PAPER • **OPEN ACCESS**

From machine learning to deep learning in agriculture – the quantitative review of trends

To cite this article: K Dokic *et al* 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **614** 012138

IOP Conf. Series: Earth and Environmental Science **614** (2020) 012138 doi:10.1088/1755-1315/614/1/012138

From machine learning to deep learning in agriculture – the quantitative review of trends

K Dokic[1*], L Blaskovic[2], and D Mandusic[2]

[1]Polytechnic in Pozega, Vukovarska 17, 34000 Pozega, Croatia, European Union
[2]Faculty of Agriculture, University of Zagreb, Svetosimunska cesta 25, 10000 Zagreb, Croatia, European Union

[*]Email: kdjokic@vup.hr

Abstract. In the last two decades, we have witnessed the intensive development of artificial intelligence in the field of agriculture. In this period, the transition from the application of simpler machine learning algorithms to the application of deep learning algorithms can be observed. This paper provides a quantitative overview of papers published in the past two decades, thematically related to machine learning, neural networks, and deep learning. Also, a review of the contribution of individual countries was given. The second part of the paper analyses trends in the first half of the current year, with an emphasis on areas of application, selected deep learning methods, input data, crop mentioned in the paper and applied frameworks. Scopus and Web of Science citation databases were used.

1. Introduction

The development of artificial intelligence and machine learning in the last two decades has led to a significant increase in the number of projects in the field of agriculture. The first papers that point on possible automation of some processes in agriculture are more than fifty years' old. Low levels of computing power did not allow for further development until the end of the twentieth century [1]. Since the beginning of the 21st century, artificial intelligence has been increasingly used in agriculture. One of the indicators of growth is the number of published scientific papers dealing with this topic.

In this paper, an analysis of papers in the field of machine learning, neural networks and deep learning is given, but only those related to agriculture. In the second section is the literature overview. In the third and fourth sections methods of analysis and results can be found. The results are divided into three parts, machine learning, neural networks and deep learning, but a more detailed analysis focused on papers published in this year is given. Finally, in the last section, discussion and conclusion can be found.

2. Literature overview

Many reviews deal with artificial intelligence (AI), computer vision (CV), machine learning (ML) and deep learning (DL) in agriculture. For machine learning, we can say that it is an approach to achieve artificial intelligence. Deep learning is a part of the machine learning field, and convolution and recurrent neural networks belong to deep learning. In Fig. 1 the relationship of some terms mentioned above can be seen, and it will be used in section three as well as in this literature overview.

Jha et al. made a review on automation in agriculture based on artificial intelligence. They analysed different technologies on the market and concluded that the combination of sensors, IoT and ML can be used to automate processes in agriculture [2]. Patricio and Rieder analysed artificial intelligence and computer vision in precision agriculture. They used six databases (ScienceDirect, Scopus, Springer, Web of Science, ACM and IEEE) and analysed 25 papers from 2013 to 2017 but only with five crops (maise, rice, wheat, soybean and barley). Interestingly, most used classifier in that period was Support Vector Machine. The most used input device was a camera [3]. Tian et al. analysed computer vision technology in agriculture. They analysed 41 papers published from 2017 to 2019 and concluded that "computer vision technology combined with artificial intelligence algorithms will improve the economic performance, general performance, coordination performance and robust performance of agricultural automation systems." [4]. Paul et al. put the focus on computer vision and machine learning in agriculture, and they analysed about fifty papers from 2007 to 2018. And they noticed a significant advance in recent time [5]. Rehman et al. made a great work analysed more than two hundred papers that deal with machine learning algorithms for agricultural machine vision systems. They suggested that "the use of ML technology for weed detection, plant diseases and stress detection, yield prediction and estimation, plant water content determination, grading and sorting, soil analysis and real-time field operations may become routine operation in near future agriculture." [6].

Liakos et al. analysed forty papers that deal with machine learning in agriculture. They used search engines from Scopus, ScienceDirect and PubMed, and all articles are published in journals. They noticed that 4 papers are related to ML in water management, 8 are associated with ML in livestock management, 4 are related to soil management. In contrast, most of the papers (24) are associated with ML in crop management [7]. Chlingaryan et al. analysed machine learning for crop yield prediction in agriculture with a focus on nitrogen management. They also concluded that ML and sensing usage have rapidly advanced during the last ten years [8]. Sharma et al. also focused on one narrower area – they analysed sustainable agriculture supply chain performance based on machine learning. They used Business Source Premier, Scopus, Emerald Insights and Web of Science databases, and analysed 93 papers. The paper reveals considerable benefits of machine learning implemented in the agriculture supply chain systems [9]. Behmann et al. analysed advanced machine learning methods for biotic stress detection in crop protection. Interestingly, authors have about a hundred papers in references, but they did not mention CNNs that are state-of-art neural networks today, six years later. This indicates the rapid development of algorithms in the field [10].

Kamilaris and Prenafeta-Boldú analysed deep learning algorithms in agriculture. They used ScienceDirect, IEEE, Web os Science and Google Scholar databases. They analysed forty papers and noticed that 57% of papers used typical CNN architectures for classification. Some of them used RNN architectures when the time dimension had to be exploited. Finally, they concluded that "deep learning offers better performance and outperforms other popular image processing techniques" [11]. Same authors analysed 23 papers that deal with convolutional neural networks in agriculture in another article. They used the same databases for papers research and concluded that CNN usually rich higher precision than other image processing technics [12].

3. Method

In this study, the first step was citation databases analyse. Many authors did it before, like Jasco Bar-Ilan or Falagas et al. [13] [14] [15]. They suggest that Scopus, Web of Science and Google Scholar are primary citation services, so in this paper, we used two of them. Falagas et al. also analysed PubMed, but this database is not a general citation service, so we excluded it [15]. On the other hand, Mahe suggests that ResearchGate provides another citation index, but like Google Scholar. it is also excluded because the lack of some advanced functions that are provided by Scopus and Web of Science [16]. Finally, Scopus and Web of Science are used for papers searching and extracting.

Web of Science provides access to multiple databases with citation data. Clarivate Analytics maintains it but the Institute for Scientific Information produced it. It has 171 million items in the database with

1.9 billion references. Scopus also provides access to citation data, and Elsevier maintains it. It has 75 million items in the database with 1.4 billion references from 1970.
The focuses of our study are using machine learning, neural networks and deep learning in agriculture, so for the survey of papers following search expression were defined:

a) "machine learning" AND agriculture
b) "neural networks" AND agriculture
c) "deep learning" AND agriculture

It is important to emphasise that we searched only in titles, abstracts and keywords. As it is mentioned before, neural networks are part of machine learning fields, and deep learning is a special version of neural network usage. This relation can be seen on Figure 1.

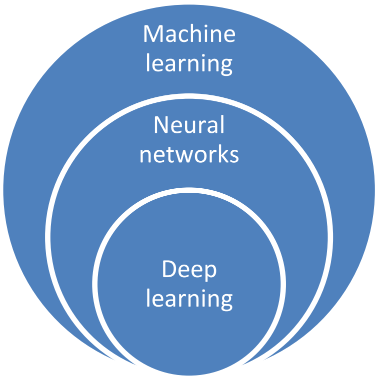


Figure 1. ML, NN and DL relationship

The time interval was defined from 2000 to 2020.

4. Results

In Table 1 search expression results can be seen. It is evident that the number of papers grows as time goes on. In the last row, the results were calculated by linear interpolation, and the obtained numbers were multiplied by 12/7, because for 2020, the results are available only for the first 7 months.

Table 1. Citation database search expression results

YEAR	SCO, ML	SCO, NN	SCO, DL	WOS, ML	WOS, NN	WOS, DL
2000	1	17	0	2	44	0
2001	1	16	0	2	44	0
2002	2	17	0	0	43	0
2003	2	36	0	4	62	0
2004	3	23	0	3	43	0
2005	2	42	0	5	71	1
2006	5	40	0	11	77	0
2007	8	37	0	7	91	0
2008	5	66	0	11	113	0
2009	10	85	0	13	131	1
2010	16	98	0	37	150	0
2011	13	83	0	31	168	0
2012	17	96	0	47	254	1
2013	20	96	0	80	264	1

2014	34	106	1	106	313	0
2015	63	118	3	144	363	8
2016	100	173	16	210	440	21
2017	137	221	45	273	520	69
2018	272	336	103	540	714	185
2019	552	598	308	833	957	389
2020	667	646	454	1152	1164	612

The results will be presented in 3 subsections, machine learning, neural networks and deep learning.

4.1. Machine learning

On Figure 2, the number of published papers about machine learning and agriculture can be seen. A base-10 logarithmic scale is used for the vertical axis.

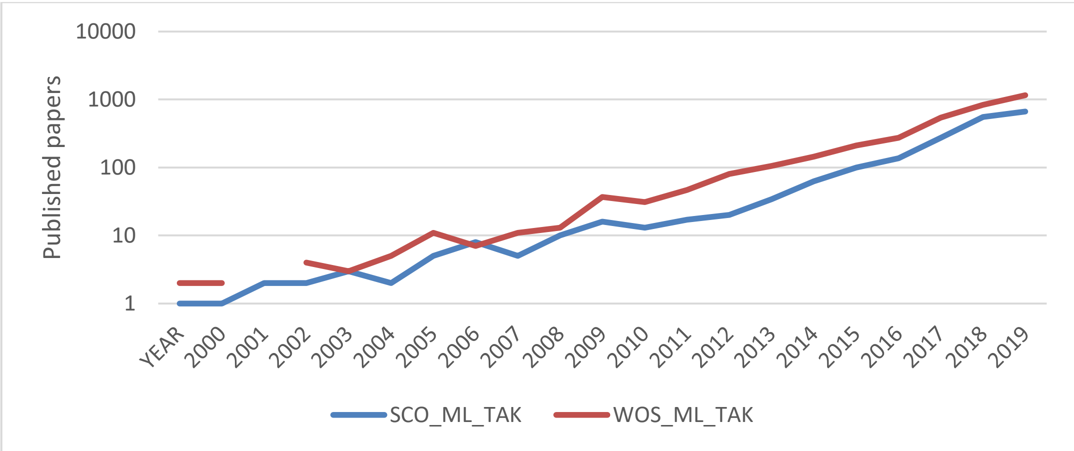
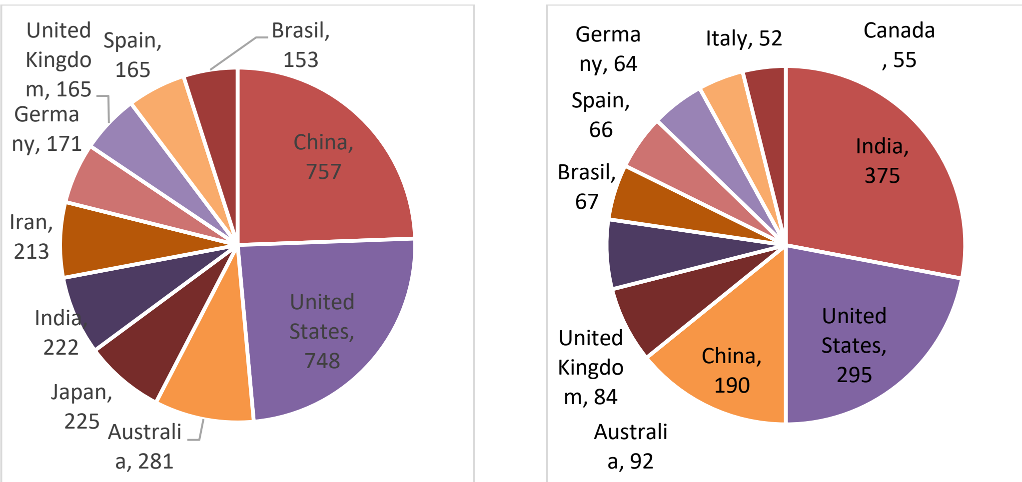


Figure 2 Number of published papers about machine learning and agriculture per year



Web of Science Scopus

Figure 3. Number of published papers about machine learning and agriculture by country

IOP Conf. Series: Earth and Environmental Science **614** (2020) 012138 doi:10.1088/1755-1315/614/1/012138

On Figure 3, the number of published articles by country between 2000 and 2020 can be seen. Only the ten countries with the largest number of published papers are shown. In the Web of Science database, most published articles are from Chinese and United States authors, but on the Scopus database, most authors are from India. There is a significant difference in the number of indexed papers in the two used databases. In the Web of Science, there are more than three thousand papers, but Scopus has about a thousand and a half indexed articles.

4.2. Neural networks

On Figure 4, the number of published papers about neural networks and agriculture can be seen. A base-10 logarithmic scale is used for the vertical axis.

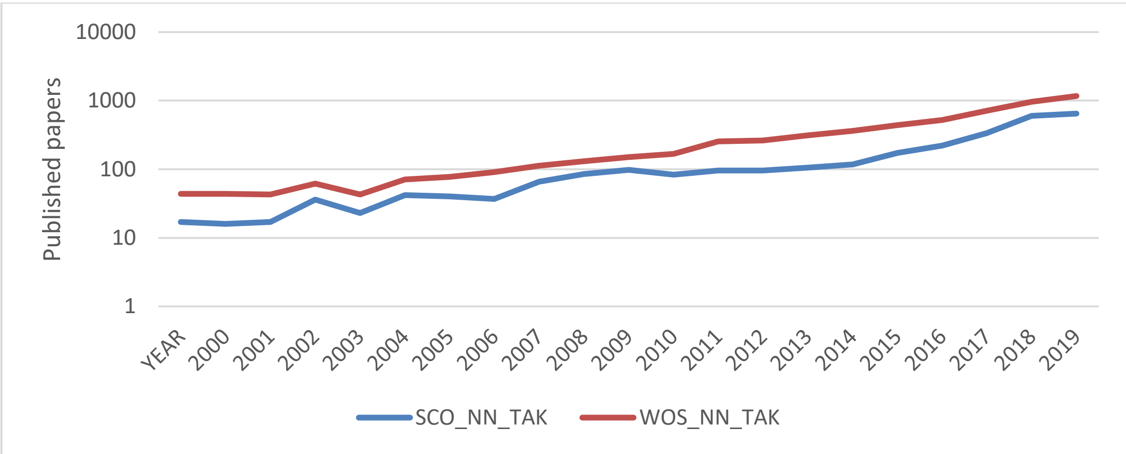


Figure 4 Number of published papers about neural networks and agriculture per year

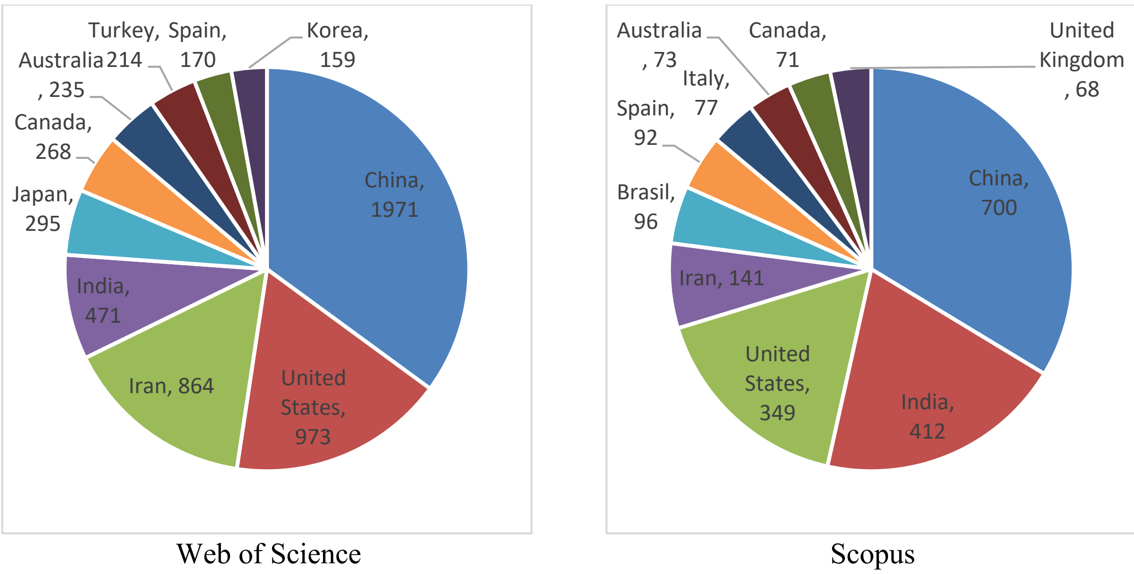


Figure 5 Number of published papers about neural networks and agriculture by country

On Figure 5, the number of published articles by country between 2000 and 2020 can be seen. Only the ten countries with the largest number of published papers are shown. In both databases, most published articles are from Chinese authors. There is a significant difference in the number of indexed papers in the two used databases. In the Web of Science, there are more than 5500 papers, but Scopus has about 2800 indexed articles.

4.3. Deep learning

On the Figure 6, the number of published papers about deep learning and agriculture can be seen. A base-10 logarithmic scale is used for the vertical axis.

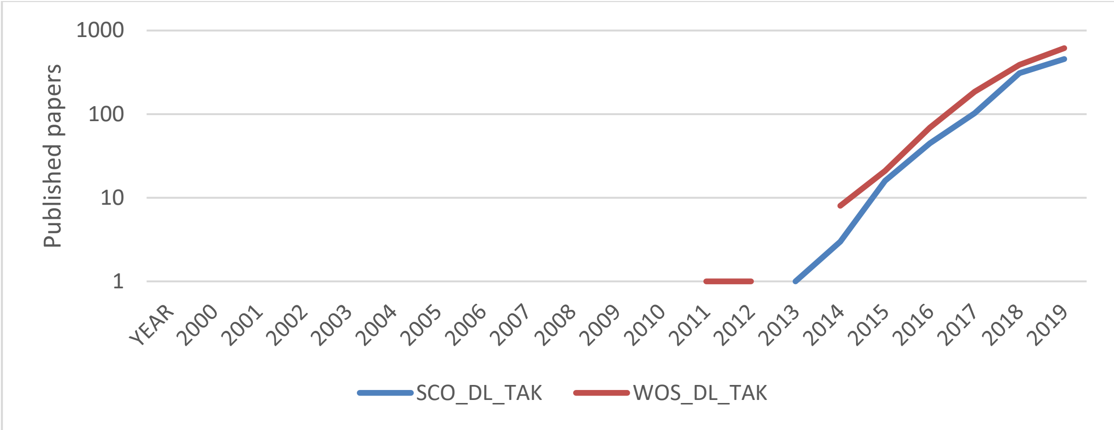
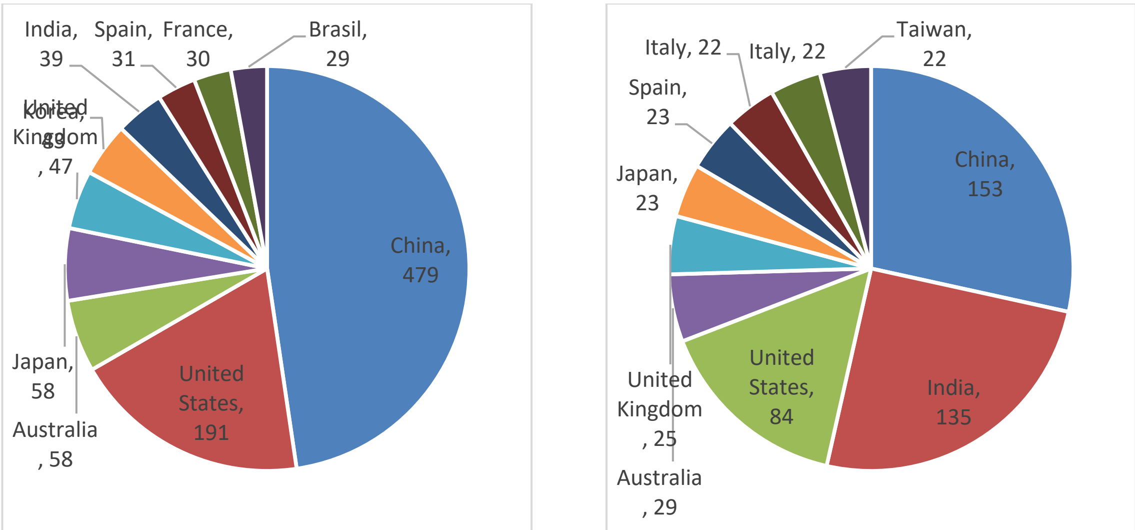


Figure 6 Number of published papers about deep learning and agriculture per year



Web of Science Scopus

Figure 7 Number of published papers about deep learning and agriculture by country

On Figure 7, the number of published articles by country between 2000 and 2020 can be seen. Only the ten countries with the largest number of published papers are shown. In the Web of Science database, most published articles are from Chinese authors, but on the Scopus database, most authors are from China and India. There is a significant difference in the number of indexed papers in the two used databases. In the Web of Science, there are more than a thousand papers, but Scopus has about 700 indexed articles.

4.3.1. Deep learning trends in 2020

The graph in Figure 6 is particularly intriguing. The extremely rapid growth in the number of papers related to deep learning is evident. To analyse new trends in the development of deep learning, we

extracted only articles published during 2020. We got different papers from used databases because they index various journals. To obtain the highest quality results, we extracted only papers that were indexed in both databases. There were 105 of them in total. After the analysis, we removed the review papers and papers that were found in the list by mistake. After that, we have got 95 articles.
All 95 papers were analysed and categorised according to five criteria, depending on the areas of application, selected deep learning methods, input data, crop mentioned in the paper and applied frameworks.

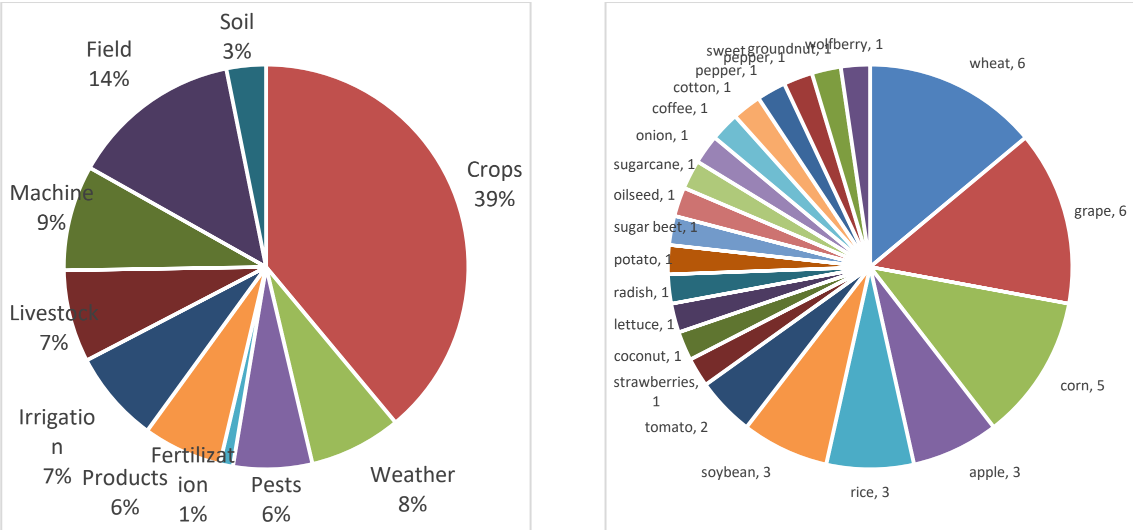


Figure 8 - Areas of application (left) and crops mentioned in the paper (right)

On the left side of Figure 8 areas of a deep learning application can be seen. Many authors suggest domains for smart agriculture model, but in this paper, eleven domains suggested by Alreshidi have been used. They are human resources, crops, weather, soil, pests, fertilisation, products, irrigation, livestock, machines and fields. Some papers fell into two categories, in which case the more dominant one was chosen. More details about the used categorisation are available in the literature [17]. Most papers deal with crops, but it can be expected.
On the right side of Fig 8 crops mentioned in the papers are aggregated. Only some articles mention crops, so the total on the graph is not 95. It can be seen that wheat, corn and grape are dominant subjects in the papers.

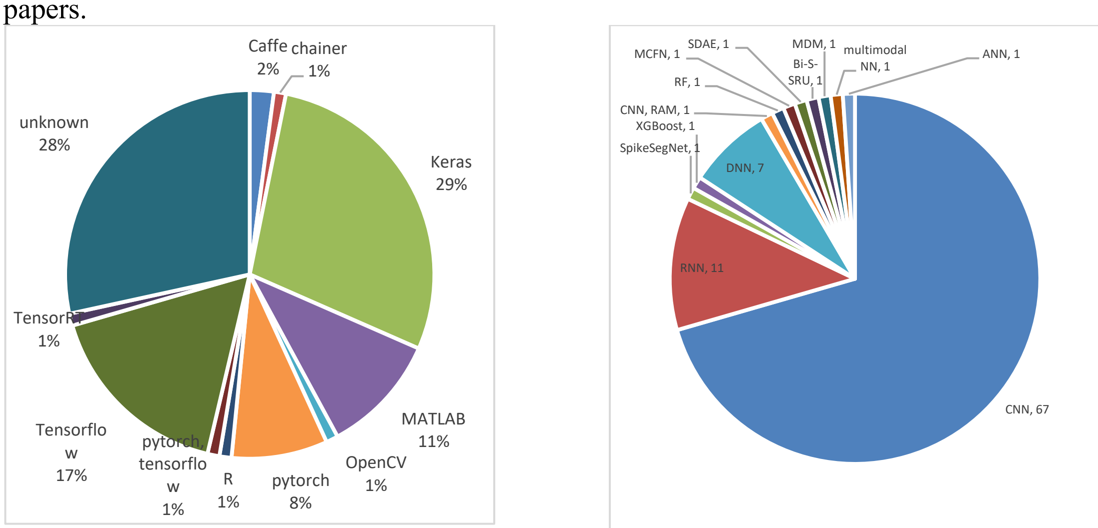


Figure 9 Applied frameworks (left) and deep learning methods (right)

On the left side of Figure 9, applied frameworks in the papers can be seen. The most used framework in the analysed papers is Keras (29%). In many papers, information about the used framework is not available (28%) and in the third place is TensorFlow (17%). In almost all papers that used Keras, TensorFlow has been used, because Keras is capable of running on top of MS Cognitive Toolkit, R, PlaidML, Theano and TensorFlow. It can be concluded that TensorFlow is the dominant framework in the papers, but it has been used with or without Keras.
On the right side of Fig 9, deep learning methods that are used in the papers can be seen. The most dominant method is convolution neural networks (67%) and recurrent neural networks (11%). Recurrent neural networks are used when temporal dynamic behaviour is needed, but for the most tasks, convolution neural networks are the “state of the art” technology.

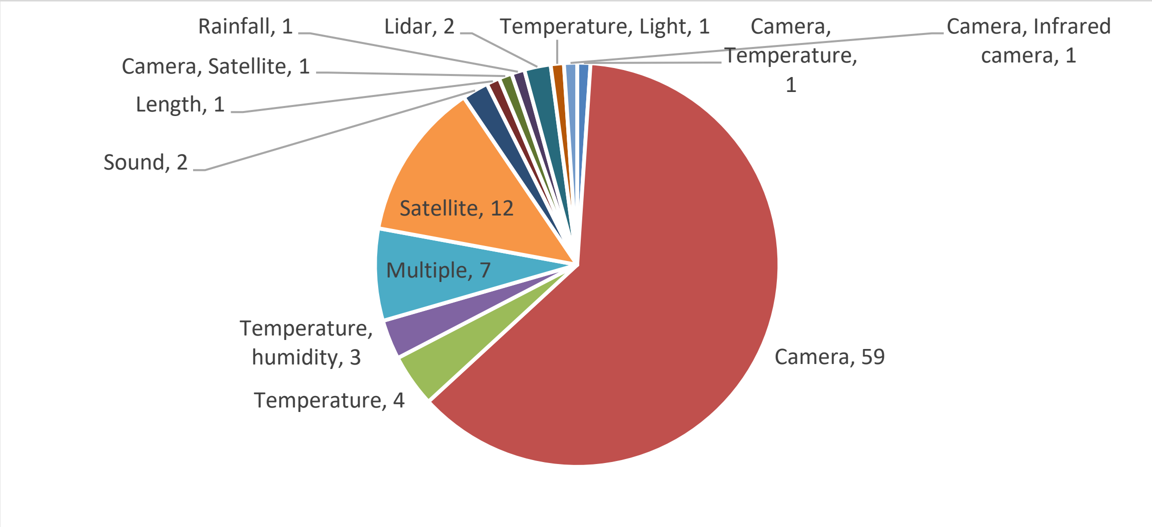


Figure 10 Input data sources for deep learning method

On Figure 10, the input data sources can be seen. A camera is a dominant data source (59 papers), but a satellite is on the second place (12 papers). The satellite as a data source is placed in another category, although it is clear that in the case of satellites, they also use cameras that can use different wavelengths in some cases. In seven papers, there are more than two (multiple) input data sources, and there are few papers that deal with temperature, humidity, rainfall, light, etc.
In the following, each paper is described in one sentence, and are categorized by an input data source. The camera is used to develop a robot that can selectively harvest broccoli heads [18], for crop harvesting system with IoT technology [19] and DNN-based automated harvesting [20]. It is used for disease detection of crops such as potato, tomato and maise [21] [22] and detection and classification of groundnut diseases [23]. It is also used for automated segmentation of grape bunches in color images [24], for fast landmark extraction in steep slope vineyard context [25], for a framework to identify and classify the selected diseases on a grape at the early stages [26], and for autonomous navigation in vineyards [27]. It is used for disease identification and classification using apple leaf image dataset [28]. Zhao et al. used a camera as an input device for automatic crop disease recognition system [29] , Wang et al. used it for semantic segmentation of crop and weed [30] and Azizi et al. used it to detect and segment different clods obtained from tilled soil [31]. The camera has been used for deep-learning solution for image recognition of Legacy blueberries in the rooting stage [32] and for deep neural network model for detecting the onion disease symptom [33] as well as for detection ripe soft fruits (strawberries) in real industrial settings [34]. Kang and Chen used a camera as input for a framework of a deep-learning-based fruit detector for apple harvesting [35] and Esgario et al. used it for a system capable of identifying and estimating the stress severity caused by biotic agents on coffee leaves [36]. For the new method that considers diseases independently of crops, the camera is also used as an input

device [37], as well as for two-stages mobile vision-based cascading pest detection approach [38]. It is used for pest detection, classification and counting by Chen et al. [39]. Santos et al. used it for grape detection, tracking and counting in vineyards [40] and Xu et al. used it for cattle counting in different situations [41]. A camera is used for novel crop/weed identification system based on CNN [42], for soybean plant diseases recognition using segmented leaf images [43], for the low-cost and scalable solution of pig recognition [44] and for detecting the position and posture of pigs with 21 cameras [45]. It is used for livestock classification and counting in quadcopter aerial images [46] and pig detection [47]. Jiang et al. proposed weed and crop recognition system with a camera [48] and Alves proposed a classification system for major cotton pests with a camera [49]. Camera is used as input for UAV solutions by Wang, Bah, Tetila, Shen, Yang, Barbero, Moghimi, Kerkech, Maimaitijiang, Mazzia, Nguyen and Zhang [38] [50] [51] [52] [53] [54] [55] [56] [57] [58] [59] [60].

The camera is used by Hamdan for a vision system that can accurately estimate the mass of sugarcane while running in real-time on a sugarcane harvester during operation [61] and by Wang to establish a large-scale multi-target standardised data set of agricultural pests [62]. Espejo-Garcia suggests that weeds identification can be improved with a repository of agricultural pre-trained deep neural networks [63], Velumani used camera in automatic method to estimate wheat heading date [64] and Misra used it to recognise and count the number of spikes of the wheat plant from the digital images [65]. The camera is used in the system for detecting the apparent defects of sour lemon fruit and grades them [66] and for classify the soil aggregates obtained from plowing [67]. It is also used for identification and differentiation of ten major varieties of basmati rice [68] and crop pest dataset and plant leaf dataset creation [69] and for segmentation method to discriminate leaf and non-leaf regions in images [70]. Some authors used a camera for diagnosing the CLR in development stage [71] and some of them suggest how to assigns a portion of the DL layers to fog nodes when data from cameras are processing [72]. Finally, the camera is used for pest and disease identification in the growth of sweet peppers using CNN [73] and for automatic detection and severity assessment of pepper bacterial spot disease [74].

Satellite images are used in papers about a general method to facilitate field boundary extraction [75], deep-learning-based shadow removal model [76], generalisable crop classification model for spatial transfer across regions [77], classify crops in VHR images based on geo-parcels [78], classification workflow using deep neural network (DNN) to produce high-quality in-season crop maps [79], weakly supervised deep learning system for cropland segmentation [80], a model for quantification of the tree cover of forests in global drylands [81], deep learning model to map agricultural areas [82], delimitation-grading for agro-production units in modern smallholder regions with satellite data and CNN [83], semantic segmentation on the aerial and satellite images [84] [85] and semantic segmentation of center pivot irrigation systems from remotely sensed data [86].

An infrared camera is used for integrating drone‐borne thermal imaging with artificial intelligence to locate bird nests on agricultural land [87] and apple length is used in the paper about complex profile monitoring development based on the deep learning technique [88].

Lidar is used as an input device in papers by Jin et al. [89] [90] and sound is input in the papers about models for predicting the precipitation based on meteorological data [91] and application of RF in classifying coconut maturity [92]. Temperature and humidity are input values in the papers about precision water resource management [93], maximum temperature forecasting [94] and for temperature and humidity prediction for sustainable precision agriculture [95]. Temperature and light are inputs for CNN for estimating and analysing crop yields [96].

The only temperature is used as input in papers about predicting reservoir temperatures based on typical hydrogeochemical parameters [92], edge computing evaluation for frost prediction in crops by estimating low temperatures through LSTM deep learning models [97] and predictive model for temperature [98].

Finally, papers with multiple sources for neural network inputs are about the comparative assessment of environmental variables and machine learning algorithms for maise yield prediction [99], accurate water quality prediction scheme is proposed for pH, water temperature and dissolved oxygen [100], integrated approach for monitoring crop health using IoT, machine learning and drone technology [101], robot system combines the current environment with weather forecasts through LSTM to predict the correct timing for watering [102], RNN network models for predicting the precipitation based on meteorological data [103], hybrid deep learning predictor for accurate predictions of temperature, wind speed, and humidity data [104] and optimised supply chain provenance system for Industry 4.0 in the food sector using state-of-the-art technologies such as IoT, blockchain, and advanced deep learning [105].

5. Discussion and Conclusions

The development of artificial intelligence and machine learning in the last two decades has led to a significant increase in the number of projects in the field of agriculture. Artificial intelligence is a general term that includes machine learning, neural networks and deep learning. The production and publication of papers linking these three subordinate terms and agriculture are covered in this paper. From the attached analysis and graphs, it is evident that there is a great interest in the scientific community in these fields.

If we look at the production of scientific papers by country, it is evident that China dominates in production. In only one of the six graphs shown is China not in first place in terms of production. A particularly significant difference is observed in the number of published scientific papers about deep learning in the Web of Science citation database. Authors from China write almost half of the papers.

Papers about deep learning published in the first half of 2020 and the trends that are looming are particularly attractive. It can be concluded that TensorFlow is a dominant framework, but most researchers use Keras to simplify the process of constructing neural networks. A camera has become the dominant input device, and images are the most common input medium used by neural networks. Wheat, corn and grape are most often in the focus of scientists, and crop analysis is the most common area of the deep learning application. Finally, the use of convolutional neural networks has become commonplace in solving problems in agriculture.

We can conclude that “the future in agriculture has already come”, based on the chart from Fig 6. We just need to use the available resources and knowledge.

References

[1] Steiner D 1970 *Geoforum* **1** 75–88.
[2] Jha K, Doshi A, Patel P, Shah M 2019 *Artificial Intelligence in Agriculture* **2** 1–12.
[3] Patrício DI, Rieder R 2018 *Computers and Electronics in Agriculture* **153** 69–81.
[4] Tian H, Wang T, Liu Y, Qiao X, Li Y 2020 *Information Processing in Agriculture* **7** 1–19.
[5] Ghosh PS, Das AK, Goswami S, Choudhury SD, Sen S 2020 A review on agricultural advancement based on computer vision and machine learning, Emerging Technology in Modelling and Graphics, Springer, pp 567–581.
[6] Rehman TU, Mahmud MS, Chang YK, Jin J, Shin J 2019 *Computers and electronics in Agriculture* **156** 585–605.
[7] Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D 2018 *Sensors* **18** 2674.
[8] Chlingaryan A, Sukkarieh S, Whelan B 2018 *Computers and Electronics in Agriculture* **151** 61–69.
[9] Sharma R, Kamble SS, Gunasekaran A, Kumar V, Kumar A 2020 *Computers & Operations Research* 104926.
[10] Behmann J, Mahlein AK, Rumpf T, Römer C, Plümer L 2015 *Precision Agriculture* **16** 239–260, 2015.
[11] Kamilaris A, Prenafeta-Boldú FX 2018 *Computers and Electronics in Agriculture* **147** 70–90.
[12] Kamilaris A, Prenafeta-Boldú FX 2018 *The Journal of Agricultural Science* **156** 312–322.
[13] Jacso P 2005 *Current Science* **89** 1537–1547.
[14] Bar-Ilan J 2010 *Scientometrics* **82** 495–506.

[15] Falagas ME, Pitsouni EI, Malietzis GA, Pappas G 2008 *The FASEB Journal* **22** 338–342.
[16] Mahé G 2017 *Último Access* **10** 2017.
[17] Alreshidi E 2019 *arXiv preprint arXiv* 1906.03106.
[18] Blok PM, van Evert FK, Tielen APM, van Henten EJ, Kootstra G 2020 *Journal of Field Robotics* 2020.
[19] Horng GJ, Liu MX, Chen CC 2019 *IEEE Sensors Journal* **20** 2766–2781.
[20] Shkanaev AY, Sholomov DL, Nikolaev DP 2020 Unsupervised domain adaptation for DNN-based automated harvesting, *Twelfth International Conference on Machine Vision (ICMV 2019)*.
[21] Khamparia A, Saini G, Gupta D, Khanna A, Tiwari S, de Albuquerque VHC 2020 *Circuits, Systems, and Signal Processing* **39** 818–836.
[22] Verma S, Chug A, Singh AP 2020 *Journal of Discrete Mathematical Sciences and Cryptography* **23** 273–282.
[23] Vaishnnave MP, Devi KS, Ganeshkumar P 2020 *SOFT COMPUTING* 2020.
[24] Marani R, Milella A, Petitti A, Reina G 2020 *Precision Agriculture* 1–27.
[25] Aguiar AS, Dos Santos FN, De Sousa AJM, Oliveira PM, Santos LC 2020 *IEEE Access* **8** 77308–77320.
[26] Adeel Q, Khan MA, Akram T, Sharif A, Yasmin M, Saba T, Javed K 2020 *Expert Systems* 2020.
[27] Aghi D, Mazzia V, Chiaberge M 2020 *Machines* **8** 27.
[28] Francis M, Deisy C 2020 *Archives of Computational Methods in Engineering* 1–17.
[29] Zhao Y, Liu L, Xie C, Wang R, Wang F, Bu Y, Zhang S *Applied Soft Computing* **89** 106128.
[30] Wang A, Xu Y, Wei X, Cui B 2020 *IEEE Access* **8** 81724–81734.
[31] Azizi A, Abbaspour-Gilandeh Y, Vannier E, Dusséaux R, Mseri-Gundoshmian T, Moghaddam HA 2020 *Biosystems Engineering* **196** 172–182.
[32] Quiroz IA, Alférez GH 2020 *Computers and Electronics in Agriculture* **168** 105044.
[33] Kim WS, Lee DH, Kim YJ 2020 *Computers and Electronics in Agriculture* **168** 105099.
[34] Kirk R, Cielniak G, Mangan M 2020 *Sensors* **20** 275.
[35] Kang H, Chen C 2020 *Computers and Electronics in Agriculture* **168** 105108.
[36] Esgario JGM, Krohling RA, Ventura JA 2020 *Computers and Electronics in Agriculture* **169** 105162.
[37] Lee SH, Goëau H, Bonnet P, Joly A 2020 *Computers and Electronics in Agriculture* **170** 105220.
[38] Wang F, Wang R, Xie C, Yang P, Liu L 2020 *Computers and Electronics in Agriculture* **169** 105222.
[39] Chen YS, Hsu CS, Lo CL 2020 An Entire-and-Partial Feature Transfer Learning Approach for Detecting the Frequency of Pest Occurrence, *IEEE Access*.
[40] Santos TT, de Souza LL, dos Santos AA, Avila S 2020 *Computers and Electronics in Agriculture* **170** 105247.
[41] Xu B, Wang W, Falzon G, Kwan P, Guo L, Chen G, Tait A, Schneider D 2020 *Computers and Electronics in Agriculture* **171** 105300.
[42] Espejo-Garcia B, Mylonas N, Athanasakos L, Fountas S, Vasilakoglou I *Computers and Electronics in Agriculture* **171** 105306.
[43] Karlekar A, Seal A 2020 *Computers and Electronics in Agriculture* **172** 10534.
[44] Marsot M, Mei J, Shan X, Ye L, Feng P, Yan X, Li C, Zhao Y 2020 *Computers and Electronics in Agriculture* **173** 105386.
[45] Riekert M, Klein A, Adrion F, Hoffmann C, Gallmann E 2020 *Computers and Electronics in*

Agriculture **174** 105391.
[46] Xu B, Wang W, Falzon G, Kwan P, Guo L, Sun Z, Li C 2020 *International Journal of Remote Sensing* 1–22.
[47] Seo J, Ahn H, Kim D, Lee S, Chung Y, Park D 2020 *Applied Sciences* **10** 2878.
[48] Jiang H, Zhang C, Qiao Y, Zhang Z, Zhang W, Song C 2020 *Computers and Electronics in Agriculture* **174** 105450.
[49] Alves AN, Souza WSR, Borges DL 2020 *Computers and Electronics in Agriculture* **174** 105488.
[50] Bah MD, Hafiane A, Canals R 2019 *IEEE Access* **8** 5189–5200.
[51] Tetila EC, Machado BB, Menezes GK, Oliveira ADS, Alvarez M, Amorim WP, Belete NADS, Da Silva GG, Pistori H 2019 *IEEE Geoscience and Remote Sensing Letters* **17** 903–907.
[52] Shen X, Teng Y, Fu H, Wan Z, Zhang X 2020 Crop identification using UAV image segmentation, *Second Target Recognition and Artificial Intelligence Summit Forum*.
[53] Yang MD, Tseng H, Hsu YC, Tsai HP 2020 *Remote Sensing* **12** 633.
[54] Barbedo JGA, Koenigkan LV, Santos PM, Ribeiro ARB 2020 *Sensors* **20** 2126.
[55] Moghimi A, Yang C, Anderson JA 2020 *Computers and Electronics in Agriculture* **172** 105299.
[56] Kerkech M, Hafiane A, Canals R 2020 *Computers and Electronics in Agriculture* **174** 105446.
[57] Maimaitijiang M, Sagan V, Sidike P, Hartling S, Esposito F, Fritschi FB 2020 *Remote Sensing of Environment* **237** 111599.
[58] Mazzia V, Comba L, Khaliq A, Chiaberge M, Gay P 2002 *Sensors* **20** 2530.
[59] Nguyen K, Huynh NT, Nguyen PC, Nguyen KD, Vo ND, Nguyen TV 2020 *Electronics* **9** 583.
[60] Zhang Z, Flores P, Igathinathane C, Naik DL, Kiran R, Ransom JK 2020 *Remote Sensing* **12** 1838.
[61] Hamdan MKA, Rover DT, Darr MJ, Just J 2020 *arXiv preprint arXiv:*2003.03192.
[62] Wang QJ, Zhang SY, Dong SF, Zhang GC, Yang J, Li R, Wang HQ 2020 *Computers and Electronics in Agriculture* **175** 105585.
[63] Espejo-Garcia B, Mylonas N, Athanasakos L, Fountas S 2020 *Computers and Electronics in Agriculture* **175** 105593.
[64] Velumani K, Madec S, de Solan B, Lopez-Lozano R, Gillet J, Labrosse J, Jezequel S, Comar A, Baret F 2020 *Field Crops Research* **252** 107793.
[65] Misra T, Arora A, Marwaha S, Chinnusamy V, Rao AR, Jain R, Sahoo RN, Ray M, Kumar S, Raju D 2020 *Plant Methods* **16** 1–20.
[66] Jahanbakhshi A, Momeny M, Mahmoudi M, Zhang YD 2020 *Scientia Horticulturae* **263** 109133.
[67] Azizi A, Gilandeh YA, Mesri-Gundoshmian T, Saleh-Bigdeli AA, Moghaddam HA, 2020 *Soil and Tillage Research* **199** 104586.
[68] Sharma A, Satish D, Sharma S, Gupta D 2019 *Frontiers in Plant Science* **10**.
[69] Li Y, Chao X 2020 *Agriculture* **10** 178.
[70] Giménez-Gallego J, González-Teruel JD, Jiménez-Buendía M, Toledo-Moreo AB, Soto-Valles F, Torres-Sánchez R 2020 *Applied Sciences* **10** 202.
[71] Velásquez D, Sánchez A, Sarmiento S, Toro M, Maiza M, Sierra B 2020 *Applied Sciences* **10** 697.
[72] Lee K, Silva BN, Han K 2020 *Applied Sciences* **10** 1544.
[73] Lin TL, Chang HY, Chen KH 2002 *Journal of Internet Technology* **21** 605–614.
[74] Wu Q, Ji M, Deng Z 2020 *International Journal of Agricultural and Environmental Information Systems* **11** 29–43.

[75] Waldner F, Diakogiannis FI 2020 *Remote Sensing of Environment* **245** 111741.
[76] Zhang Y, Chen G, Vukomanovic J, Singh KK, Liu Y, Holden S, Meentemeyer RK 2020 *Remote Sensing of Environment* **247** 111945.
[77] Xu J, Zhu Y, Zhong R, Lin Z, Xu J, Jiang H, Huang J, Li H, Lin T 2020 *Remote Sensing of Environment* **247** 111946.
[78] Sun Y, Luo J, Xia L, Wu T, Gao L, Dong W, Hu X, Hai Y 2020 *International Journal of Remote Sensing* **41** 1603–1624.
[79] Sun Z, Di L, Fang H, Burgess A 2020 *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.
[80] Wang S, Chen W, Xie SM, Azzari G, Lobell DB 2020 *Remote Sensing* **12** 207.
[81] Guirado E, Alcaraz-Segura D, Cabello J, Puertas-Ruíz S, Herrera F, Tabik S 2020 *Remote Sensing* **12** 343.
[82] Liao C, Wang J, Xie Q, Baz AA, Huang X, Shang J, He Y 2020 *Remote Sensing* **12** 832.
[83] Lv Y, Zhang C, Yun W, Gao L, Wang H, Ma J, Li H, Zhu D 2020 *Remote Sensing* **12** 1074.
[84] Bachhofner S, Loghin AM, Otepka J, Pfeifer N, Hornacek M, Siposova A, Schmidinger N, Hornik K, Schiller N, Kähler O 2020 *Remote Sensing* **12** 1289.
[85] Panboonyuen T, Jitkajornwanich K, Lawawirojwong S, Srestasathiern P, Vateekul P 2020 *Remote Sensing* **12** 1233.
[86] de Albuquerque AO, de Carvalho Júnior OA, d. Carvalho OLF, de Bem PP, Ferreira PHG, de Moura RDS, Silva CR, Trancoso Gomes RA, Fontes Guimarães R 2020 *Remote Sensing* **12** 2159.
[87] Santangeli A, Chen Y, Kluen E, Chirumamilla R, Tiainen J, Loehr J 2020 *Scientific Reports* **10** 1–8.
[88] Chen S, Yu J, Wang S 2020 *Computers & Industrial Engineering* 106402.
[89] Jin S, Su Y, Gao S, Wu F, Ma Q, Xu K, Hu T, Liu J, Pang S, Guan H 2019 *IEEE Transactions on Geoscience and Remote Sensing* **58** 2644–2658.
[90] Jin S, Su Y, Song S, Xu K, Hu T, Yang Q, Wu F, Xu G, Ma Q, Guan H 2020 *Plant Methods* **16** 1–19.
[91] Caladcad JA, Cabahug S, Catamco MR, Villaceran PE, Cosgafa L, Cabizares KN, Hermosilla M 2020 *Computers and Electronics in Agriculture* **172** 105327.
[92] Haklidir FST, Haklidir M 2020 *Natural Resources Research* **29** 2333–2346.
[93] Afzaal H, Farooque AA, Abbas F, Acharya B, Esau T 2020 *Applied Sciences* **10** 1621.
[94] Thi Kieu Tran T, Lee T, Shin JY, Kim JS, Kamruzzaman M 2020 *Atmosphere* **11** 487.
[95] Jin XB, Yu XH, Wang XY, Bai YT, Su TL, Kong JL 2020 *Sustainability* **12** 1433.
[96] Wolanin A, Mateo-García G, Camps-Valls G, Gómez-Chova L, Meroni M, Duveiller G, Liangzhi Y, Guanter L 2020 *Environmental Research Letters* **15** 024019.
[97] Guillén MA, Llanes A, Imbernón B, Martínez-España R, Bueno-Crespo A, Cano JC, Cecilia JM 2020 *Journal of Supercomputing*.
[98] Guillén-Navarro MA, Martínez-España R, Llanes A, Bueno-Crespo A, Cecilia JM 2020 *Journal of Ambient Intelligence and Smart Environments* 1–14.
[99] Kang Y, Ozdogan M, Zhu X, Ye Z, Hain CR, Anderson MC 2020 *Environmental Research Letters*.
[100] Liu J, Yu C, Hu Z, Zhao Y, Bai Y, Xie M, Luo J 2020 *IEEE Access* **8** 24784–24798.
[101] Shafi U, Mumtaz R, Iqbal N, Zaidi SMH, Zaidi SAR, Hussain I, Mahmood Z 2020 *IEEE Access,* **8** 112708–112724.

[102] Wu CH, Lu CY, Zhan JW, Wu HT 2020 *Frontiers in Neurorobotics* **14** 27.
[103] Kang J, Wang H, Yuan F, Wang Z, Huang J, Qiu T 2002 *Atmosphere* **11** 246.
[104] Jin XB, Yang NX, Wang XY, Bai YT, Su TL, Kong JL 2020 *Sensors* **20** 1334.
[105] Khan PW, Byun YC, Park N 2020 *Sensors* **20** 2990.