.0; Climate-Smart Agriculture

1. Introduction

The agricultural land suitability assessment is an interesting approach to land use planning and to achieve food security goals, and where the new technologies may contribute significantly [1]. The digital transition's contributions to food security and agricultural

planning come from the collection of information to support policy and decision makers [2] and the processing of these data to predict plausible scenarios [3]. Cropland mapping is a case where machine learning, for instance, may produce important insights for sustainable land management [4]. This is particularly important in African countries [5], for example, where the challenges related to food security are serious and deserve special attention to find adjusted solutions [6]. The application of new technologies in the African context is not an easy task [7].

Agricultural land management and planning are interrelated with other land uses, such as urbanization [8]. With respect to agricultural land planning, the current challenges are diverse and range from the food supply to the ecosystem services [9]. In these frameworks, specifically for policy design, it is important to be aware of the diversity of stakeholders with different objectives and skills [10]. Additionally, the contexts associated with climate change bring new concerns [11].

Machine learning is a part of artificial intelligence applied to consider data and approaches to learn similarly to humans. The machine learning methods use remote sensing information [12], for example, to predict farming yields [13] and promote an adjusted agricultural planning [14] in the framework of the digital transition [15]. The outputs of machine learning are important and bring added value to the following domains: food security [16] and nutrition [17]; planetary health [18]; water management [19]; irrigated areas identification [20]; land susceptibilities mapping [21]; farm area mapping [22]; soil fertility assessment [23]; soil salinization analysis [24]; smart honey chains [25]; agricultural resources management [26]; agricultural production planning [27]; and climate change impacts assessment [28] and agricultural modelling [29].

Based on the contexts described above, and taking into account the gaps in the literature about the use of bibliometric analysis to assess dimensions related to the consideration of machine learning approaches for food security prediction and agricultural planning, the main objective of this research is to show insights from the scientific literature about the interconnections between machine learning and food security and their interrelationships with agricultural planning in the Era 4.0. Indeed, a search in the Scopus database for the topics "machine learning", "food security" and "bibliometric" (within the "Article title, Abstract and Keywords") identified only one study, related to ecological restoration [30], thus highlighting the novelty of the research presented here and its relevance to the literature and to the agricultural and food sectors.

2. Materials and Methods

Considering the objectives proposed for this research, 499 documents were considered from the Scopus database [31] for the topics "machine learning" and "food security" in a search carried out on the 9th of September 2022 within the article title, abstract and keywords.

This bibliometric information was explored through the VOSviewer software [32,33], considering text and bibliographic data. For text data, co-occurrence links, terms as items and binary counting were considered. Binary counting means that the occurrence metrics represent the number of documents where the term appears at least once [32]. For bibliographic data, co-occurrence and bibliographic coupling links were considered (with full counting). All keywords were taken into account as items for the co-occurrence links (relatedness is based on the number of documents where the items appear together) and countries, organizations and sources were considered as items for the bibliographic coupling links (relatedness is based on the number of references the items share) [32].

To identify the most relevant networked items for the objectives proposed for this study, the total link strength metric was taken into account [34]. This metric shows the total strength of the links of the term, for example, with other terms, indicating the relevance of the item for the network. This bibliometric analysis was used as support to carry out a systematic literature review [35] for the top 40 documents with the highest total link

strength. The consideration of the bibliometric assessment as a basis for the systematic review has been explored, for example, by Martinho [36–38].

In figures presented for bibliometric assessment, the dimension of the circle (and respective label) associated with each item indicates the number of occurrences (for co-occurrence links), documents (for bibliographic coupling links and countries, organizations and sources as items) and citations (for bibliographic coupling links and documents as items). The proximity of the items indicates greater relatedness. In tables, average publication year is the average year of publication of the documents where a keyword or term appears, or the average year of publication of the documents published by an author, country, organization, or source. Average citations are the average number of citations received by the documents. The normalized citations are corrected for the fact that older documents have had more time to receive citations [32].

In summary, following the PRISMA statement (Preferred Reporting Items for Systematic reviews and Meta-Analyses) [35], a search of the Scopus database for the topics "machine learning" and "food safety" was conducted on 9 September 2022 and 499 documents were identified. To select the studies to be surveyed through the literature review, a bibliometric assessment was considered, based on co-occurrence and bibliographic coupling links and total link strength metrics. This approach to the topics explored here is new and shows the relevance of this research. When the number of documents found in the search is high, there is a need to select the most relevant ones. This selection is critical [39], but bibliometric analysis can make important contributions here. There are other approaches considered for other topics [40–43]; nonetheless, the approach here presented was considered adjusted for the objectives proposed.

3. Bibliometric Assessment

This section is organized into two subsections, one for text data (considering binary counting and 1 as the minimum number of occurrences of a term) and the other for bibliographic data (full counting, 1 as the minimum number of occurrences of a keyword, country, organization or source and 0 as the minimum number of citations of a document). In this section, the results presented in figures and tables are those obtained from the outputs of the VOSviewer software.

3.1. Text Data

Figure 1, Table 1 and the remaining information obtained from the VOSviewer software highlight the importance of terms, such as the following: learning model; insecurity; mining; reconstruction; information system; knowledge gap; agricultural machinery; functional food product; industrial building; inverter unit; object detection; and polluted air.

These terms reveal the importance given by several stakeholders to worldwide food security, where the digital transition and the frameworks associated with Agriculture 4.0, Food 4.0 and Industry 4.0 may be fundamental to mitigate world undernourishment. The great challenge is to increase agricultural production, with efficiency and profitability, to deal with the increased demand for food by the world population without compromising the sustainability of natural resources. These concerns are already present, for example, in the Climate-Smart Agriculture (CSA) approach launched by the FAO (Food and Agriculture Organization) [44,45], but there is still a long way to run.

This text data assessment also reveals the importance of information, learning models and spatial planning to deal with the contexts of food security. In fact, in the era of artificial intelligence, information and big data are crucial for the development of autonomous equipment and the internet of things (IoT). In turn, spatial planning, namely, in terms of industrial building and farm organizations, has its relevance for the frameworks here described.

(**a**)

(**b**)

Figure 1. Network visualization map for text data (co-occurrence links and terms as items), considering binary counting and 1 as the minimum number of occurrences of a term. (**a**) Full network; (**b**) network around the items with the highest occurrences.

Table 1. Top 20 terms with the highest total link strength for text data, considering binary counting and 1 as the minimum number of occurrences of a term.

Terms	Total Link Strength	Occurrences	Average Publication Year	Average Citations	Average Normalized Citations
learning model	569	47	2021	47	1
insecurity	427	20	2021	6	0
vehicle	396	15	2021	33	2
proceeding	238	6	2022	0	0
content	236	15	2021	9	2
mean square error	234	13	2021	30	2
mining	231	7	2020	8	0
depth	228	9	2021	12	5
cover	224	16	2020	44	1
zone	221	16	2020	26	2
reconstruction	216	6	2022	1	0
information system	209	9	2020	4	0
reflectance	200	9	2020	18	1
enterprise	196	6	2022	0	0
agreement	191	7	2021	12	1
knowledge gap	186	4	2021	4	1
user need	186	3	2021	2	0
waste	173	6	2021	13	1
agricultural machinery	171	5	2022	0	0
alkylphenol	171	5	2022	0	0

3.2. Bibliographic Data

This subsection will be structured in two parts, one for the co-occurrence links and all keywords as items, and the other part for bibliographic coupling links and countries, organizations and sources as items.

3.2.1. Co-Occurrence Links

All keywords with the highest total link strength are the following: machine learning; food supply; food security; crops; remote sensing; decision trees; climate change; agricultural robots; artificial intelligence; maize; wheat; prediction; land use; and China (Figure 2, Table 2 and the remaining output from the VOSviewer software). The several dimensions related to food security are interrelated with the different domains of the agricultural sector (crops production), global warming, Era 4.0 (big data, internet of things, machine learning and remote sensing), land use changes, grain production (maize and wheat) and specific contexts (such as those from China).

Generally, and considering the full information, all the keywords with the highest relatedness are also those with the greatest number of occurrences, but are not the items with the greatest average citations, or average normalized citations. The average publication year for the top 20 all keywords is recent and ranges, namely, between 2020 and 2021.
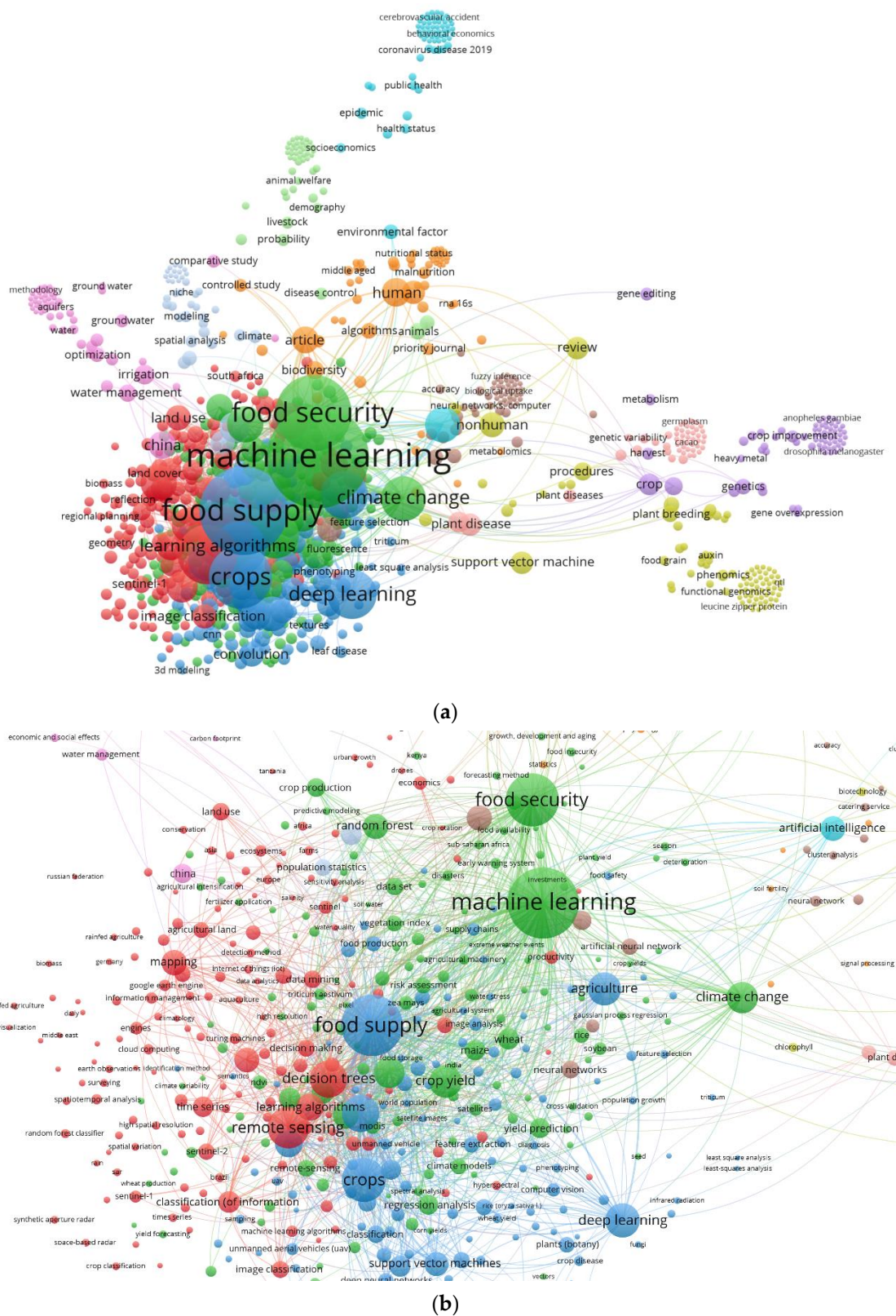
(**a**)

(**b**)

Figure 2. Network visualization map for bibliographic data (co-occurrence links and all keywords as items), considering full counting and 1 as the minimum number of occurrences of a keyword. (**a**) Full network; (**b**) network around the items with the highest occurrences.

Table 2. Top 20 all keywords with the highest total link strength for bibliographic data, considering full counting and 1 as the minimum number of occurrences of a keyword.

All Keywords	Total Link Strength	Occurrences	Average Publication Year	Average Citations	Average Normalized Citations
machine learning	4291	332	2020	19	1
food supply	3810	249	2020	15	1
food security	2325	186	2020	15	1
crops	2041	126	2020	13	1
remote sensing	1738	113	2020	17	1
decision trees	1621	91	2021	15	1
learning systems	1505	93	2020	22	1
agriculture	1145	73	2020	20	1
climate change	1041	65	2020	15	1
forecasting	1011	63	2021	12	1
deep learning	994	77	2021	38	1
crop yield	976	69	2020	24	2
agricultural robots	811	52	2021	10	1
random forests	780	45	2021	18	1
algorithm	755	42	2020	21	1
mapping	737	42	2020	19	2
learning algorithms	724	49	2020	13	1
support vector machines	686	39	2020	15	1
artificial intelligence	664	40	2019	23	1
satellite imagery	631	40	2020	22	1

3.2.2. Bibliographic Coupling Links

The United States, China, Australia, India, the United Kingdom, Germany, Italy, France, The Netherlands and Kenya are among the countries with the highest total link strength for the topics addressed (Figure 3 and Table 3). These countries of affiliation for the researchers reveal the concerns of the scientific community with some specific contexts, such as China and India (considering their population), for example, because of the risks of food insecurity, and where machine learning and agricultural planning may bring relevant contributions. Another context that deserves special attention is Brazil where, despite the technological advances in agriculture and this country being one of the biggest producers of grain, the problems with food insecurity remain, calling for more adjusted policies.

In general, the countries with the greatest total link strength have also a high number of documents, citations and normalized citations. The correlations among the total link strength and the average citations and the average normalized citations are not so evident. The average publication year for the top 20 countries ranges between 2019 and 2021.

The top five organizations with the greatest relatedness are the following (Figure 4 and Table 4): the University of the Chinese Academy of Sciences, Beijing, China; Agri-Science Queensland, Department of Agriculture & Fisheries (DAF), Warwick, Australia; Bayer Crop Science, United States; the Center for Soybean Research of The State Key Laboratory of Agrobiotechnology and School of Life Sciences, the Chinese University of Hong Kong, Shatin, Hong Kong; and the Center of Excellence in Genomics & Systems Biology, International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad, India. The information presented in Figure 4 and Table 4 (and the remaining output from the VOSviewer software) highlight the interest of institutions and the scientific communities in countries, such as China and India, in topics related to food security and machine learning. In this case, the correlations between the total link strength and the other metrics, for the full information, are not so obvious.
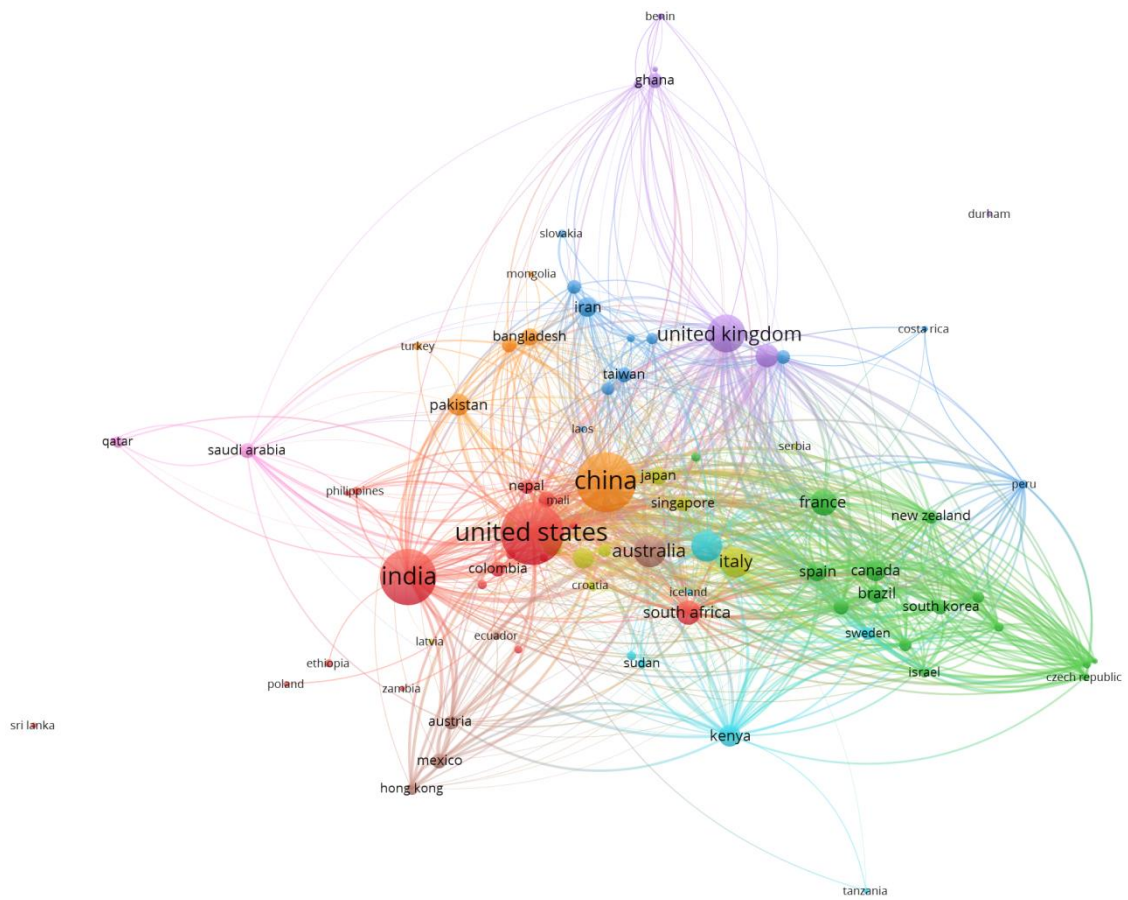
Figure 3. Network visualization map for bibliographic data (bibliographic coupling links and countries as items), considering full counting and 1 as the minimum number of occurrences of a country.

Table 3. Top 20 countries with the highest total link strength for bibliographic data, considering full counting and 1 as the minimum number of occurrences of a country.

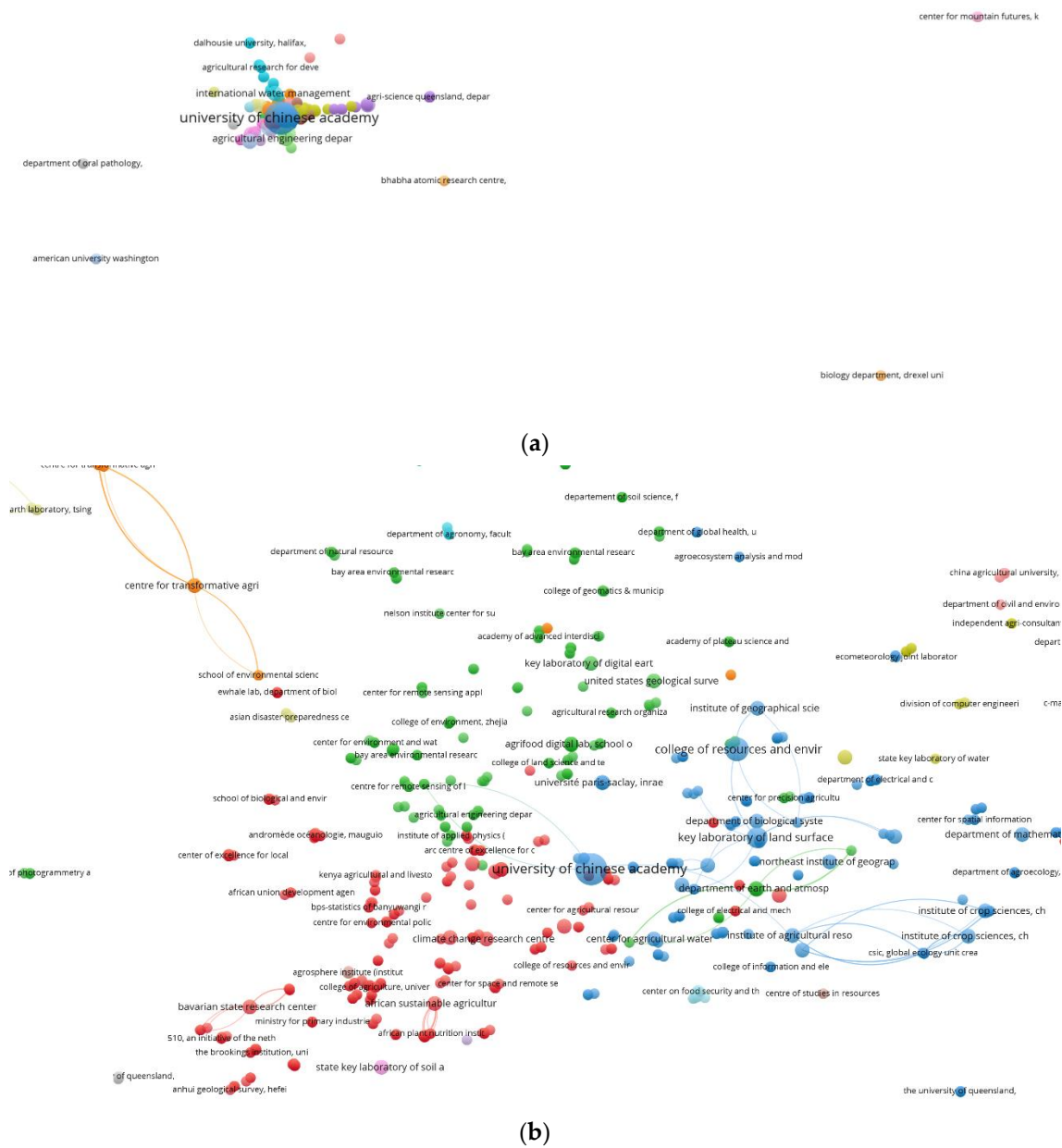| Countries	Total Link Strength	Documents	Citations	Normalized Citations	Average Publication Year	Average Citations	Average Normalized Citations
United States	33504	113	4780	162	2020	42	1
China	32447	104	1965	176	2021	19	2
Australia	18443	31	1122	66	2020	36	2
India	14040	90	754	64	2021	8	1
United Kingdom	13363	42	1073	80	2020	26	2
Germany	13326	28	813	33	2020	29	1
Italy	10569	29	750	28	2021	26	1
France	10003	21	556	30	2020	26	1
Netherlands	9926	15	511	31	2020	34	2
Kenya	9906	14	555	14	2020	40	1
Belgium	9330	7	663	32	2019	95	5
South Africa	8981	17	497	12	2020	29	1
Spain	7946	12	753	16	2020	63	1
New Zealand	7885	6	443	26	2020	74	4
Brazil	7225	10	538	11	2021	54	1
Canada	6545	14	667	17	2020	48	1
South Korea	6231	7	401	3	2020	57	0
Sweden	6210	5	396	2	2020	79	0
Finland	5837	3	422	3	2019	141	1
Denmark	5814	4	464	5	2020	116	1

(**a**)

(**b**)

Figure 4. Network visualization map for bibliographic data (bibliographic coupling links and organizations as items), considering full counting and 1 as the minimum number of occurrences of an organization. (**a**) Full network; (**b**) network around some of the items with the highest documents.

Remote Sensing, the *International Journal of Applied Earth Observation and Geoinformation*, *Agricultural and Forest Meteorology*, *Remote Sensing of Environment*, *Computers and Electronics in Agriculture*, *Sustainability* (Switzerland), the *ISPRS Journal of Photogrammetry and Remote Sensing*, *Science of the Total Environment*, the *International Journal of Remote Sensing* and *Agricultural Systems* are the top 10 sources with the highest relatedness (Figure 5 and Table 5). These sources have scopes associated with new technologies, agriculture and sustainability. Considering the full information, the more evident correlation with the total link strength comes from the number of documents, citations and normalized citations (in some cases, however, not very strong).

Table 4. Top 20 organizations with the highest total link strength for bibliographic data, considering full counting and 1 as the minimum number of occurrences of an organization.

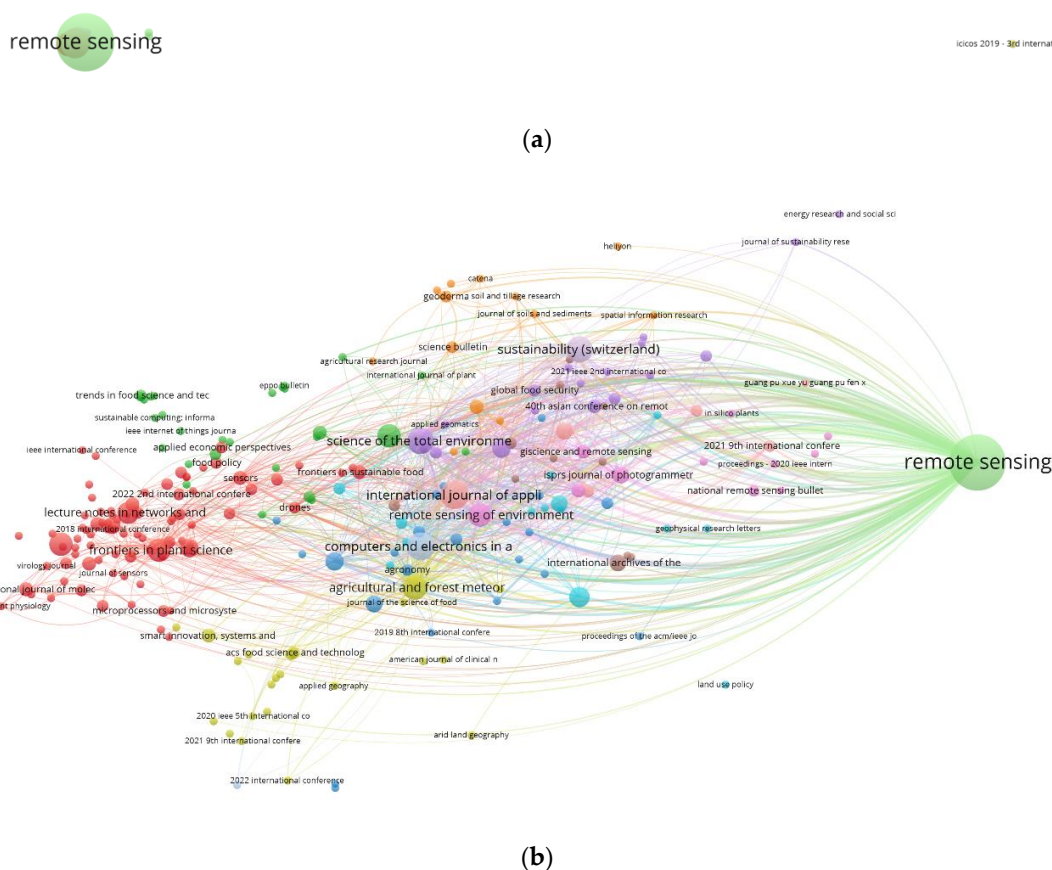| Organizations	Total Link Strength	Documents	Citations	Normalized Citations	Average Publication Year	Average Citations	Average Normalized Citations
University of Chinese Academy of Sciences, Beijing, China	5790	9	46	20	2021	5	2
Agri-Science Queensland, Department of Agriculture & Fisheries (DAF), Warwick, Australia	5449	1	27	4	2021	27	4
Bayer Crop Science, United States	5449	1	27	4	2021	27	4
Center for Soybean Research of the State Key Laboratory of Agrobiotechnology and School of Life Sciences, The Chinese University of Hong Kong, Shatin, Hong Kong	5449	1	27	4	2021	27	4
Center of Excellence in Genomics & Systems Biology, International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad, India	5449	1	27	4	2021	27	4
Chinese Academy of Agricultural Sciences, Beijing, China	5449	1	27	4	2021	27	4
Crops Research Institute, Guangdong Academy of Agricultural Sciences, Guangzhou, China	5449	1	27	4	2021	27	4
Department of Biotechnology, Ministry of Science and Technology, Government of India, India	5449	1	27	4	2021	27	4
Indian Council of Agricultural Research (ICAR)–Indian Agricultural Research Institute (IARI), New Delhi, India	5449	1	27	4	2021	27	4
International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Nairobi, Kenya	5449	1	27	4	2021	27	4
International Maize and Wheat Improvement Center (CYMMIT), Mexico	5449	1	27	4	2021	27	4
Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, Vienna, Austria	5449	1	27	4	2021	27	4
National Center for Soybean Research, University of Missouri, Columbia, United States	5449	1	27	4	2021	27	4
Shandong Academy of Agricultural Sciences, Jinan, China	5449	1	27	4	2021	27	4
South Asia Hub, International Rice Research Institute (IRRI), Hyderabad, India	5449	1	27	4	2021	27	4
University of California, Riverside, United States	5449	1	27	4	2021	27	4
University of Maryland, United States	5449	1	27	4	2021	27	4
University of Nebraska-Lincoln, United States	5449	1	27	4	2021	27	4
University of Southern Queensland, Toowoomba, Australia	5449	1	27	4	2021	27	4
Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China	4392	4	104	14	2021	26	3

(**a**)

(**b**)

Figure 5. Network visualization map for bibliographic data (bibliographic coupling links and sources as items), considering full counting and 1 as the minimum number of occurrences of a source. (**a**) Full network; (**b**) network around some of the items with the highest documents.

Table 5. Top 20 sources with the highest total link strength for bibliographic data, considering full counting and 1 as the minimum number of occurrences of a source.

Sources	Total Link Strength	Documents	Citations	Normalized Citations	Average Publication Year	Average Citations	Average Normalized Citations
Remote Sensing	6668	45	785	63	2021	17	1
International Journal of Applied Earth Observation and Geoinformation	2094	12	166	16	2021	14	1
Agricultural and Forest Meteorology	2050	9	348	22	2021	39	2
Remote Sensing of Environment	1608	8	509	30	2020	64	4
Computers and Electronics in Agriculture	1464	11	75	8	2020	7	1
Sustainability (Switzerland)	1217	10	35	4	2021	4	0
ISPRS Journal of Photogrammetry and Remote Sensing	885	4	106	8	2021	27	2
Science of the Total Environment	869	10	75	18	2021	8	2
International Journal of Remote Sensing	829	4	6	1	2022	2	0
Agricultural Systems	584	5	97	5	2020	19	1
European Journal of Agronomy	557	2	67	5	2020	34	3
GIScience and Remote Sensing	524	3	41	2	2020	14	1
Frontiers in Plant Science	517	8	1493	14	2020	187	2
Geo-Spatial Information Science	507	3	12	2	2021	4	1
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	483	5	28	3	2021	6	1
Sensors	454	3	5	5	2022	2	2
Precision Agriculture	403	2	2	2	2022	1	1
ISPRS International Journal of Geo-Information	386	3	30	2	2020	10	1
Environmental Research Letters	380	6	306	9	2020	51	2
Studies in Big Data	334	2	0	0	2022	0	0

4. Systematic Literature Review

Table 6 presents the top 40 documents with the highest total link strength that will be considered in this section to carry out the literature review based on bibliometric assessment. This table highlights also that there is no strong correlation (analyzing coefficients of correlation) among the total link strength and the other metrics considered.

Table 6. Top 40 documents with the highest total link strength for bibliographic data (bibliographic coupling links), considering full counting and 0 as the minimum number of citations of a document.

Documents	URL	Total Link Strength	Citations	Normalized Citations	Publication Year
Han J. (2020) [46]	https://doi.org/10.3390/rs12020236	523	76	4	2020
Wang Y. (2020) [47]	https://doi.org/10.3390/rs12081232	432	46	2	2020
Ma Y. (2021) [48]	https://doi.org/10.1016/j.rse.2021.112408	431	27	4	2021
Zhang L. (2020) [49]	https://doi.org/10.3390/rs12010021	416	39	2	2020
Cao J. (2020) [50]	https://doi.org/10.3390/rs12050750	414	28	1	2020
Cao J. (2021) [51]	https://doi.org/10.1016/j.eja.2020.126204	401	25	4	2021
Maimaitijiang M. (2020) [52]	https://doi.org/10.1016/j.rse.2019.111599	386	211	11	2020
Bian C. (2022) [53]	https://doi.org/10.3390/rs14061474	380	5	5	2022
Mashaba-Munghemezulu Z. (2021) [54]	https://doi.org/10.3390/su13094728	360	3	0	2021
Htitiou A. (2021) [55]	https://doi.org/10.3390/rs13214378	357	3	0	2021
Van Tricht K. (2018) [56]	https://doi.org/10.3390/rs10101642	347	160	4	2018
Zhang C. (2021) [57]	https://doi.org/10.1016/j.compag.2020.105978	346	9	1	2021
Wang S. (2019) [58]	https://doi.org/10.1016/j.rse.2018.12.026	344	118	3	2019
Sakamoto T. (2020) [59]	https://doi.org/10.1016/j.isprsjprs.2019.12.012	342	37	2	2020
Wang S. (2020) [60]	https://doi.org/10.3390/rs12182957	334	25	1	2020
Schwalbert R.A. (2020) [61]	https://doi.org/10.1016/j.agrformet.2019.107886	330	90	5	2020
Maimaitijiang M. (2020) [62]	https://doi.org/10.3390/rs12091357	325	58	3	2020
Cai Y. (2019) [63]	https://doi.org/10.1016/j.agrformet.2019.03.010	322	178	5	2019
Panjala P. (2022) [64]	https://doi.org/10.1007/978-981-16-5847-1_8	320	0	0	2022
Pott L.P. (2021) [65]	https://doi.org/10.1016/j.isprsjprs.2021.04.015	318	14	2	2021
Cao J. (2021) [66]	https://doi.org/10.1016/j.agrformet.2020.108275	317	50	8	2021
Löw F. (2018) [67]	https://doi.org/10.1080/15481603.2017.1414010	311	22	1	2018
Abubakar G.A. (2020) [68]	https://doi.org/10.3390/su12062539	310	17	1	2020
Liao D. (2021) [69]	https://doi.org/10.1007/s00704-021-03799-3	305	0	0	2021
Chaves M.E.D. (2021) [2]	https://doi.org/10.1080/01431161.2021.1978584	304	6	1	2021
Ju S. (2021) [13]	https://doi.org/10.1016/j.agrformet.2021.108530	303	3	0	2021
He Y. (2019) [70]	https://doi.org/10.3390/rs11050535	301	14	0	2019
Meroni M. (2021) [71]	https://doi.org/10.1016/j.agrformet.2021.108555	296	5	1	2021
Masrur Ahmed A.A. (2022) [72]	https://doi.org/10.3390/rs14051136	293	1	1	2022
Shangguan Y. (2022) [73]	https://doi.org/10.1080/01431161.2022.2049913	283	0	0	2022
Samasse K. (2020) [74]	https://doi.org/10.3390/rs12091436	281	12	1	2020
Servia H. (2022) [75]	https://doi.org/10.1016/j.jag.2022.102725	278	0	0	2022
Oliphant A.J. (2019) [76]	https://doi.org/10.1016/j.jag.2018.11.014	278	88	3	2019
Jiang J. (2022) [77]	https://doi.org/10.1007/s11119-021-09870-3	274	2	2	2022
Cao J. (2022) [78]	https://doi.org/10.3390/rs14071707	272	2	2	2022
Zhou W. (2022) [79]	https://doi.org/10.1016/j.jag.2022.102861	266	0	0	2022
Zepp S. (2021) [80]	https://doi.org/10.3390/rs13163141	263	5	1	2021
Estes L.D. (2022) [81]	https://doi.org/10.3389/frai.2021.744863	261	0	0	2022
Sitokonstantinou V. (2021) [82]	https://doi.org/10.3390/rs13091769	261	3	0	2021
Tran K.H. (2022) [83]	https://doi.org/10.1016/j.jag.2022.102692	251	3	3	2022

The summary findings from the systematic review are presented in the next subsection. Some of the best results for accuracy (Figure 6) were found, for example, by Htitiou A. (2021) [55], Masrur Ahmed A.A. (2022) [72] and Jiang J. (2022) [77]. Htitiou A. (2021) [55] and Jiang J. (2022) [77] used Random Forest methods and vegetation indices as predictors.
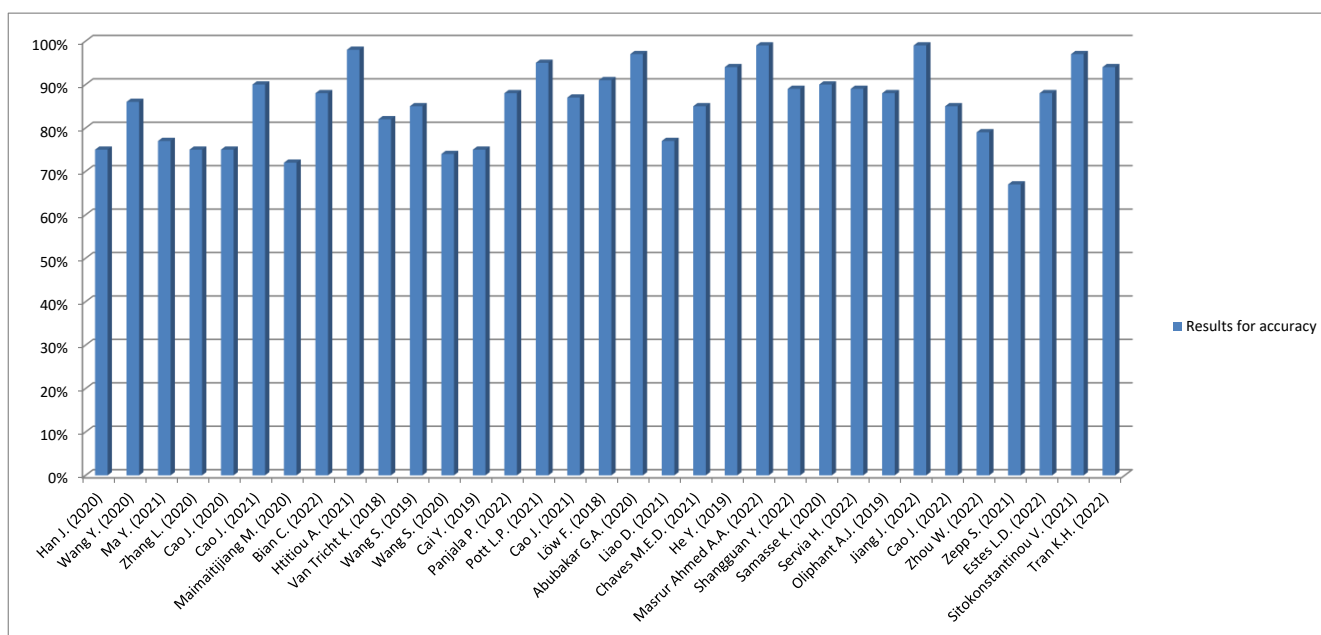
Figure 6. Results for accuracy found by the different studies.

4.1. Main Findings

From reviewing and assessing deeper the several documents presented in Table 6, the main findings are exhibited in Table 7. It is worth mentioning that remote sensing data and machine learning models are buzzwords in the contexts of agriculture 4.0 for food security frameworks assessment and agricultural planning. Remote sensing may be considered unmanned aerial vehicle (UAV) platforms, and for machine learning the following models can be used [53], for example: Gaussian process regression (GPR); support vector machine (SVM) regression; and random forest (RF) regression. Other approaches and designations are usually taken into account for machine learning, such as neural network (NN) [63], deep neural network (DNN), 1D convolutional neural network (CNN), long short-term memory (LSTM) networks [51], ridge regression (RR), light gradient boosting (LightGBM) [50], Bayesian neural network (BNN) [48] and adaptive boosting (AdaBoost) [47]. For the data collection, satellite information [62] is also considered, such as that from the Sentinel-1 and Sentinel-2 [54] under the Copernicus program [56]. Shuttle radar topographic mission (SRTM) [65] and moderate resolution imaging spectroradiometer (MODIS) [59] are other methodologies and designations used in approaches considered to collect information. Regarding data gathering, the Google Earth Engine (GEE) is a useful platform [58] that allows converting every satellite image into Normalized Difference Vegetation Index [64].

Agricultural yield prediction is crucial in times of volatility and uncertainty as currently happening worldwide, to deal with the implications of climate change, pandemics [55], international conflicts and policy design [52]. The new technologies associated with the digital transition, such as those related to machine learning, bring important contributions [57] to mitigate the risks of food insecurity and for better agricultural planning [46] in specific contexts such as those of Brazil [61], India [60] and China [49].

In the following subsections, deeper dimensions related to land mapping and crop yield prediction will be explored.

Table 7. Summary insights from the systematic review.

Documents	Goal	Area	Methods	Predictors	Platforms	Results
Han J. (2020) [46]	Winter wheat yield prediction	China	SVM GPR RF	EVI TMIN PRE NDVI SM TMAX DI	GEE	R^2: >0.75 yield error: <10%
Wang Y. (2020) [47]	Winter wheat yield prediction	United States	OLS LASSO SVM RF AdaBoost DNN	Vegetation indices (NDVI, EVI, GCI) Climate and soil variables	GEE MODIS	R^2: 0.86 RMSE: 0.51 t/ha MAE: 0.39 t/ha
Ma Y. (2021) [48]	Predict corn yield	United States	BNN	Vegetation indices Climate variables	GEE MODIS	R^2: 0.77 R^2: ~0.75 for the timeliness of the prediction achieved 2 months before the harvest
Zhang L. (2020) [49]	Predict maize yield	China	LASSO RF XGBoost LSTM	Vegetation metrics Climate and soil variables Management factor	GEE MODIS	Results explanation: >75% of yield variation
Cao J. (2020) [50]	Predict winter wheat yield	China	RR RF LightGBM	Vegetation indices Climate and socio-economic variables	GEE MODIS	R^2: 0.68~0.75 Individual contribution: climate (~0.53), followed by VIs (~0.45) and SC variables (~0.30)
Cao J. (2021) [51]	Predict wheat yield	China	RF DNN 1D-CNN LSTM	Crop planting areas Climate, satellite, soil and spatial information	GEE MODIS SRTM	R^2: 0.83–0.90 RMSE: 561.18–959.62 kg/ha
Maimaitijiang M. (2020) [52]	Predict soybean yield	Columbia, Missouri, United States	DNN PLSR RFR SVR	Vegetation indices Canopy height and vegetation fraction Normalized relative canopy temperature index Gray-level co-occurrence matrix	UAV	R^2: 0.720 RMSE: 15.9%
Bian C. (2022) [53]	Wheat yield prediction	China	GPR SVR RFR	Vegetation indices	UAV	R^2 0.87–0.88 RMSE: 49.18–49.22 g/m^2 MAE: 42.57–42.74 g/m^2

Table 7. *Cont.*

Documents	Goal	Area	Methods	Predictors	Platforms	Results
Mashaba-Munghemezulu Z. (2021) [54]	Mapping maize farms	South Africa	RF SVM ST	Vegetation indices	Sentinel-1 Sentinel-2	Combined Sentinel-1 and Sentinel-2 information improved the RF, SVM and ST approaches by 24.2%, 8.7% and 9.1%.
Htitiou A. (2021) [55]	Mapping cropland	Morocco	RF	Vegetation indices	GEE Sentinel-2A Sentinel-2B MODIS	Overall accuracy: 97.86%
Van Tricht K. (2018) [56]	Crop mapping	Belgium	RF	NDVI	GEE Sentinel-1 radar Sentinel-2 optical imagery	Maximum accuracy: 82%
Zhang C. (2021) [57]	Mapping paddy rice	China	RF SDBT	NDVI PMI	Sentinel-2	Effectiveness of RF for the objectives proposed
Wang S. (2019) [58]	Crop mapping	United States Midwest	RF GMM	Vegetation indices	GEE	Accuracy: >85%
Sakamoto T. (2020) [59]	Corn and soybean yield estimation	United States	RF	Vegetation indices Environmental variables (temperature, precipitation, soil moisture, etc.)	MODIS	RMSE: 0.539 t/ha for corn; 0.206 t/ha for soybeans
Wang S. (2020) [60]	Crop mapping	India	CNN RF	Vegetation indices	GEE Sentinel-2 DigitalGlobe imagery	Accuracy: 74%
Schwalbert R.A. (2020) [61]	Soybean yield prediction	Brazil	OLS RF LSTM	NDVI EVI Land surface temperature and precipitation variables	GEE CAR	MAE: 0.24 Mg ha-1
Maimaitijiang M. (2020) [62]	Crop monitoring	Columbia, Missouri, United States	PLSR RFR SVR ELR	Vegetation indices Canopy height and canopy cover	UAV	ELR and RFR presented the most accurate approaches
Cai Y. (2019) [63]	Wheat yield prediction	Australia	LASSO SVM RF NN	EVI SIF Climate variables	MODIS EnviSat Eumetsat's MetOp-A/B	R^2: ~0.75
Panjala P. (2022) [64]	Mapping crop	India	RF SVM CART SMT	NDVI	GEE	Accuracy: 81.8% for RF, 68.8% for SVM, 64.9% for CART and 88% for SMT

Table 7. *Cont.*

Documents	Goal	Area	Methods	Predictors	Platforms	Results
Pott L.P. (2021) [65]	Mapping crop	Brazil	RF Moran's I Index Cluster k-means	Vegetation indices	GEE Sentinel-2 Sentinel-1 SRTM	Overall accuracy: 0.95
Cao J. (2021) [66]	Rice yield prediction	China	LASSO RF LSTM	EVI SIF Climate	GEE	R^2: 0.77–0.87 RMSE: 298.11–724 kg/ha Two to one month leading time
Löw F. (2018) [67]	Yield prediction and mapping of cotton and winter wheat	Central Asia	RF SVM	Vegetation Indexes	MODIS Landsat	Land cover accuracy: 91% Yield R^2: 0.81 Acreage R^2: 0.87
Abubakar G.A. (2020) [68]	Maize mapping	Nigeria	RF SVM	Multi-temporal spectral indices and bands	Sentinel-1A Sentinel-2A	Overall accuracy: 97%
Liao D. (2021) [69]	Yield prediction	China	SVM KNN GPR	Climate Vegetation Indexes	MODIS	R^2 max: 0.77 RMSE max: 42×10^4 kg grid^{-1}
Chaves M.E.D. (2021) [2]	Land use/cover mapping	Brazil	RF	Vegetation Indices Spectral bands	CBERS data cubes MODIS	Classification accuracy: >85%
Ju S. (2021) [13]	Yield prediction of paddy rice, corn and soybeans	South Korea, USA	SVM DT RF ANN SSAE CNN LSTM	Vegetation indices	MODIS	Best RRMSE: 7.45 for rice; 7.81 for corn; 8.91 for soybean
He Y. (2019) [70]	Wheat mapping	China	RF	Vegetation indices PCA features Spectral bands NDBI method	Landsat-8 Sentinel-2	Accuracy: 94%
Meroni M. (2021) [71]	Yield prediction (barley, soft wheat and durum wheat)	Algeria	SVR LASSO MLP	Vegetation indices Climate	MODIS CHIRPS/ ECMWF	Accuracy: 0.16–0.2 t/ha (13–14% of mean yield)
Masrur Ahmed A.A. (2022) [72]	Yield prediction of wheat	Australia	KRR feature selection (grey wolf, ant colony, atom search, particle swarm)	Hydro-climatic	MERRA-2	R: 0.998 NRMSE: 0.437%

Table 7. *Cont.*

Documents	Goal	Area	Methods	Predictors	Platforms	Results
Shangguan Y. (2022) [73]	Soybean mapping	Argentina	RF	Vegetation indices Spectral bands	GEE Landsat-8	Accuracy: 86% Producer's accuracy: 81.72% User's accuracy: 89.04%
Samasse K. (2020) [74]	Cropland mapping	West African Sahel	RF	Vegetation indices Spectral bands	GEE Landsat-8	Accuracy: 90.1% User's accuracy: 79%
Servia H. (2022) [75]	Field biomass prediction	China	MLR SMLR BRT SVR RFR	Vegetation indices Evapotranspiration Radar Net primary production	Sentinel-1 Sentinel-2 FAO WaPOR	Accuracy: 89% (4 months prior to the harvest)
Oliphant A.J. (2019) [76]	Cropland mapping	Northeast Asia	RF	Vegetation indices Spectral bands Elevation	GEE	Accuracy: 88.1% Producer's accuracy: 81.6% User's accuracy: 76.7%
Jiang J. (2022) [77]	Quinoa abiotic stress prediction	Saudi Arabia	RF	Vegetation indices Spectral bands	UAVs	Leaf area index (R^2: 0.977–0.980, RMSE: 0.119–0.167) Soil-plant analysis development (R^2: 0.983–0.986, RMSE: 2.535–2.86)
Cao J. (2022) [78]	Yield prediction of winter wheat	China	RF XGBoost SVR MLR	Atmospheric prediction Climate Vegetation indices	CRU MODIS	(3–4 months before the harvest) R^2: 0.81–0.85 RMSE: 0.78–0.89 t//ha
Zhou W. (2022) [79]	Yield prediction of wheat	China	RF SVM LASSO	Climate (water, temperature) Vegetation indices	CMA CRU MODIS	R^2: 0.66–0.79
Zepp S. (2021) [80]	Soil organic carbon estimation	Bavaria	RF	Spectral bands Vegetation indices	Landsat	R^2 = 0.67 RMSE = 1.24%
Estes L.D. (2022) [81]	Field mapping	Ghana	RF	Spectral bands	CubeSats PlanetScope	Cropland accuracy: 88% Field boundaries accuracy: 86.7%
Sitokonstantinou V. (2021) [82]	Paddy rice mapping	South Korea	K-means RF	Spectral bands Vegetation indices	Sentinel-1 Sentinel-2	Accuracy: 96.69%
Tran K.H. (2022) [83]	Crop mapping	South Dakota/California	RF	Spectral bands Vegetation indices	Sentinel-2	R^2: $\geq$0.94 RMSE: $\leq$3%

Note: SVM, support vector machine; GPR, Gaussian process regression; RF, random forest; OLS, ordinary least square; AdaBoost, adaptive boosting; XGBoost, extreme gradient boosting; LASSO, least absolute shrinkage and selection operator; DNN, deep neural network; BNN, Bayesian Neural Network; LSTM, long short-term memory networks; RR, Ridge Regression; LightGBM, Light Gradient Boosting; CNN, convolutional neural networks; PLSR, partial least squares regression; RFR, random forest regression; SVR, support vector regression; ST, model stacking; SDBT, spatial domain bridge transfer; GMM, Gaussian mixture models; ELR, extreme learning regression; MetOp, Meteorological Operational satellite programme; NN, neural network; CART, classification and regression trees; SMT, spectral matching technique; KNN, k-nearest neighbor regression; DT, decision tree; ANN, artificial neural network; SSAE,

stacked-sparse autoencoder; MLP, multi-layer perceptron; KRR, kernel ridge regression; MLR, multivariate linear regression; SMLR, stepwise multivariate linear regression; BRT, boosted regression trees; GEE, Google Earth Engine; MODIS, moderate resolution imaging spectroradiometer; EVI, enhanced vegetation index; TMIN, monthly minimum temperature; PRE, monthly precipitation accumulation; NDVI, normalized vegetation index; SM, soil moisture; TMAX, monthly maximum temperature; DI, Palmer drought severity index; GCI, green chlorophyll index; PMI, perpendicular moisture index; SIF, solar-induced chlorophyll fluorescence; SRTM, shuttle radar topography mission; UAV, unmanned aerial vehicle; CAR, Rural Environmental Registry; CBERS, China–Brazil earth resources satellite; RRMSE, average root mean square error; PCA, Principal Component Analysis; NDBI, normalized difference built-up index; CHIRPS/ECMWF, Climate Hazards Group InfraRed Precipitation with Station data/European Centre for Medium-Range Weather Forecasts; NRMSE, normalized root mean squared error; MERRA, modern-era retrospective analysis; FAO, Food and Agriculture Organization; WaPOR, water productivity through open-access remotely sensed data platform; CRU, Climatic Research Unit; CMA, China Central Meteorological Agency; RMSE, root mean square error; MAE, mean absolute error.

4.1.1. Land Mapping

Land-use mapping represents a critical research topic that addresses approaches for identifying crop areas in counties, regions and countries. Crop maps are the basis of accurate agricultural statistics for estimation, stratification purposes and food security studies.

Machine learning, deep learning and statistical methods provide tools for automatically classifying zones dedicated to specific crop types. Most of the work on land-use mapping uses vegetation indices and spectral bands derived from satellite imagery. MODIS and Landsat image datasets were explored to perform cotton and winter wheat mapping in Central Asia [67]. By applying Random Forest and Support Vector Machines algorithms to these datasets, it was possible to reach a land cover accuracy of 91%.

Maize mapping in Nigeria was studied in [68], using the same algorithms over multitemporal spectral indices and bands retrieved from Sentinel-1A and Sentinel-2A datasets. Another study [2] followed a similar approach for delimiting land use and cover mapping in Brazil, using a CBERS (China–Brazil earth resources satellite) data cube technology and MODIS datasets. Wheat mapping is proposed in [70] using Chinese Landsat-8 and Sentinel-2 datasets. The authors of the work explored Principal Component Analysis (PCA) to increase the accuracy provided by vegetation indices and spectral bands in classifying Brazilian rainfed crops, irrigated crops, savannas/shrublands, grasslands, forestlands, pasturelands and perennial crops. The NDVI (normalized vegetation index) predictors showed the best performance in delimiting crops, while the NDBI (normalized difference built-up index) method proved valuable for excluding buildings. Soybean mapping and cropland mapping in Argentina, the West African Sahel and Northeast Asia are studied in [73,74,76]. Vegetation indices and spectral bands obtained using the Google Earth Engine were selected as predictors for an RF model. Research on field mapping in Ghana, using similar methods, is presented in [81] using CubeSats and PlanetScope datasets. RF models were also used for Quinoa abiotic stress prediction [77].

Supervised learning models depend on labeled datasets for training and evaluation. Data labeling represents a manual, work-intensive process. Automatization of the data labeling process significantly reduces the cost of datasets and promotes their readiness. In [82], paddy rice mapping in South Korea resorts to the K-means clustering algorithm to create pseudo-labels for datasets and RF for classification, using Sentinel-1 and Sentinel-2 datasets. Another study on crop mapping in South Dakota [83] adopted a similar approach using high-resolution images (10 m crop-type maps).

4.1.2. Crop Yield Prediction

Crop yield prediction is fundamental for farmers and decision makers to control yield losses and ensure food security.

Rice represents one of the essential worldwide crops. Rice yield prediction in China is studied in [66], using climate variables and vegetation indices as predictors over the GEE platform. LASSO (least absolute shrinkage and selection operator), RF and LSTM (long short-term memory networks) methods yielded the best results for prediction periods of two- to one-month leading time. Yield prediction has been applied to other crop types. In [67], RF and K-means were explored to predict cotton and winter wheat in Central Asia, using vegetation indices derived from MODIS and Landsat imagery with high accuracy levels. In [69], the SVM, KNN (k-nearest neighbor regression) and GPR methods revealed the best performance of eight ML methods explored for crop yield prediction in China at the county and regional levels. Climate variables and vegetation indices derived from MODIS imagery were used as predictors, taking the interannual variability of planting area as a constraint. This study used spatial resolution as an essential prediction performance factor. However, climate data achieved significantly better predictive performance than satellite data. In [13], seven methods from the machine learning and deep learning categories were used along with vegetation indices (MODIS) for yield prediction of rice, corn and soybeans in South Korea and the USA. SVMs presented the best prediction performance. Yield prediction of barley, soft wheat and durum wheat in Algeria was presented in [71].

Vegetation indices and climate data obtained from MODIS and CHIRPS/ECMWF (Climate Hazards Group InfraRed Precipitation with Station data/ European Centre for Medium-Range Weather Forecasts) datasets provided predictors for SVR (support vector regression), LASSO and MLP (multi-layer perceptron) methods. It was observed that the performance of ML models is much less affected when focusing on low-yield years, while one-Hot Encoded features appear to increase the overall accuracy.

In [72], yield prediction of wheat in Australia resorts to hydro-climatic predictors derived from MERRA-2 (modern-era retrospective analysis) datasets. Feature selection using grey wolf, ant colony, atom search and particle swarm methods significantly increased the KRR (kernel ridge regression) method's prediction performance. In [79], climate data across the growing season provided additional information necessary for yield prediction compared to remote sensing data. Remote sensing data increased the prediction performance when covering the sowing to maturity periods. Additionally, some biotic factors (pathogens and insects) influencing crop growth reflected in leaf characteristics were detected from satellite images. In another study [78], the atmospheric prediction data significantly improved the wheat yield prediction performance provided by climate and vegetation indices from CRU (Climatic Research Unit) and MODIS datasets up to four months before the harvest.

Prediction of field biomass in China from vegetation indices, evapotranspiration, radar and net primary production variables, derived from Sentinel-1, Sentinel-2, FAO and WaPOR (water productivity through open-access remotely sensed data platform) datasets is studied in [75], using several ML regression methods. Results showed that cumulative vegetation indices have higher predictive power than standard vegetation indices. Additionally, the prediction accuracies of machine-learning models were not consistent as these increased or decreased unexpectedly as the lead time increased.

Soil organic carbon estimation in Bavaria is addressed in [80] using spectral bands and vegetation indices from Landsat. Data for organic carbon estimation is scarce since images only respect periods when soil is not covered with vegetation. Thus, composite techniques of multitemporal satellite Landsat images were explored for prediction using the RF method.

5. Discussion and Conclusions

Considering the trends for the current issues addressed here, this research intended to reveal insights from the scientific literature about the interlinkages between the digital transition and food security, and their interrelationships with agricultural planning and organization. In this context, 499 documents were considered in the Scopus database from a search performed on 9 September 2022 for the topics "machine learning" and "food security". These documents were first assessed through bibliometric approaches with text and bibliographic data. The top 40 documents with the highest total link strengths were thereafter further explored. In the text data, the items are terms and the links are co-occurrences. For the bibliographic data, co-occurrence and bibliographic coupling links were considered, as well as keywords, countries, organizations and sources as items.

5.1. Bibliometric Analysis

The bibliometric analysis highlighted the importance of the digital transition, in the frameworks of Era 4.0 (Agriculture 4.0, Food 4.0 and Industry 4.0), to deal with food security challenges from a perspective of sustainable development. In fact, one of the great tasks for the future is to increase agricultural production without compromising the several dimensions of sustainability, particularly the environmental, economic and socio-cultural. The new technologies and approaches, such as those related to Climate-Smart Agriculture, will be decisive to improve the efficiency of farms and food chains, as well as to promote better agricultural planning and organization. This will be particularly important to manage the most critical farming resources, such as labor, soil, water and energy. There are relevant advances with autonomous equipment and the internet of things (in some cases

used to better support farmers' decisions). The main concerns of the several stakeholders seem to be with grain production (maize and wheat) and with the most populous countries (China and India). In any case, there is still a field to be explored, specifically by other countries which also have great expertise in these domains, such as Brazil.

5.2. Platforms, Methods and Results

The systematic review shows the relevance of concepts such as remote sensing data and machine learning approaches in the contexts of the digital transition and food security worldwide. Unmanned aerial vehicle platforms, satellite information, the Copernicus program, shuttle radar topographic mission, moderate resolution imaging spectroradiometer and Google Earth Engine are platforms/methodologies/designations considered to collect/gather/analyze big data. Gaussian process regression, support vector machine regression, random forest regression, neural network, deep neural networks, 1D convolutional neural networks, long short-term memory networks, ridge regression, light gradient boosting, Bayesian neural network and adaptive boosting are some of the approaches/designations highlighted by the literature for the machine learning assessments. This literature review highlights the relevance of the Google Earth Engine platform and the Random Forest in the interrelationships between the machine learning and food security topics. These approaches are considered to predict crop mapping and yield with high precision, in some cases with R squares of about 99% and root mean squared error around 1%. These technologies are in some contexts in the beginning of being implemented in the agricultural and food frameworks, but there is an enormous field to be explored [84,85] and this research may be a relevant contribution to show gaps, trends and opportunities for the several stakeholders.

5.3. Data Sources

Data is the principal critical factor for success in machine-learning- and deep-learning-based work. Crop mapping and yields are commonly estimated from vegetation indices (e.g., NDVI), crop biophysical variables (e.g., Fraction of Photosynthetically Active Radiation), representing green biomass, and the dynamics of a vegetation index over time (e.g., green-up rate or senescence). Using multi-temporal satellite images covering several moments of cropping seasons may cover different features relevant to the research outcomes. Additionally, available climate forecasting data spanning each growing season increases the prediction capabilities of remote sensing data for yield prediction problems. Atmospheric predictions can even outperform those based on observational data [78]. The reason is that atmospheric predictions use not only observational climate data but also other data relevant to predict the climate during the growing season (e.g., climate change, climate connections between the region and other parts of the globe).

The research work revisited in this article pinpoints several limitations offering opportunities for improvement in future work. Firstly, current tools cannot predict crop yields based on open-access high-resolution data. Even with the 10 m spatial resolution of Sentinel-2 A/B datasets, their geographical availability still needs to be improved. Additionally, the temporal resolution of the five-day revisit time may still be low for some objectives. Secondly, cloud cover contaminates Sentinel data over more than half of the earth's surface throughout the year. Synthetic Aperture Radar (SAR) captures cloud-free data and is sensitive to the crop plant structure, geometry and water content, but provides higher spatial resolutions. Finally, the increase in temporal and spatial resolution demands increased computational power to enable effective and efficient exploitation. Thus, the importance of computational cost analysis will increase along with imagery resolution. Adaptive temporal resolution, for example, can be exploited for high-resolution images when computational constraints are involved. Crop growth sensitivities to climatic events vary with the growth stage [79]. For example, the grain formation process is more sensitive to drought and heat stress than the vegetative.

Countries with smallholder-dominated croplands present additional prediction challenges. The spatial and temporal mismatches between satellite data and smallholder fields, and the lack of high-quality labels required to train machine learning classifiers, are problems still being solved [76,81]. Other identified challenges are the high spatial and temporal variability within and between fields and the tendency to intergrade with the surrounding vegetation. UAVs offer the potential for new insights into relative plant performance in terms of phenotypic traits and abiotic stress experiments [77]. UAVs offer high spatial resolution data at a smallholder cropland scale. In addition to crop prediction and mapping, these data can be explored for crop monitoring activities—e.g., crop density analysis, irrigation scheduling, and detection and diagnosis of diseases, an emergent area with vast potential in the future.

5.4. Practical Implications, Policy Recommendations and Future Research

The new technologies are here, and there is relevant research about the digital transition in Era 4.0, as well as about its contribution to improvements in the farms and food chain efficiency. Nonetheless, some constraints remain, namely, those related to the difficulties felt by farmers in implementing digital approaches. In terms of practical implications, it seems that there is still significant work to be done in these fields to motivate and prepare farmers to adopt these new approaches. For policy recommendations, it is suggested to governments, national and international institutions and organizations that they create and make available more scientific and technical financing programs, supplying resources and promoting skills among farmers and informing them about the advantages of new technologies. The main limitations of this research are related to the need to investigate databases with information from applied social sciences (economics, management and business) that allow comparing their results with this research, as well as to explore dimensions associated with the limitations felt by farmers and food chain operators in implementing the digital transition in their respective activities and sectors. These can be explored in future studies.

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