sustainability

Review

Enhancing Coffee Supply Chain towards Sustainable Growth with Big Data and Modern Agricultural Technologies

Yotsaphat Kittichotsatsawat [1], Varattaya Jangkrajarng [2,3,*] and Korrakot Yaibuathet Tippayawong [2,4,*]

[1] Graduate Program in Industrial Engineering, Department of Industrial Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai 50200, Thailand; yotsaphat_jant@cmu.ac.th
[2] Excellence Center in Logistics and Supply Chain Management, Chiang Mai University, Chiang Mai 50200, Thailand
[3] Department of Management and Entrepreneurship, Faculty of Business Administration, Chiang Mai University, Chiang Mai 50200, Thailand
[4] Department of Industrial Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai 50200, Thailand
* Correspondence: varattaya.j@cmu.ac.th (V.J.); korrakot@eng.cmu.ac.th (K.Y.T.); Tel.: +66-8-1884-1221 (V.J.); +66-8-1671-9019 (K.Y.T.)

Abstract: Modern agricultural technology management is nowadays crucial in terms of the economy and the global market, while food safety, quality control, and environmentally friendly practices should not be neglected. This review aims to give perspectives on applying big data analytic and modern technologies to increase the efficacy and effectiveness of the coffee supply chain throughout the process. It was revealed that several tools such as wireless sensor networks, cloud computing, Internet of Things (IoT), image processing, convolutional neural networks (CNN), and remote sensing could be implemented in and used to improve the coffee supply chain. Those tools could help in reducing cost as well as time for entrepreneurs and create a reliable service for the customer. It can be summarized that in the long term, these modern technologies will be able to assist coffee business management and ensure the sustainable growth for the coffee industry.

Keywords: modern technology; smart technology; big data analytic; coffee supply chain

Citation: Kittichotsatsawat, Y.; Jangkrajarng, V.; Tippayawong, K.Y. Enhancing Coffee Supply Chain towards Sustainable Growth with Big Data and Modern Agricultural Technologies. *Sustainability* **2021**, *13*, 4593. https://doi.org/10.3390/su13084593

Academic Editors: Anna Irene De Luca and Marc A. Rosen

Received: 30 January 2021
Accepted: 15 April 2021
Published: 20 April 2021

1. Introduction

Recently, many problems have arisen in the agricultural sector of Thailand. Especially, the agri-products do not meet international standards because of farmers' lack of knowledge and marketing insight. Thus, they cannot be competitive with other entrepreneurs. Moreover, this will lead to a lack of opportunities for finding new markets and increasing market share in the future [1].

These issues reflect the fact that farmers still lack the tools for sustainable development, particularly in terms of know-how about increasing productivity in the production process in the long term. Therefore, entrepreneurs are focusing on big data analysis for raising productivity and controlling the quality of the production process system. Thus, big data analysis can be applied for developing, improving, and increasing productivity and efficiency. Likewise, big data can be applied to operations and operating systems' control to meet both farmers' and consumers' needs. Nowadays, more people are becoming interested in studying big data and applying it to organizations in the agricultural industry sector, as shown in Figure 1.

Moreover, big data can be applied in supply chain management for building organizations' competitive advantage by using a data supply chain (DSC). It will help in examining interconnected data characteristics and their relationship to and impact on the organization. In the same way, it can assist with the agile monitoring and management of supply chain risks in the process management framework [2,3]. Therefore, big data is one of the most essential tools in organization management and will likewise enable entrepreneurs to operate their businesses sustainably in the future [4].

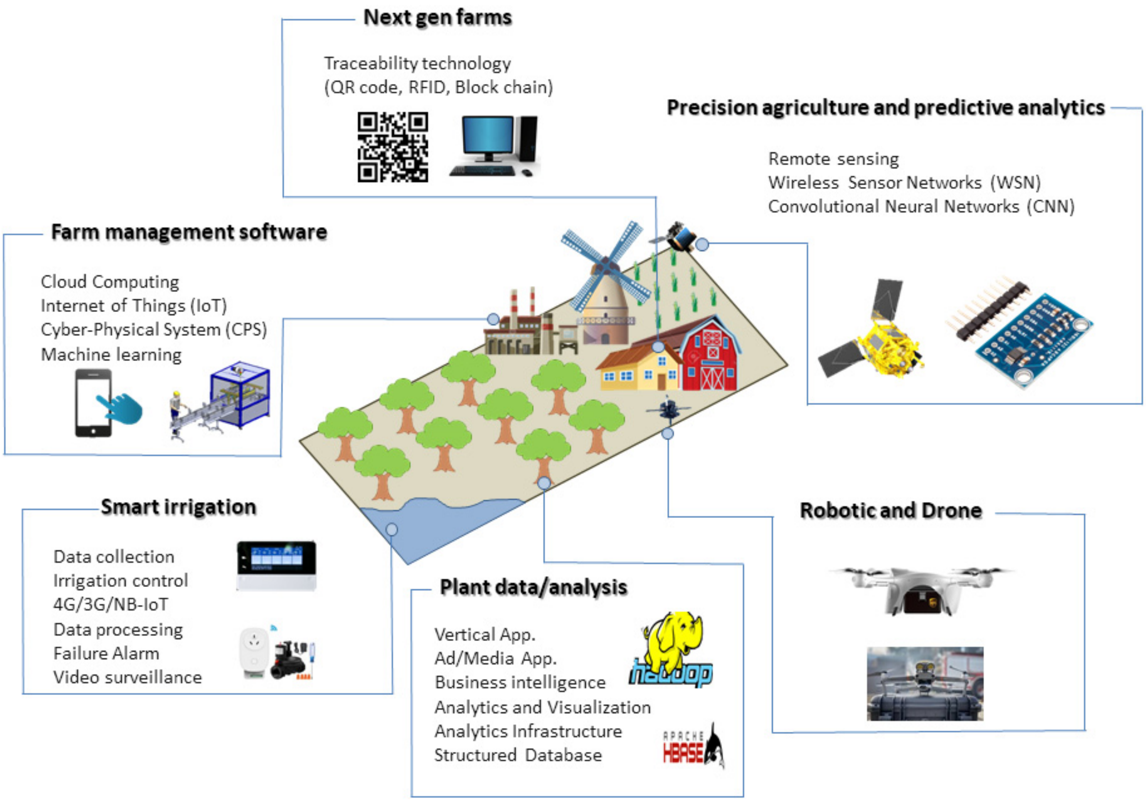

Figure 1. Big data and ICT in smart farming.

Currently, technology is being applied in many agricultural sectors, where it is adopted to increase operational efficiency and create value in the business. Technology is used in the production industry to increase opportunities and productivity as well as to reduce costs, resources, and management. As a result, modern technology is progressing and contributing to greater efficiency [5]. Agricultural technology refers to technology or machines used for the agricultural production process, such as farmland, operations, and production [6]. It can help in the design and practical use of the agricultural process at all stages [7]. It comprises emerging digital technologies such as remote sensing [8–11], wireless sensor networks (WSN) [12,13], cloud computing [12,14,15], the Internet of Things (IoT) [13,16–18], image processing [19–21], and convolutional neural networks (CNN) [19].

Meanwhile, a smart farm is part of the agricultural revolution towards green agriculture necessary for the new world, with science and technology at the center of its operation process. Smart farming can increase a coffee plantation's productivity and create high-quality coffee beans following customers' needs [20]. Additionally, it is used to create innovation and improve the reality of customer demand and the appropriate redesign of the value chain. Smart farming can be used to control the quality of the environment and resources based on human food needs [21,22]. Likewise, smart farming will lead to creating safe and environmentally friendly practices [23,24]. Big data can help improve the forecasting and operational efficiency of large-scale farms in the future [25].

Hence, smart farming will lead to modern farms in which agricultural management with suitable and sophisticated technology will consist of sensors, devices, machines, and information technology. Additionally, smart farming will increase the efficiency and effectiveness of the agricultural production process, for example, using new technology to increase the value of products and integrating smart technology for cross-industry technology. These advanced technologies include (a) next-generation farms use traceability technology such as QR code, RFID, and blockchain; (b) precision agriculture and predictive analytics, for example, remote sensing, WSN, and CNN; (c) robotic and drone; (d) plant data/analysis such as vertical application, ad/media application, business intelligence, analytics and visualization, analytics infrastructure, and structured database; (e) smart irrigation, for example, data collection, irrigation control, 4G/3G/NB-IoT, data processing, failure alarm, and video surveillance; (f) farm management software consisting of cloud computing, the Internet of Things, CPS, and machine learning). Those technologies will help businesses increase their profitability, efficiency, safety, and environmentally friendly operations, as shown in Figure 1.

According to the outline mentioned above, the smart farming technologies played important roles in supplying organic agriculture products, which are now in higher demand [26]. The technologies could assist in control and reduce the use of chemicals, antibiotics, and synthetic chemical fertilizers, which is good for the health of both consumers and farmers. Big data can also enhance the production industry's business model to become the future's modern agricultural technology [27].

Sustainable growth is defined as the optimal growth rate that can be preserved without creating other significant economic, environmental, and human problems into the future [28]. Currently, sustainability has three aspects: (a) Economics—relevant to practically obtainable growth in operation and finance that a company could maintain without problems, also increased efficiency and productivity effectiveness. (b) Environment—the environmental aspect is manufacturing that is environmentally friendly (reuse, reverse, and recycle) in the long term without creating pollution to the environment, for example, economizing of water, reducing waste in production process and zero waste implementation, protecting soils by stopping insecticide and fertilizer, preserving land use, reducing the destruction of nature and forest to keep high biodiversity, and reducing pesticides and chemical usage. (c) Human—creating engagement within the community and creating cooperation between company and community [29]. It is among the most important issue for modern agricultural management.

Coffee is popular in the modern world. It is considered an important consumer product and economic crop that creates value for the food industry in domestic and export markets [30,31]. Typical coffee supply chain from utmost upstream to downstream customer is shown in Figure 2. When analyzing the process, it was found that the cost of coffee production in Thailand from plantings to the roasted beans coffee is relatively high when compared with coffee-making from neighboring countries [32]. The major problems such as high cultivation costs, lack of cultivation standards to produce high-quality coffee, and unplanned incoming material (coffee cherry) that led to continuous losses and disappearing customer confidence were identified [33–35].

Problems and challenges in managing the coffee supply chain were identified. It was realized that they may be solved largely by adopting big data and smart technology in coffee farmer database management. Big data can potentially increase the coffee supply chain's effectiveness in the long run [36–40]. Several technologies and related tools were discovered in solving coffee operations and production problems. Han et al. [41] applied SVM to increase production crop through yield prediction (90%). Pinto et al. [19] used the image processing technique for sorting defective coffee beans with higher efficiency of 72.4–98.7%. Moreover, Apiletti and Pastor [42] applied data mining for improving coffee quality when serving to downstream customers. It was clear that improving the performance of the coffee supply chain could be done via big data. Additionally, the sustainability aspect of the application is also of great interest to modern agricultural management.

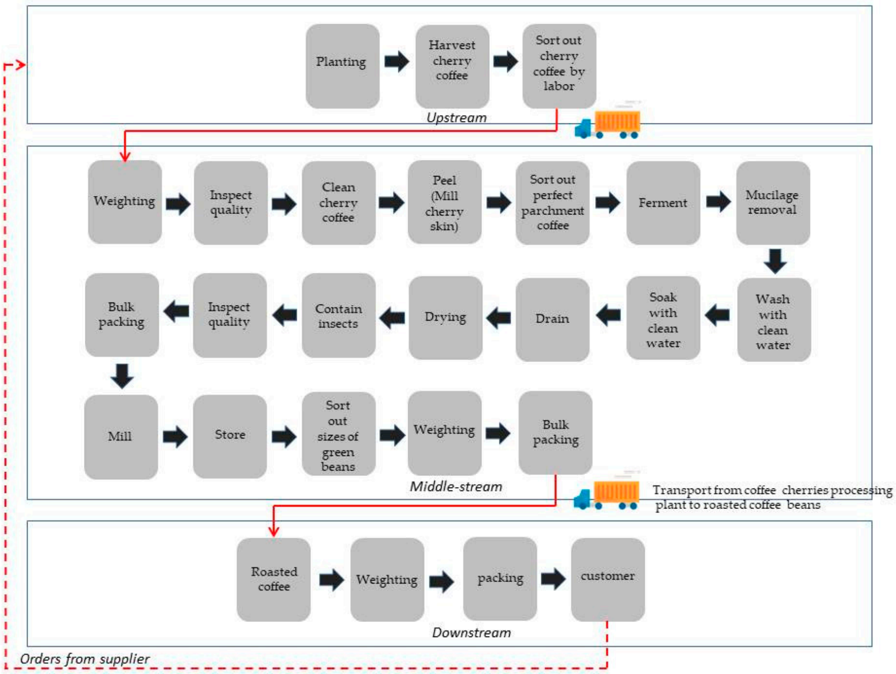

Figure 2. Details of the coffee supply chain from farming to customers.

This review article will make an attempt to provide the insight that big data technology can create several benefits for coffee production to improve efficiency and quality in the coffee supply chain from upstream to downstream, driving it towards sustainable growth. These technologies allow entrepreneurs to upgrade coffee production. The strengths, weaknesses, opportunities, and threats will be sought to improve the coffee production quality to meet international standards. The gap between existing applications of big data and modern technology in general agricultural practices will be identified, with emphasis on the coffee supply chain. If entrepreneurs can integrate big data in coffee supply chain, it is expected that they will be able to operate their businesses more sustainably in the future.

2. Big Data in Agricultural Management

The literature review conducted for this study was based on three steps: (a) gathering of related work; (b) filtering of essential work; (c) analysis of relevant work in detail. The related work keywords were filtered from articles and conference papers based on scientific databases, including Science Direct, IEEE Explore, Emerald Insight, Web of Science, and Google Scholar. Then, most of the papers were searched by the selected keywords, and the relevant related work was filtered. After that, these papers were checked on the database application system. Finally, a review and analysis of the overall data of each article were performed.

2.1. Big Data Application in Agriculture

According to Chi et al. [20], the characteristics of big data can be grouped under three dimensions as follows:

- Volume (V1): The size of data collected for analysis.
- Velocity (V2): The time window is beneficial and relevant to the data.
- Variety (V3): Multi-technology application (for example, images, videos, remote sensing, and sensors), multi-temporal (differentiation of dates/times of data collection), and multi-resolution (differentiation of spatial resolution of data).

Big data can be expressed according to the three "V"s above and can present complex data in a simple data structure that is easy to understand [14,43–46].

In this study, the review and investigation have been conducted over the application of techniques and tools for solving problems in 10 agricultural areas using big data analytic.

The big data techniques applied in previous research in those areas were assessed through three aspects, volume, velocity and variety, scoring on three levels, low, medium, and high. The result is initially displayed in Figure 3. The list of related references is shown in Table 1.

The assessment approach implemented in this work has been inspired by Kamilaris et al. [41]. The application of big data in agriculture has recently been gaining attention, which is evidently realized from Table 1. Big data was used in agricultural management in weather and climate change to predict the yield of croppers and apply digital technology in land management to increase the planting system's efficiency. Moreover, crop management applied big data and machine learning to protect against plant and soil diseases, weeds, and other pests in order to get a good quality of the product. Additionally, farmers' decision-making in relation to the process was assisted by defining the function of problems or elements, for example, value and goals, problem detection, problem definition, observation, analysis, analysis of intention, implementation, and responsibility. The big data applications were exposed in farmers' insurance and finance, which could increase commercial agriculture production. Big data logical can also increase the agri business value chain in the agriculture industry or even in animal husbandry research. Machine learning and big data were detected in predicting animals or pests per crop, which could increase the precision farming forecast.

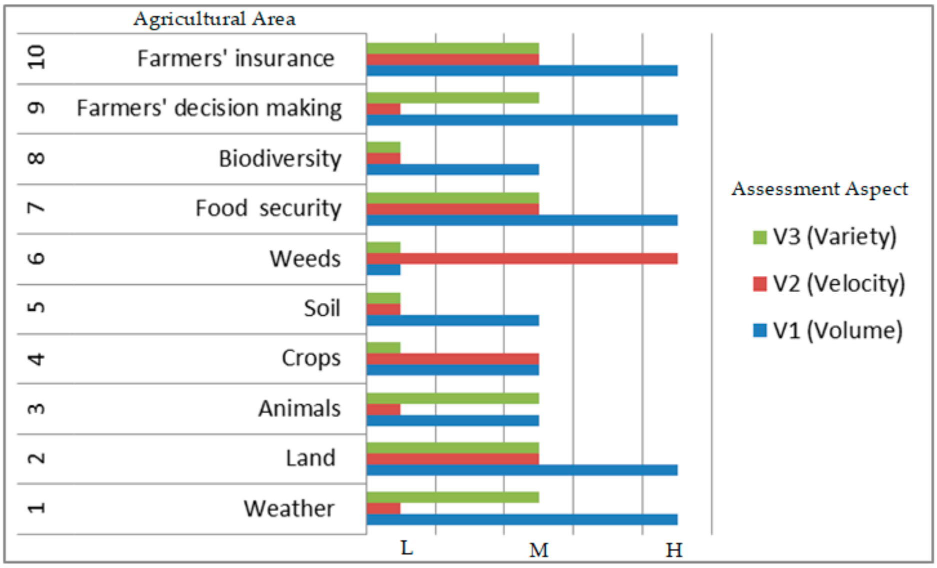

Figure 3. Implementation of big data in 10 agricultural areas based on three aspects: volume (V1), velocity (V2), and variety (V3).

Table 1 reveals recent research where big data techniques were applied in ten agricultural areas. After reviewing and analyzing relevant related work, we can identify and classify each group (volume, velocity, and variety) from the author's average rating, which specifies the three levels of high, medium, and low. The results found that most of the papers concern medium-to-high volume and low-to-medium levels of velocity and variety.

However, the literature gaps can be observed from the three aspects analysis. In terms of volume, it was found that weeds area data encountered were rather limited while a high volume of data were detected among weather, land, food security, farmers decision-making, and farmers insurance. For the velocity aspect, a low level of data were found in weather, animals, soil, biodiversity, and farmers' decision-making, which was in contrast to a high level of data concerning weeds. Finally, in terms of variety, none of the agricultural area was found to have high level of technology variety. The areas of crops, soil, weeds, and biodiversity were found to have the lowest variety of big data technology implemented.

Table 1. List of previous works that implemented big data in 10 listed agricultural areas.

NO	Agricultural Area	Ref
1	Weather	Lechthaler, F. and Vinogradova, A. (2016) [47], Gunathilaka R.P.D. et al. (2018) [48], and Iglesias et al. (2012) [49], Cherrie et al. (2018) [50], Rao (2018) [51], Ingale and Jadhav (2016) [52]
2	Land	Mitiku, F. (2017) [53], Bosselmann, A.S. (2012) [54], and Estrada et al. (2017) [55], Papaskiri et al. (2019) [56], Zeng et al. (2017) [57], Volkov et al. (2019) [58]
3	Animals	McQueen et al. (1995) [59], Kempenaar et al. (2016) [60], Chedad et al. (2001) [44], and Pierna et al. (2004) [61]
4	Crops	Hipólito, J. (2018) [62], Perdonáa M.J. and, Sorattob R.P. (2015) [63] and Mota L.H.C.(2017) [64] (Mota), Van Evert et al. (2017) [65], Tseng and Wu (2019) [66], Palanivel et al. (2019) [67]
5	Soil	Nzeyimana et al. (2017) [68], Tumwebaze and Byakagaba (2016) [69], Alves and Cruvinel (2016) [70], Kim et al. (2019) [71], Rajeswari and Arunesh (2017) [72], Ingale and Jadhav (2016) [52]
6	Weeds	Martins et al. (2015) [73], Pires, L.F. (2017) [74], Jareen et al. (2019) [75], Thorp and Tian (2004) [76]
7	Food security	Frelat et al. (2016) [77], Jozwiak et al. (2016) [78], Lucas and Chhajed (2004) [79], Mabalay et al. (2013) [80], Tsiligiridis and Ainali (2018) [81]
8	Biodiversity	Hardt et al. (2015) [82], Hallgren et al. (2016) [83], Conversa et al. (2020) [84], Kumar and Kumar (2018) [85]
9	Farmers' decision making	Bravo-Monroy et al. (2016) [86], Nguyen et al. (2017) [87], Cabrera et al. (2020) [88], Cambra Baseca et al. (2019) [89], Bartkowski and Bartke (2018) [90], Jones and Barnes [91]
10	Farmers' insurance	Emeana et al. (2010) [92], Martin and Clapp (2015) [73], Songa W. (2018) [93], Akinboro (2014) [94], Sufyadi and I (2020) [95]

2.2. Techniques and Tools for Big Data Analysis in Agriculture Practice

Currently, supply chain management (SCM) has enabled effective changes to be made towards business management by using integrated technology to increase organizations' effectiveness and efficiency.

SCM focuses on global issues, including environmentally friendly practices, labor protection law, and economic globalization. On the other hand, SCM requires certain enabling factors to achieve its targets effectively, such as cost and time reduction and customer satisfaction.

In future trends, SCM will concern the inclusion of sustainability and corporate social responsibility and organizations' risk management. A new approach for collecting supply chain action is being used to redesign supply and demand for increasing profitability and response [96].

Technology and information systems have been used to improve and increase an organization's profit, and four examples are given below.

(a) Traceability technology such as machine learning, cloud computing, image processing, modelling, and simulation was used to track and trace products from upstream to downstream.

(b) Real-time technology is one of the automated technologies created to perform data collection to replace human labor, and includes sensors, RFID tags, GPS, and so forth.

(c) The Internet of Things (IoT) is a command technology using a voice system. The voice systems are transmitted into an analog computer. Then, the data will be transferred over a network without requiring human-to-human or human-to-computer interaction. For example, Aliev et al. [97] studied the application of smart agriculture by using IoT for measuring the temperature, humidity, and soil moisture of plants. Kulalvaimozhi et al. [98] used an image processing technique to greatly improve the productivity of agriculture to increase output to meet demand. Yao et al. [99] used convolutional neural networks to improve the accuracy of image classification and image recognition in agriculture.

(d) An optimized inventory was proposed using smart technology or artificial intelligence to measure, evaluate, and enable data analysis decision-making. The technology helps to reduce risk and determine factors to make decisions for profitability. For example, the usability of machine learning for predicting an inventory plan was investigated [60,100–102], clustering was used for classification and problem-solving [61,103,104], while image processing and remote sensing were used to collect and analyze data. After data detection, the machine system is analyzed and read by a sensor system [20,21,105,106].

Moreover, Rajeswari et al. [107] applied big data to improve agricultural activities by integrating IoT, remote sensing, and cloud computing to increase crop production quality and reduce agricultural products' cost.

To highlight the techniques and tools applied in big data identification in agricultural practices, six groups of techniques were found extensively from the previous studies. Those research works were assessed based on the three aspects: volume (V1), velocity (V2), and variety (V3) with the level of high, medium, and low. The primary result is shown in Figure 4.

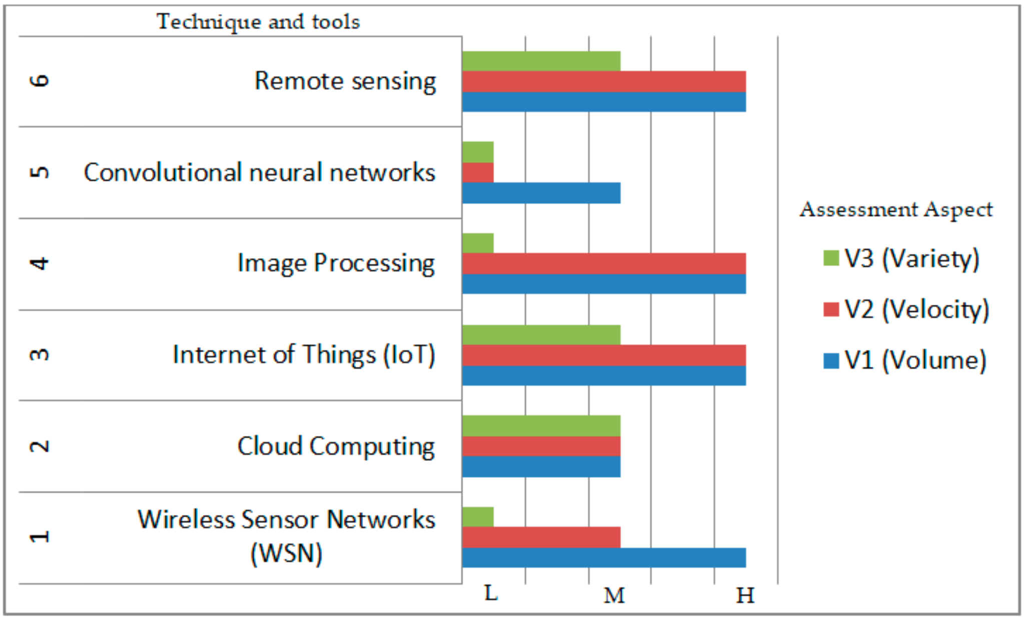

Figure 4. Several techniques and tools for big data identification and classification in agricultural areas based on three aspects; volume (V1), velocity (V2), and variety (V3).

From Figure 4, the literature gaps are clear. The application of IoT and remote sensing was popular in agricultural research in all aspects: volume, velocity and variety. Meanwhile, the application of convolutional neural networks (CNN) was in the initial stage with low level of velocity and variety. More works should be dedicated in this area. The contribution of cloud computing in agriculture seems balanced between the three aspects and the growth is still ongoing.

Related researches were gathered and classified into six groups, as shown in Table 2. Sustainable growth for agricultural supply chain has been frequently raised these days. This review attempted to identify three sustainable factors that are related to (a) economics, (b) environment, and (c) human [31] that could be affected when implementing those specific techniques and tools into existing agricultural practice. The first factor, "economics", can be achieved using modern technologies of image processing, wireless sensor networks (WSN), cloud computing, and convolutional neural networks. Those tools will help with quality control and monitoring, reducing defects and waste products, increasing revenue and profit, and reducing the cost of operation and unit cost. The second factor, "environment", could be achieved by the Internet of Things (IoT) and remote sensing. These tools can conserve and enhance natural resources and reduce environmental emissions. Finally, the third factor, "human," could be achieved where less volume but more labor ability are the goals. Digital agriculture could improve human skills and knowledge performance, and replace labor in some agricultural supply chain stages. However, the "human" factor" has not yet been reported as a noticeable result from using current techniques and tools in agricultural practice.

It was proved that the implementation of these big data techniques and tools in the agriculture arena resulted in several benefits. They could support the product control and cost reduction when applying big data [108]. Food safety and security were improved through product traceability technology [109]. The qualities were found better via big data for analyzing and optimizing the contamination risk [110].

Table 2. Techniques and tools for big data analysis.

NO	Techniques and Tools	Related Sustainable Aspect	Ref
1	Wireless sensor networks (WSN)	Economic	Kassim et al. (2014) [12], Biradar and Shabadi (2017) [13], Ojha et al. (2015) [111], Shinghal and Srivastava (2017) [112], Rathinam et al. (2019) [113]
2	Cloud computing	Economic	Kassim et al. (2014) [12], Mekala and Viswanathan, (2017) [15], Mocanu et al. (2015) [114], Goraya and Kaur (2015) [115]
3	Internet of Things (IoT)	Environment	Biradar and Shabadi (2017) [13], Li (2012) [18], Elijah et al. (2018) [116], Yoon et al. (2018) [117]
4	Image processing	Economic	Pinto et al. (2017) [21], Chi et al. (2016) [20], Manickavasagan et al. (2005) [21], Umamaheswari et al. (2018) [118], Khirade et al. (2015) [119]
5	Convolutional neural networks	Economic	Pinto et al. (2017) [21], Barbosa et al. (2020) [120], Nevavuori et al. (2019) [121], Adhitya et al. (2019) [122]
6	Remote sensing	Environment	Chemura et al. (2017) [9], Takahashi and Todo (2014) [10], Hochrainer-Stigler (2014) [11], Asfaw et al. (2018) [123], Huang et al. (2018) [124]

Section 2 concludes the agricultural areas where the roles of big data have been placed. In addition, techniques and tools for big data identification and classification in general agriculture practice are displayed herein. These tools could be promoted in coffee supply chain to some extent. The potential tools will be discussed in a subsequent section.

3. Big Data and Modern Technologies Used in Coffee Supply Chain

This section presents potential smart technologies that can be used in different stages of the coffee supply chain in the context of a review of articles related to the coffee industry from upstream plantation to final downstream customer.

Coffee is one of the major economic crops with high market growth. Specifically, Arabica coffee was promoted as a suitable replacement plant for opium and helped in part to stop shifting cultivation, which deploys large mountainous lands. Arabica coffee can be grown successfully on high slopes that are not suitable for other field crops. Since coffee is a perennial shrub that can be harvested for many years, it helps prevent shifting cultivation. The harvesting and processing of coffee beans are not complicated. The product can be stored without rotting like some other agricultural products and it is convenient to transport. Moreover, good-quality coffee also has a high price and is always in demand both in domestic and in international markets [34].

Currently, the coffee business is becoming interested in using smart technology in their operations, with the prospect of using smart machines in the processing, production, and all parts of the organization in combination. Components of the intelligent factory may include automatic machines, robots, the Internet, cyber-physical systems, big data, advanced devices, sensors, and so forth in the automatic work process [125]. All technologies, when combined, can be a substitute for human labor, help to analyze big data, and improve the organization's management. The techniques for smart coffee farming involving big data are summarized in Table 3.

Table 3. Techniques and tools for big data analysis in coffee supply chain.

No	Technique and Tool	Ref.
1	Wireless sensor networks (WSN)	Kodali et al. (2016) [126], Bolaños et al. (2018) [127]
2	Cloud computing	Rodríquez et al. (2020) [128]
3	Internet of Things (IoT)	Bolaños et al. (2018) [127]
4	Image processing	Faridah et al. (2013) [129]
5	Remote sensing	Santos et al. (2010) [130]
6	Traceability technology	Smith (2018) [131]
7	Blockchain	Thiruchelvam et al. (2018) [132]

Wireless sensor networks (WSN) are a form of network communication with many sensors enabling wireless communication among themselves [133]. A WSN system is composed of an analog-to-digital converter (ADC) and a transceiver with an antenna [134]. These sensors monitor all types of data, including soil and weather parameters, with a soil moisture sensor and a leaf wetness sensor. These data were used as input data for an agricultural support system.

After that, these sensors were connected to an eKo node. Then, all the data were transmitted to the eKo base station for network communication with the eKo gateway and connected with a PC for analysis of all the data input [135]. In this way, the system increased the efficiency of water-saving irrigation, sprinkler irrigation, and localized irrigation techniques by 40%, 60–80%, and 60–90%, respectively. Thus, WSNs can improve coffee production yield, while sprinklers and drip irrigation can improve coffee production efficiency and effectiveness [126,127].

Cloud computing is an advanced technology that refers to the manufacturing and support of the Internet of Things (IoT) and Internet of Service (IoS) and virtualization. It can be circulated and share the manufacturing resources into the operation and service. The system can cover all parts of the product lifecycle, product design, simulation, production, and maintenance, enabling manufacturing to have intelligent processes, production, and management [4,136]. The Internet of Things is the key technology and is connected to a cloud system, allowing automatic management [137].

In general, the coffee production computer version (CV) was used by coffee farmers to deal with money investment and planning time. The coffee farmers' integrated system comprises image acquisition (photo capture), pre-processing (space of image), noise reduction (picture element), segmentation (image detection), and feature extraction (finding the contour function). Coffee farmers utilized cloud computing to reduce the money needing to be invested and increase their planning time efficiency. The system was applied in the coffee farming process to reduce the time taken to estimate coffee production and increase the quality of coffee cherries.

A CNN (Faster R-CNN) model was used to detect coffee's color shade in four groups (white, green, cane green, and blue-green); in this study, the CV could be classified, and the neural network model could extract each color shade of the coffee. The dataset of colors was then analyzed by applying the Canny method [138,139]. A mobile application was used to develop the process and store records. Photos and videos of coffee tree branches were taken on a mobile phone app using an inertial sensor. The photos or videos were then evaluated, and different algorithms were implemented for quality detection before storage and synchronization of each record [128].

The Internet of Things (IoT) is an interrelated computing system including mechanical devices and digital machines for identifying and transferring a data network without requiring human-to-human or human-to-machine interaction [4,137]. In agricultural practices, the IoT was used to monitor farming, for example, collecting data on temperature, rainfall, humidity, wind speed, pest infestation, and soil content. In the coffee process, IoT can be used to solve the problems and control the quality of coffee, such as using a drone for fertilizing, garden irrigation by using the smart valve, and soil moisture sensor module [4].

In coffee production, an integrated system was composed of environmental sensors (temperature, humidity, coffee bean moisture, and pH) and a micro-controller [140]. The IoT was used in the coffee process to increase efficiency and reduce the cost of production. The system was applied in the production process in order to eliminate the frequency of human monitoring and remove the possibility of human error causing processing failures. Data were collected from the fermentation stage. Then, the pH level data during the process were sent to the Ubidots cloud platform to analyze the process monitoring and control. For the steps of washing, fermentation, drying, and storage/export, a water temperature sensor, pH level sensor, moisture sensor, and DHP sensor were applied in the coffee production process [141,142].

Smart machines and devices can communicate in machine-to-machine and machine-to-human mode [143]. These machines give businesses with high potential the ability to manage products by an automatically controlled operation. They can improve and report the results of production and any period of self-repair.

A color sorter is a smart machine that can sort colors and defects from agricultural products by performing highly repetitive tasks. Color sorters have been used in agricultural products such as grain, tomato, and coffee beans [120,144–146]. A color sorter was specially designed and fabricated for use in coffee bean production. This machine comprises three parts: a conveyor belt, color sensor, and DC motor. The color sorter has the function of examining the accuracy of the coffee color. Users can set the standards of the color they require. The coffee bean color is extracted by a CCD sensor using image processing principles. CIALAB will set the standard of color with three shade levels (red, blue, and green). Thus, the smart machine can improve the quality of the coffee beans. It can increase coffee sorting efficiency in the coffee production process and reduce the time and costs [146].

Remote sensing is one of the prominent tools for detecting and monitoring specific physical characteristics of an area by measuring reflection and emitting radiation over an area at a distance from a satellite or aircraft. Unique cameras are used to collect and capture several images of the Earth in order to analyze the cultivation of rice, grain, beans [147], and so forth. In the coffee crop, RSI was used to image and describe the coffee seeds by applying genetic programming (GP) to combine texture and spectral information, which can be characterized through two functions, including feature vector extraction (image properties, color, texture, and shape) and similarity computation, differentiating between two images of the feature vectors' distance. In the coffee crop, RSI was used for analyzing coffee image data by using the SPOT satellite. Then, the images were classified using the Maxver program, and a kappa index analyzed the data for color classification [130].

Currently, creating a product brand is essential, creating confidence in the quality of products, hence the popularity of traceability to know the origin of the product. The application of traceability can maintain an unbroken record of a crop as it moves through the agricultural production and distribution system. The application of traceability is of interest in the detail of coffee farmland. It is essential to ensure the dominant coffee bean and organoleptic test characteristics, odor, color, and texture [130,148,149].

Big data also was used in the coffee industry to create the "Taste of Something" and differently create the unique fragrance/aroma, flavor, aftertaste, acidity, body, balance, uniformity, clean cup, and sweetness in potential areas for coffee farm and green bean production [150]. Thus, the system generated re-farming traceability using system management, which led to the creation of exceptional coffee aroma and taste [109]. Additionally, big data technology can dramatically help farmers, such as coffee traceability, quality prediction of coffee crop yields in terms of physical characteristics (color, odor, and texture) and chemical characteristics (caffeine level in coffee beans) [151]. Additionally, the system was applied to the farmland in order to reduce operating costs and increase productivity while improving customer safety, branding, and customer reliability [131].

A blockchain is one of the systems used to record information to protect data and prevent hackers from changing the data or cheating the system. A blockchain is essentially a digital ledger of repeated, replicated, and spread transactions across all the networks of a computer system [152]. A blockchain was used in the coffee supply chain for cost-saving, faster delivery, shorter manufacturing times, and good inventory management. The application of a blockchain can improve the coffee supply chain's efficiency and effectiveness [132]. Moreover, a blockchain will increase transparency and efficiency and covers all the transaction data of every supply chain network [153]. Furthermore, blockchain technology can improve farmers' market access, sustainability, and traceability, and secure high prices, leading to increased fair trade and transparency through the coffee supply chain to the customers [132].

Big data is necessary for managing the coffee supply chain and operations in the organization. Moreover, big data is beneficial when data are used to develop and direct the organization's strategies. All parts of the data can be linked to each node in the organization, including marketing, product development, production, processes, and management. Therefore, the organization can implement all the concepts of intelligent agricultural technologies. These can help to improve and increase the efficiency and effectiveness of the agricultural supply chain (through the saving of costs, time, and resources, high quality, and on-time supply). They can even create more value for agricultural products, including ensuring reliability and customer satisfaction as well as the ability to operate their business sustainably. The application of blockchain in the agricultural sector has appeared for the first time in managing coffee operations. It can later be adopted by other high-value agri-products. However, work applying convolutional neural networks (CNN) to coffee research was not yet found. This may present an opportunity for a future study area in the coffee supply chain.

According to the abovementioned, coffee is a significant product and an economic plant that creates value for the food industry worldwide. Coffee products and coffee supply chains are very significant and face several challenges in improving the coffee production process, such as fluctuating production, climate change, market uncertainty, and emerging digital transformation towards innovative technology.

Smart technology can be divided into several techniques (wireless sensor networks (WSN), cloud computing, and the Internet of Things (IoT), etc.) that have been implemented across other industries to enhance transparency and traceability in the supply chain process. Meanwhile, the product's origin can be traced back and followed through the big data infrastructure system.

4. Towards Sustainable Growth with Big Data and Modern Agricultural Technologies

Lack of sustainable practice in the agriculture or coffee plantation could consist of (1) poor water management, leading to low yield productivity in farming and coffee cherries production [154]; (2) poor pest and disease management, causing economic loss in coffee farms, such as coffee leaf rust, black rot, and dieback [155]; (3) lack of cropping systems, affecting loss in the overall production of coffee or agriculture farming [156]; (4) scarcity of nutrient management, bringing about impaired quality of a product [157]; (5) lack of labor availability, high-cost investment, and lack of good management, leading to the poor competitiveness [158]; (6) inferior processing methods, affecting the quality of the product [159]; (7) poor drying and storage facilities that damage coffee beans [160]; (8) lack of waste and pollution management, causing severe environmental problems [33]. Additionally, poor farming management can lead to (1) land degradation from poor land and water management, endangering food security and increasing poverty [161]; (2) threatening food security and possibility of water scarcity [162]; (3) poverty due to drop in the GDP [163]; (4) adverse risk in human health from environmental pollution and high-risk pesticides [164].

Big data and modern technologies can be applied to the process of agricultural production and also simultaneously create sustainable growth. For example, wireless sensor networks (WSN) may be applied in managing the water usage in order to improve the yield of coffee and using sprinklers and irrigation for a high growth rate of coffee trees [27,126]. Internet of Things (IoT) may be used to collect data on pests and diseases, with drone for fertilizer feeding, and by using the smart valve for irrigating coffee trees and a sensor module for soil moisture control [4]. Moreover, utilization of IoT, remote sensing, and cloud computing in crop management can increase crop production yield and quality [72]. Machine learning may be employed to control the quality of product and reduce the production process cost, such as in a color sorter machine, used to separate coffee cherries before delivering them to fermentation and drying [144–146,165]. A modern drying machine with automation technology for moisture control and improved heat transfer may be introduced to the modern coffee farm [166–169]. Finally, the convolutional neural networks (CNN) and mathematical modelling can be used to optimize the process to reduce the defects and wastes and maximize the yield and product qualities [138,139].

This way, big data can drive towards the sustainable growth in terms of economics, environments, and human: the technology of wireless sensor networks (WSN), Internet of Things (IoT), remote sensing, and cloud computing and machine learning focuses on economics, Internet of Things (IoT) and convolutional neural networks (CNN) will help in terms of the environment, and finally, machine learning will enable the sustainable growth of human. It is rather obvious that big data acts as a brain, while mechanical equipment is used as process facilities, and they work together to enhance the sustainability of the agricultural productions.

5. Discussion and Suggestions for Future Works

In the past, agricultural management has not been widely applied because entrepreneurs did not possess much knowledge about farming management. Thus, this lack of knowledge results in the loss of tracing opportunities, leading to high production costs, irregularity of products, product unsafety, low customer reliability, and poor product accuracy, and so forth.

Currently, smart technology has been applied in many agricultural sectors and also adopted to improve operational efficiency and create value in the business. Moreover, smart technology has been used in agricultural management to raise productivity and increase internal and external market opportunities.

In this case, smart technologies and tools applied in the coffee supply chain were explored. In the upstream, the Internet of Things (IoT) and remote sensing help in monitoring the data on each section of the plantation from seeding to harvesting. Moreover, wireless sensor networks (WSN) can help by checking and supporting the data that is input into the system by the digital sensor system. In the mid-stream, cloud computing and image processing help create reliability and product standards for the customer. Likewise, the customer can also trace back to the original source of plantation [129]. Downstream blockchain technology will help record data and protect data in the system so that it cannot be modified or lost. In the future, blockchain technology may be applied to increase transparency, sustainability, safety and security, fair trade, and price equality [127,170]. This technology can identify suppliers or buyers for the farmers. The price data can be transparently transferred through the farm gate and recorded in the system.

Great effort has been paid in identifying big data technology implementation gaps between general agriculture practice and specific coffee operations. It was revealed that the application of the blockchain in the agricultural sector appeared for the first time in managing coffee operations. This was a good example for other high-value agri-products. Furthermore, none of convolutional neural networks (CNN) work was found on coffee research, while there were many studies in other agriculture areas. Its application to coffee supply chain will be of great interest.

As mentioned in the articles reviewed above, it is considered that the issues that entrepreneurs encounter could be solved using design and smart agricultural technology models to support coffee farmers' database management. Suppose farmers or entrepreneurs apply these smart technologies for farming management and the production process. These technologies will lead to a surge in the agricultural supply chain's efficiency and effectiveness. Also, they will help to trace back and follow up agricultural products precisely from upstream to downstream.

In the future, digital agriculture will be important for the agricultural system and lead to sustainable agriculture systems [171]. Digital agriculture is related to digital and geospatial information technologies that combine sensors, analytics, and automation to investigate, evaluate, and manage the landscape's physical geography and genetic resources [172].

In the same way, digital agriculture can be used to redesign areas for environmental sustainability and sustainably increase high-yield areas and predict product development in the future [173]. Furthermore, digital agriculture could enable real-time data collection and help record data from upstream to downstream [174]. Digital agriculture will help monitor the risks in farmland, from the first step of planting to the end product [154].

Therefore, if farmers or entrepreneurs apply digital agriculture in their farm operations, it may help them to develop the agriculture in a sustainable way [175], including in the following ways: (a) economic: increasing the value of the product and being competitive with other countries; (b) environmental: it can control and reduce waste from the production process and reduce the risks arising from the processing (reducing CO_2 in ozone, carbon footprint measurement, reducing the adverse effects of using chemical fertilizer, etc), and (c) human: it can increase income and increase the knowledge of farmers and entrepreneurs.

Entrepreneurs could benefit from implementing this digital agriculture in farms. Hence, this requires knowledge of entrepreneurs' readiness and the factors that need to be improved to upgrade production. Strengths, weaknesses, opportunities, threats, and useful suggestions for agricultural production can be presented for manufacturing methods using new agricultural technology.

6. Conclusions

This paper offers a critical review of research articles related to the use of big data in general agriculture and specifically in coffee operations. The gap between the existing application of big data and modern technology in general agriculture practices and in the coffee supply chain was identified.

Initially, the literature was classified into 10 agricultural areas. The big data-related studies in those areas were assessed based on three "V" aspects: volume, velocity, and variety with a level of low, medium, and high. There were mainly six techniques obtainable. For a second time, those techniques and tools were assessed based on three "V" aspects. From this stage, the literature gap on techniques and tools was detected. Subsequently, the big data research on coffee operations was investigated and compared against studies from general agriculture practice. It was realized, herein, that coffee leads in terms of blockchain implementation while lacking in the area of convolutional neural networks (CNN) research.

Sustainability was focused on when applying available big data tools and techniques in the coffee supply chain operations. Only "economic" and "environment" aspects were achieved through the techniques implemented. However, "human" factors remained elusive. Data analytic tools that are concerned with "human" aspects should be prioritized in the near future.

According to the extensive review in related fields, techniques and tools are available and have been used for big data analysis. These datasets support smart agriculture in the future. This research proposed the use of big data in agriculture and digital agriculture (DA). These technologies may raise the product quality and increase its reliability for customers. Products can be accepted internationally while ensuring sustainability for agriculture and farming in the future.

Accordingly, the outcomes of applying big data and digital agriculture are expected to (a) increase the quality standards and improve the product's reliability; (b) reduce costs with better production efficiency; (c) raise the standards of production and products, and d) combine new technologies by introducing database management from research to maximize the profitability of the production process. As a result, big data combined with digital agriculture has promising potential in smart coffee farm operations, ultimately bringing greater profits for this sector.

In the future, all data wireless sensor networks (WSN), cloud computing, Internet of Things (IoT), image processing, remote sensing, traceability technology, and blockchain will be used in the coffee supply. Those big data applications were used to increase the production and business management efficiency that serves the customer needs. The value data can also be applied and predicted all activities, including weather and climate change, land management, crops, soil, food availability and security, farmers' insurance, and finance in order to produce sustainable coffee growth.

Author Contributions: Conceptualization, K.Y.T.; methodology, Y.K., V.J., and K.Y.T.; validation, Y.K. and K.Y.T.; formal analysis, Y.K. and V.J.; investigation, Y.K. and V.J.; writing—original draft preparation, Y.K.; writing—review and editing, K.Y.T.; visualization, Y.K.; supervision, K.Y.T.; project administration, K.Y.T. and V.J.; funding acquisition, K.Y.T. All authors have read and agreed to the published version of the manuscript.

Funding: Chiang Mai University.

Data Availability Statement: Not applicable.

Acknowledgments: The authors wish to acknowledge the CMU Graduate School for partial financial support and the Department of Industrial Engineering, Excellence Center in Logistics and Supply Chain Management (E-LSCM), Chiang Mai University for providing research facilities. This research is part of the project "Industry 4.0 for SMEs" from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No 734713.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. FAO. *The Future of Food and Agriculture—Trends and Challenges*; Annual Report; FAO: Rome, Italy, 2017.
2. Spanaki, K.; Adams, R.; Mulligan, C.; Lupu, E. Data Supply Chain (DSC): Development and validation of a measurement instrument. *Engineering* **2016**. [CrossRef]
3. He, M.; Ji, H.; Wang, Q.; Ren, C.; Lougee, R. Big data fueled process management of supply risks: Sensing, prediction, evaluation and mitigation. In Proceedings of the Winter Simulation Conference 2014, Savannah, GA, USA, 7–10 December 2014; pp. 1005–1013.
4. Bibby, L.; Dehe, B. Defining and assessing industry 4.0 maturity levels–case of the defence sector. *Prod. Plan. Control* **2018**, *29*, 1030–1043. [CrossRef]
5. ODI. *Technology and Its Contribution to Pro-Poor Agricultural Development*; Pakistan Statistical Year Book; ODI: London, UK, 2016.
6. Gifford, R. *Agricultural Mechanization in Development: Guidelines for Strategy Formulation*; FAO: Rome, Italy, 1981.
7. Rahman, H.; Pamidimarri, D.S.; Valarmathi, R.; Muthurajan, R. Genomics, Proteomics and Metabolomics: Tools for Crop Improvement under Changing Climatic Scenarios. In *OMICS: Applications in Biomedical, Agricultural, and Environmental Sciences*; CRC Press: Boca Raton, FL, USA, 2013. [CrossRef]
8. Bastiaanssen, W.G.; Molden, D.J.; Makin, I.W. Remote sensing for irrigated agriculture: Examples from research and possible applications. *Agric. Water Manag.* **2000**, *46*, 137–155. [CrossRef]
9. Chemura, A.; Mutanga, O.; Dube, T. Remote sensing leaf water stress in coffee (Coffea arabica) using secondary effects of water absorption and random forests. *Phys. Chem. Earth Parts A/B/C* **2017**, *100*, 317–324. [CrossRef]

10. Takahashi, R.; Todo, Y. The impact of a shade coffee certification program on forest conservation using remote sensing and household data. *Environ. Impact Assess. Rev.* **2014**, *44*, 76–81. [CrossRef]
11. Hochrainer-Stigler, S.; van der Velde, M.; Fritz, S.; Pflug, G. Remote sensing data for managing climate risks: Index-based insurance and growth related applications for smallhold-farmers in Ethiopia. *Clim. Risk Manag.* **2014**, *6*, 27–38. [CrossRef]
12. Kassim, M.R.M.; Mat, I.; Harun, A.N. Wireless Sensor Network in precision agriculture application. In Proceedings of the 2014 International Conference on Computer, Information and Telecommunication Systems (CITS), Jeju, Korea, 7–9 July 2014; pp. 1–5.
13. Biradar, H.B.; Shabadi, L. Review on IOT based multidisciplinary models for smart farming. In Proceedings of the 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 19–20 May 2017; pp. 1923–1926.
14. Hashem, I.A.T.; Yaqoob, I.; Anuar, N.B.; Mokhtar, S.; Gani, A.; Khan, S.U. The rise of "big data" on cloud computing: Review and open research issues. *Inf. Syst.* **2015**, *47*, 98–115. [CrossRef]
15. Mekala, M.S.; Viswanathan, P. A Survey: Smart agriculture IoT with cloud computing. In Proceedings of the 2017 International Conference on Microelectronic Devices, Circuits and Systems (ICMDCS), Vellore, India, 10–12 August 2017; pp. 1–7.
16. Weber, R.H. Internet of things: Privacy issues revisited. *Comput. Law Secur. Rev.* **2015**, *31*, 618–627. [CrossRef]
17. Tyagi, A.C. Towards a second green revolution. *Irrig. Drain.* **2016**, *4*, 388–389. [CrossRef]
18. Li, S.; Xu, L.; Wang, X.; Wang, J. Integration of hybrid wireless networks in cloud services oriented enterprise information systems. *Enterp. Inf. Syst.* **2012**, *6*, 165–187. [CrossRef]
19. Pinto, C.; Furukawa, J.; Fukai, H.; Tamura, S. Classification of Green coffee bean images basec on defect types using convolutional neural network (CNN). In Proceedings of the 2017 International Conference on Advanced Informatics, Concepts, Theory, and Applications (ICAICTA), Denpasar, Indonesia, 16–18 August 2017; pp. 1–5.
20. Chi, M.; Plaza, A.; Benediktsson, J.A.; Sun, Z.; Shen, J.; Zhu, Y. Big data for remote sensing: Challenges and opportunities. *Proc. IEEE* **2016**, *104*, 2207–2219. [CrossRef]
21. Manickavasagan, A.; Jayas, D.S.; White, N.D.; Paliwal, J. Applications of thermal imaging in agriculture—A review. In Proceedings of the CSAE/SCGR 2005 Meeting, Winnipeg, MB, Canada, 26–29 June 2005; pp. 26–29.
22. Sisang, K.; Jamieson, I.; Wongwatcharapaiboon, J.; Chulerk, R. SATI (Smarter Agriculture Thai Initiative): A Smarter Organic Farming Model for Thai Farmers. In Proceedings of the 11th Built Environment Research Associates Conference (BERAC2020), Bangkok, Thailand, 25 June–2 July 2020.
23. Senanayake, R. Sustainable agriculture: Definitions and parameters for measurement. *J. Sustain. Agric.* **1991**, *1*, 7–28. [CrossRef]
24. Bongiovanni, R.; Lowenberg-DeBoer, J. Precision agriculture and sustainability. *Precis. Agric.* **2004**, *5*, 359–387. [CrossRef]
25. Pretty, J. Agricultural sustainability: Concepts, principles and evidence. *Philos. Trans. R. Soc. B Biol. Sci.* **2008**, *363*, 447–465. [CrossRef] [PubMed]
26. Santiteerakul, S.; Sopadang, A.; Tippayawong, K.Y.; Tamvimol, K. The Role of Smart Technology in Sustainable Agriculture: A Case Study of Wangree Plant Factory. *Sustainability* **2020**, *12*, 4640. [CrossRef]
27. Ribarics, P. Big Data and its impact on agriculture. *Ecocycles* **2016**, *2*, 33–34. [CrossRef]
28. Goodland, R. The concept of environmental sustainability. *Annu. Rev. Ecol. Syst.* **1995**, *26*, 1–24. [CrossRef]
29. Chen, H.-Y.; Gupta, M.C.; Lee, A.C.; Lee, C.F. Sustainable growth rate, optimal growth rate, and optimal payout ratio: A joint optimization approach. In *Handbook of Financial Econometrics, Mathematics, Statistics, and Machine Learning*; World Scientific: Singapore, 2021; pp. 3413–3464.
30. Kongsom, C.; Panyakul, V. Production and market of certified organic products in Thailand. *Int. J. Econ. Manag. Eng.* **2016**, *10*, 2723–2727.
31. Ditlevsen, K.; Sandøe, P.; Lassen, J. Healthy food is nutritious, but organic food is healthy because it is pure: The negotiation of healthy food choices by Danish consumers of organic food. *Food Qual. Prefer.* **2019**, *71*, 46–53. [CrossRef]
32. Ghosh, P.; Venkatachalapathy, N. Processing and drying of coffee—A review. *Int. J. Eng. Res. Technol.* **2014**, *3*, 784–794.
33. Murthy, P.S.; Naidu, M.M. Sustainable management of coffee industry by-products and value addition—A review. *Resour. Conserv. Recycl.* **2012**, *66*, 45–58. [CrossRef]
34. Angkasith, P. Coffee production status and potential of organic Arabica coffee in Thailand. In Proceedings of the First Asian Regional Round-table on Sustainable, Organic and Speciality Coffee Production, Processing and Marketing, Chiang Mai, Thailand, 26–28 February 2001; pp. 26–28.
35. Dowding, T.J. *The Coffee Bean: A Value Chain and Sustainability Initiatives Analysis Melissa Murphy*; University of Connecticut: Stamford, CT, USA, 2017.
36. Lilavanichakul, A. The Economic Impact of Arabica Coffee Farmers' Participation in Geographical Indication in Northern Highland of Thailand. *J. Rural Probl.* **2020**, *56*, 124–131. [CrossRef]
37. Noppakoonwong, U.; Khomarwut, C.; Hanthewee, M.; Jarintorn, S.; Hassarungsee, S.; Meesook, S.; Daoruang, C.; Naka, P.; Lertwatanakiat, S.; Satayawut, K. Research and development of Arabica coffee in Thailand. In Proceedings of the 25th International Conference on Coffee Science (ASIC), Armenia, Colombia, 8–13 September 2014.
38. Lezoche, M.; Hernandez, J.E.; Díaz, M.D.M.E.A.; Panetto, H.; Kacprzyk, J. Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Comput. Ind.* **2020**, *117*, 103187. [CrossRef]

39. Contreras-Medina, D.I.; Contreras-Medina, L.M.; Pardo-Nuñez, J.; Olvera-Vargas, L.A.; Rodriguez-Peralta, C.M. Roadmapping as a Driver for Knowledge Creation: A Proposal for Improving Sustainable Practices in the Coffee Supply Chain from Chiapas, Mexico, Using Emerging Technologies. *Sustainability* **2020**, *12*, 5817. [CrossRef]
40. Beuchelt, T.D.; Zeller, M. The role of cooperative business models for the success of smallholder coffee certification in Nicaragua: A comparison of conventional, organic and Organic-Fairtrade certified cooperatives. *Renew. Agric. Food Syst.* **2013**, *28*, 195–211. [CrossRef]
41. Han, J.; Zhang, Z.; Cao, J.; Luo, Y.; Zhang, L.; Li, Z.; Zhang, J. Prediction of winter wheat yield based on multi-source data and machine learning in China. *Remote Sens.* **2020**, *12*, 236. [CrossRef]
42. Apiletti, D.; Pastor, E. Correlating Espresso Quality with Coffee-Machine Parameters by Means of Association Rule Mining. *Electronics* **2020**, *9*, 100. [CrossRef]
43. Kamilaris, A.; Kartakoullis, A.; Prenafeta-Boldú, F.X. A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.* **2017**, *143*, 23–37. [CrossRef]
44. Chedad, A.; Moshou, D.; Aerts, J.-M.; Van Hirtum, A.; Ramon, H.; Berckmans, D. AP—Animal production technology: Recognition system for pig cough based on probabilistic neural networks. *J. Agric. Eng. Res.* **2001**, *79*, 449–457. [CrossRef]
45. Rodriguez, D.; de Voil, P.; Rufino, M.C.; Odendo, M.; van Wijk, M.T. To mulch or to munch? Big modelling of big data. *Agric. Syst.* **2017**, *153*, 32–42. [CrossRef]
46. Karmas, A.; Tzotsos, A.; Karantzalos, K. Geospatial big data for environmental and agricultural applications. In *Big Data Concepts, Theories, and Applications*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 353–390. [CrossRef]
47. Lechthaler, F.; Vinogradova, A. The climate challenge for agriculture and the value of climate services: Application to coffee-farming in Peru. *Eur. Econ. Rev.* **2017**, *99*, 5–30. [CrossRef]
48. Gunathilaka, R.; Smart, J.C.; Fleming, C.M. Adaptation to climate change in perennial cropping systems: Options, barriers and policy implications. *Environ. Sci. Policy* **2018**, *82*, 108–116. [CrossRef]
49. Iglesias, A.; Garrote, L.; Quiroga, S.; Moneo, M. A regional comparison of the effects of climate change on agricultural crops in Europe. *Clim. Chang.* **2012**, *112*, 29–46. [CrossRef]
50. Cherrie, M.P.C.; Nichols, G.; Iacono, G.L.; Sarran, C.; Hajat, S.; Fleming, L.E. Pathogen seasonality and links with weather in England and Wales: A big data time series analysis. *BMC Public Health* **2018**, *18*, 1–13. [CrossRef]
51. Rao, N. Big data and climate smart agriculture-status and implications for agricultural research and innovation in India. *Proc. Indian Natl. Sci. Acad.* **2018**, *96*, 625–640. [CrossRef]
52. Ingale, V.B.; Jadhav, D.K. Big Data A Great Revolution in Precision Agriculture using Predictive Weather Analysis and Soil Analysis. *Int. J. Agric. Innov. Res.* **2016**, *5*. [CrossRef]
53. Mitiku, F.; Nyssen, J.; Maertens, M. Can Coffee Certification Promote Land-sharing and Protect Forest in Ethiopia? *Sustainability* **2017**. [CrossRef]
54. Bosselmann, A.S. Mediating factors of land use change among coffee farmers in a biological corridor. *Ecol. Econ.* **2012**, *80*, 79–88. [CrossRef]
55. Estrada, L.L.; Rasche, L.; Schneider, U.A. Modeling land suitability for Coffea arabica L. in Central America. *Environ. Model. Softw.* **2017**, *95*, 196–209. [CrossRef]
56. Papaskiri, T.V.; E Kasyanov, A.; Alekseenko, N.N.; Semochkin, V.N.; Ananicheva, E.P.; Volkov, I.V. Modern technologies of digital land management. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2019.
57. Zeng, C.; Yang, L.; Dong, J. Management of urban land expansion in China through intensity assessment: A big data perspective. *J. Clean. Prod.* **2017**, *153*, 637–647. [CrossRef]
58. Volkov, S.N.; Cherkashina, E.V.; A Shapovalov, D. Digital land management: New approaches and technologies. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2019.
59. McQueen, R.J.; Garner, S.R.; Nevill-Manning, C.G.; Witten, I.H. Applying machine learning to agricultural data. *Comput. Electron. Agric.* **1995**, *12*, 275–293. [CrossRef]
60. Kempenaar, C.; Lokhorst, C.; Bleumer, E.; Veerkamp, R.; Been, T.; van Evert, F.; Boogaardt, M.; Ge, L.; Wolfert, J.; Verdouw, C. *Big Data Analysis for Smart Farming: Results of TO2 Project in Theme Food Security*; Wageningen University & Research: Wageningen, The Netherlands, 2016.
61. Pierna, J.F.; Baeten, V.; Renier, A.M.; Cogdill, R.; Dardenne, P. Combination of support vector machines (SVM) and near-infrared (NIR) imaging spectroscopy for the detection of meat and bone meal (MBM) in compound feeds. *J. Chemom. A J. Chemom. Soc.* **2004**, *18*, 341–349. [CrossRef]
62. Hipólito, J.; Boscolo, D.; Viana, B.F. Landscape and crop management strategies to conserve pollination services and increase yields in tropical coffee farms. *Agric. Ecosyst. Environ.* **2018**, *256*, 218–225. [CrossRef]
63. Perdoná, M.J.; Soratto, R.P. Higher yield and economic benefits are achieved in the macadamia crop by irrigation and intercropping with coffee. *Sci. Hortic.* **2015**, *185*, 59–67. [CrossRef]
64. Mota, L.H.C.; Silva, W.D.; Sermarini, R.A.; Demétrio, C.G.B.; Bento, J.M.S.; Delalibera, I., Jr. Autoinoculation trap for management of Hypothenemus hampei (Ferrari) with Beauveria bassiana (Bals.) in coffee crops. *Biol. Control* **2017**, *111*, 32–39. [CrossRef]
65. Van Evert, F.K.; Fountas, S.; Jakovetic, D.; Crnojevic, V.; Travlos, I.; Kempenaar, C. Big Data for weed control and crop protection. *Weed Res.* **2017**, *57*, 218–233. [CrossRef]

66. Tseng, F.-H.; Cho, H.-H.; Wu, H.-T. Applying big data for intelligent agriculture-based crop selection analysis. *IEEE Access* **2019**, *7*, 116965–116974. [CrossRef]
67. Palanivel, K.; Surianarayanan, C. An approach for prediction of crop yield using machine learning and big data techniques. *Int. J. Comput. Eng. Technol.* **2019**, *10*, 110–118. [CrossRef]
68. Nzeyimana, I.; Hartemink, A.E.; Ritsema, C.; Stroosnijder, L.; Lwanga, E.H.; Geissen, V. Mulching as a strategy to improve soil properties and reduce soil erodibility in coffee farming systems of Rwanda. *Catena* **2017**, *149*, 43–51. [CrossRef]
69. Tumwebaze, S.B.; Byakagaba, P. Soil organic carbon stocks under coffee agroforestry systems and coffee monoculture in Uganda. *Agric. Ecosyst. Environ.* **2016**, *216*, 188–193. [CrossRef]
70. Alves, G.M.; Cruvinel, P.E. Big data environment for agricultural soil analysis from CT digital images. In Proceedings of the 2016 IEEE Tenth International Conference on Semantic Computing (ICSC), Laguna Hills, CA, USA, 4–6 February 2016.
71. Kim, M.; Peng, J.-L.; Sung, K. Causality between climatic and soil factors on Italian ryegrass yield in paddy field via climate and soil big data. *J. Anim. Sci. Technol.* **2019**, *61*, 324. [CrossRef]
72. Rajeswari, V.; Arunesh, K. Analysing soil data using data mining classification techniques. *Indian J. Sci. Technol.* **2016**, *9*, 1–4. [CrossRef]
73. Martins, B.H.; Araujo-Junior, C.F.; Miyazawa, M.; Vieira, K.M.; Milori, D.M. Soil organic matter quality and weed diversity in coffee plantation area submitted to weed control and cover crops management. *Soil Tillage Res.* **2015**, *153*, 169–174. [CrossRef]
74. Pires, L.; Araujo-Junior, C.; Auler, A.; Dias, N.; Junior, M.D.; de Alcântara, E. Soil physico-hydrical properties changes induced by weed control methods in coffee plantation. *Agric. Ecosyst. Environ.* **2017**, *246*, 261–268. [CrossRef]
75. Jareen, B.; Anwar, P.; Yeasmin, S.; Islam, A.K.M.M.; Rashid, H.O.; Sultana, M.T.; Juraimi, A.S. Evaluation of the cultivar mixture strategy as a sustainable tool for managing weeds and enhancing rice yield. *Big Data Agric.* **2019**, *1*, 01–09. [CrossRef]
76. Thorp, K.; Tian, L. A review on remote sensing of weeds in agriculture. *Precis. Agric.* **2004**, *5*, 477–508. [CrossRef]
77. Frelat, R.; Lopez-Ridaura, S.; Giller, K.E.; Herrero, M.; Douxchamps, S.; Djurfeldt, A.A.; Erenstein, O.; Henderson, B.; Kassie, M.; Paul, B.K. Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 458–463. [CrossRef]
78. Jozwiak, A.; Milkovics, M.; Lakner, Z. A network-science support system for food chain safety: A case from Hungarian cattle production. *Int. Food Agribus. Manag. Rev.* **2016**, *19*, 1–26.
79. Lucas, M.T.; Chhajed, D. Applications of location analysis in agriculture: A survey. *J. Oper. Res. Soc.* **2004**, *55*, 561–578. [CrossRef]
80. Mabalay, M.R.; Nelson, A.; Setiyono, T.; Quilang, E.J.; Maunahan, A.; Abonete, P.; Rala, A.; Raviz, J.; Skorzus, R.; Loro, J. Remote Sensing-Based Information and Insurance for Crops in Emerging Economies (Riice): The Philippine's Experience. In Proceedings of the 34th Asian Conference on Remote Sensing, ACRS 2013: Bridging Sustainable Asia, Bali, Indonesia, 20–24 October 2013; pp. 1465–1470.
81. Ainali, K.; Tsiligiridis, T. Remote sensing Big AgriData for food availability 2018 International Conference on Image and Video Processing, and Artificial Intelligence. In Proceedings of the 2018 International Society for Optics and Photonics, Shanghai, China, 29 October 2018.
82. Hardt, E.; Borgomeo, E.; dos Santos, R.F.; Pinto, L.F.G.; Metzger, J.P.; Sparovek, G. Does certification improve biodiversity conservation in Brazilian coffee farms? *For. Ecol. Manag.* **2015**, *357*, 181–194. [CrossRef]
83. Hallgren, W.; Beaumont, L.; Bowness, A.; Chambers, L.; Graham, E.; Holewa, H.; Laffan, S.; Mackey, B.; Nix, H.; Price, J.; et al. The biodiversity and climate change virtual laboratory: Where ecology meets big data. *Environ. Model. Softw.* **2016**, *76*, 182–186. [CrossRef]
84. Conversa, G.; Lazzizera, C.; Bonasia, A.; Cifarelli, S.; Losavio, F.; Sonnante, G.; Elia, A. Exploring on-farm agro-biodiversity: A study case of vegetable landraces from Puglia region (Italy). *Biodivers. Conserv.* **2019**, *29*, 747–770. [CrossRef]
85. Kumar, P.; Kumar, A.; Panwar, S.; Dash, S.; Sinha, K.; Ray, M. Role of big data in agriculture-A statistical prospective 2018. *Agric. Res. New Ser.* **2018**, *39*, 210–215.
86. Bravo-Monroy, L.; Potts, S.G.; Tzanopoulos, J. Drivers influencing farmer decisions for adopting organic or conventional coffee management practices. *Food Policy* **2016**, *58*, 49–61. [CrossRef]
87. Nguyen, T.T.; Nguyen, L.D.; Lippe, R.S.; Grote, U. Determinants of farmers' land use decision-making: Comparative evidence from Thailand and Vietnam. *World Dev.* **2017**, *89*, 199–213. [CrossRef]
88. Cabrera, V.E.; Barrientos-Blanco, J.A.; Delgado, H.; Fadul-Pacheco, L. Symposium review: Real-time continuous decision making using big data on dairy farms. *J. Dairy Sci.* **2020**, *103*, 3856–3866. [CrossRef]
89. Baseca, C.C.; Sendra, S.; Lloret, J.; Tomas, J. A smart decision system for digital farming. *Agronomy* **2019**, *9*, 216. [CrossRef]
90. Bartkowski, B.; Bartke, S. Leverage points for governing agricultural soils: A review of empirical studies of European Farmers' decision-making. *Sustainability* **2018**, *10*, 3179. [CrossRef]
91. Jones, D.; Barnes, E. Fuzzy composite programming to combine remote sensing and crop models for decision support in precision crop management. *Agric. Syst.* **2000**, *65*, 137–158. [CrossRef]
92. Emeana, E.M.; Trenchard, L.; Dehnen-Schmutz, K. The Revolution of Mobile Phone-Enabled Services for Agricultural Development (m-Agri Services) in Africa: The Challenges for Sustainability. *Sustainability* **2020**, *12*, 485. [CrossRef]
93. Songa, W. (Syngenta Foundation for Sustainable Agriculture) Presentation on Seed Marketing (SEMIs), Rome, Italy. 2018. Available online: http://erepository.uonbi.ac.ke/bitstream/handle/11295/103523/Songa_%20(Syngenta%20Foundation%20

for%20Sustainable%20Agriculture)%20Presentation%20on%20Seed%20Marketing%20(SEMIs).pdf?sequence=1 (accessed on 10 February 2021).
94. Akinboro, B. Bringing mobile wallets to Nigerian farmers. Financial Innovation for Smallholder Families. In Digital Financial Services, Pakistan. 2014. Available online: https://www.cgap.org/blog/bringing-mobile-wallets-nigerian-farmers (accessed on 10 February 2021).
95. Sufyadi, D.; Apriadi, I. Factors affecting the response of farmers insurance program for farming rice (Autp). *Eur. Asian J. Biosci.* **2020**, *14*, 7149–7157.
96. Quarshie, A.M.; Salmi, A.; Leuschner, R. Sustainability and corporate social responsibility in supply chains: The state of research in supply chain management and business ethics journals. *J. Purch. Supply Manag.* **2016**, *22*, 82–97. [CrossRef]
97. Aliev, K.; Pasero, E.; Jawaid, M.M.; Narejo, S.; Pulatov, A. Internet of plants application for smart agriculture. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 421–429. [CrossRef]
98. Kulalvaimozhi, V.; Germanus, A.; Peter, J. Image processing in agriculture. *Int. J. Adv. Eng. Technol. Manag. Appl. Sci. (IJAETMAS)* **2017**, *4*, 142–151.
99. Yao, C.; Zhang, Y.; Zhang, Y.; Liu, H. Application of convolutional neural network in classification of high resolution agricultural remote sensing images. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2017**, *42*. [CrossRef]
100. Ma, C.; Zhang, H.H.; Wang, X. Machine learning for Big Data analytics in plants. *Trends Plant Sci.* **2014**, *19*, 798–808. [CrossRef]
101. Mucherino, A.; Papajorgji, P.; Pardalos, P.M. A survey of data mining techniques applied to agriculture. *Oper. Res.* **2009**, *9*, 121–140. [CrossRef]
102. Tripathi, S.; Srinivas, V.; Nanjundiah, R.S. Downscaling of precipitation for climate change scenarios: A support vector machine approach. *J. Hydrol.* **2006**, *330*, 621–640. [CrossRef]
103. Armstrong, L.; Diepeveen, D.; Maddern, R. The application of data mining techniques to characterize agricultural soil profiles. In Proceedings of the 6th Australasian Data Mining Conference (AusDM 2007), Gold Coast, QLD, Australia, 3–4 December 2007; pp. 85–100.
104. Meyer, G.E.; Neto, J.C.; Jones, D.D.; Hindman, T.W. Intensified fuzzy clusters for classifying plant, soil, and residue regions of interest from color images. *Comput. Electron. Agric.* **2004**, *42*, 161–180. [CrossRef]
105. Galford, G.L.; Mustard, J.F.; Melillo, J.; Gendrin, A.; Cerri, C.C.; Cerri, C.E. Wavelet analysis of MODIS time series to detect expansion and intensification of row-crop agriculture in Brazil. *Remote Sens. Environ.* **2008**, *112*, 576–587. [CrossRef]
106. Vibhute, A.; Bodhe, S.K. Applications of image processing in agriculture: A survey. *Int. J. Comput. Appl.* **2012**, 52. [CrossRef]
107. Rajeswari, S.; Suthendran, K.; Rajakumar, K. A smart agricultural model by integrating IoT, mobile and cloud-based big data analytics. In Proceedings of the 2017 international conference on intelligent computing and control (I2C2), Coimbatore, India, 23–24 June 2017; pp. 1–5.
108. Mekonnen, Y.; Namuduri, S.; Burton, L.; Sarwat, A.; Bhansali, S. Machine learning techniques in wireless sensor network based precision agriculture. *J. Electrochem. Soc.* **2020**, *167*, 037522. [CrossRef]
109. King, T.; Cole, M.; Farber, J.M.; Eisenbrand, G.; Zabaras, D.; Fox, E.M.; Hill, J.P. Food safety for food security: Relationship between global megatrends and developments in food safety. *Trends Food Sci. Technol.* **2017**, *68*, 160–175. [CrossRef]
110. Ahearn, M.C.; Armbruster, W.; Young, R. Big data's potential to improve food supply chain environmental sustainability and food safety. *Int. Food Agribus. Manag. Rev.* **2016**, *19*, 155–171.
111. Ojha, T.; Misra, S.; Raghuwanshi, N.S. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Comput. Electron. Agric.* **2015**, *118*, 66–84. [CrossRef]
112. Shinghal, D.; Srivastava, N. Wireless Sensor Networks in Agriculture: For Potato Farming. Neelam, Wireless Sensor Net-works in Agriculture: For Potato Farming, Malaysia. 2017. Available online: https://ssrn.com/abstract=3041375 (accessed on 10 February 2021).
113. Rathinam, D.D.K.; Surendran, D.; Shilpa, A.; Grace, A.S.; Sherin, J. Modern agriculture using wireless sensor network (wsn). In Proceedings of the 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Coimbatore, India, 15–16 March 2019.
114. Mocanu, M.; Cristea, V.; Negru, C.; Pop, F.; Ciobanu, V.; Dobre, C. Cloud-based architecture for farm management. In Proceedings of the 2015 20th International Conference on Control Systems and Computer Science, Bucharest, Romania, 27–29 May 2015.
115. Goraya, M.S.; Kaur, H. Cloud computing in agriculture. *HCTL Open Int. J. Technol. Innov. Res. (IJTIR)* **2015**, *16*, 1814–2321.
116. Elijah, O.; Rahman, T.A.; Orikumhi, I.; Leow, C.Y.; Hindia, M.N. An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet Things J.* **2018**, *5*, 3758–3773. [CrossRef]
117. Yoon, C.; Huh, M.; Kang, S.-G.; Park, J.; Lee, C. Implement smart farm with IoT technology. In Proceedings of the 2018 20th International Conference on Advanced Communication Technology (ICACT), Chuncheon, Korea, 11–14 February 2018.
118. Umamaheswari, S.; Arjun, R.; Meganathan, D. Weed detection in farm crops using parallel image processing. In Proceedings of the 2018 Conference on Information and Communication Technology (CICT), Jabalpur, India, 26–28 October 2018.
119. Khirade, S.D.; Patil, A. Plant disease detection using image processing. In Proceedings of the 2015 International Conference on Computing Communication Control and Automation, Pune, India, 26–27 February 2015.
120. Barbosa, A.; Trevisan, R.; Hovakimyan, N.; Martin, N.F. Modeling yield response to crop management using convolutional neural networks. *Comput. Electron. Agric.* **2020**, *170*, 105197. [CrossRef]

121. Nevavuori, P.; Narra, N.; Lipping, T. Crop yield prediction with deep convolutional neural networks. *Comput. Electron. Agric.* **2019**, *163*, 104859. [CrossRef]
122. Adhitya, Y.; Prakosa, S.W.; Köppen, M.; Leu, J.-S. Convolutional Neural Network Application in Smart Farming. In *International Conference on Soft Computing in Data Science*; Springer: Singapore, 2019.
123. Asfaw, E.; Suryabhagavan, K.; Argaw, M. Soil salinity modeling and mapping using remote sensing and GIS: The case of Wonji sugar cane irrigation farm, Ethiopia. *J. Saudi Soc. Agric. Sci.* **2018**, *17*, 250–258. [CrossRef]
124. Huang, Y.; Chen, Z.-X.; Tao, Y.; Huang, X.-Z.; Gu, X.-F. Agricultural remote sensing big data: Management and applications. *J. Integr. Agric.* **2018**, *17*, 1915–1931. [CrossRef]
125. Pereira, A.C.; Romero, F. A review of the meanings and the implications of the Industry 4.0 concept. *Procedia Manuf.* **2017**, *13*, 1206–1214. [CrossRef]
126. Kodali, R.K.; Soratkal, S.; Boppana, L. WSN in coffee cultivation. In Proceedings of the 2016 International Conference on Computing, Communication and Automation (ICCCA), Greater Noida, India, 29–30 April 2016; pp. 661–666.
127. Bolaños, P.; Céspedes, S.; Cuéllar, J.C. Prototype of a Wireless Sensor Network for Monitoring the Coffee Drying Process. In Proceedings of the IV School of Systems and Networks (SSN 2018), Valdivia, Chile, 29–31 October 2018; pp. 61–63.
128. Rodríguez, J.P.; Corrales, D.C.; Aubertot, J.-N.; Corrales, C. A computer vision system for automatic cherry beans detection on coffee trees. *Pattern Recognit. Lett.* **2020**. [CrossRef]
129. Faridah, F.; Parikesit, G.O.; Ferdiansjah, F. Coffee bean grade determination based on image parameter. *Telkomnika (Telecommun. Comput. Electron. Control)* **2013**, *9*, 547–554. [CrossRef]
130. Santos, J.; Faria, F.; Calumby, R.; Torres, R.d.S.; Lamparelli, R.A. A genetic programming approach for coffee crop recognition. In Proceedings of the 2010 IEEE International Geoscience and Remote Sensing Symposium, Honolulu, HI, USA, 25–30 July 2010; pp. 3418–3421.
131. Smith, J. Coffee Landscapes: Specialty Coffee, Terroir, and Traceability in Costa Rica. *Cult. Agric. Food Environ.* **2018**, *40*, 36–44. [CrossRef]
132. Thiruchelvam, V.; Mughisha, A.S.; Shahpasand, M.; Bamiah, M. Blockchain-based technology in the coffee supply chain trade: Case of burundi coffee. *J. Telecommun. Electron. Comput. Eng. (JTEC)* **2018**, *10*, 121–125.
133. Valverde, J.; Rosello, V.; Mujica, G.; Portilla, J.; Uriarte, A.; Riesgo, T. Wireless sensor network for environmental monitoring: Application in a coffee factory. *Int. J. Distrib. Sens. Netw.* **2011**, *8*, 638067. [CrossRef]
134. Kodali, R.K.; Rawat, N.; Boppana, L. WSN sensors for precision agriculture. In Proceedings of the 2014 IEEE Region 10 Symposium, Kuala Lumpur, Malaysia, 14–16 April 2014; pp. 651–656.
135. Kodali, R.K.; Rawat, N. Wireless sensor network in mango farming. In Proceedings of the 2013 Nirma University International Conference on Engineering (NUiCONE), Ahmedabad, India, 28–30 November 2013; pp. 1–6.
136. Nath, B.; Chaudhuri, S. Application of cloud computing in agricultural sectors for economic development. In *Interplay of Economics, Politics and Society for Inclusive Growth-International Conference organized by RTC and GNHC*; UNDP: New York, NY, USA, 2012.
137. Zhong, R.Y.; Lan, S.; Xu, C.; Dai, Q.; Huang, G.Q. Visualization of RFID-enabled shopfloor logistics Big Data in Cloud Manufacturing. *Int. J. Adv. Manuf. Technol.* **2016**, *84*, 5–16. [CrossRef]
138. de Oliveira, E.M.; Leme, D.S.; Barbosa, B.H.G.; Rodarte, M.P.; Pereira, R.G.F.A. A computer vision system for coffee beans classification based on computational intelligence techniques. *J. Food Eng.* **2016**, *171*, 22–27. [CrossRef]
139. Kılıç, K.; Boyacı, I.H.; Köksel, H.; Küsmenoğlu, İ. A classification system for beans using computer vision system and artificial neural networks. *J. Food Eng.* **2007**, *78*, 897–904. [CrossRef]
140. Zhong, R.Y.; Xu, X.; Klotz, E.; Newman, S.T. Intelligent manufacturing in the context of industry 4.0: A review. *Engineering* **2017**, *3*, 616–630. [CrossRef]
141. Shams, S.; Newaz, S.H.S.; Karri, R.R. Information and Communication Technology for Small-Scale Farmers: Challenges and Opportunities. In *Smart Village Technology*; Springer: Cham, Switzerland, 2020; pp. 159–179.
142. Rutayisire, J.; Markon, S.; Raymond, N. IoT based Coffee quality monitoring and processing system in Rwanda. In Proceedings of the 2017 International Conference on Applied System Innovation (ICASI), Sapporo, Japan, 13–17 May 2017; pp. 1209–1212.
143. Shrouf, F.; Ordieres, J.; Miragliotta, G. Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm. In Proceedings of the 2014 IEEE International Conference on Industrial Engineering and Engineering Management, Selangor, Malaysia, 9–12 December 2014; pp. 697–701.
144. Zhong, W.; Xie, Y.; He, X. Research of the Rice Image Segmentation Based on Color Linear Array CCD. *Int. J. Control Autom.* **2014**, *7*, 223–232. [CrossRef]
145. Jie, Y.; Za, K.; Ruoyu, Z.; Xiaoli, S.; Wanchao, H.; Zhangtao, Y.; Yang, L. Data acquisition system for pneumatic actuator of the Tomato Color Sorter based on virtual instrument. In Proceedings of the 2011 IEEE International Conference on Computer Science and Automation Engineering, Shanghai, China, 10–12 June 2011; pp. 671–675.
146. Burugupalli, C.C.; Deekshith, D.; KR, K.B.; Kumar, D.D.; HR, M.N. Design and fabrication of coffee bean sorter machine. *Int. J. Adv. Res. Ideas Innov. Technol.* **2019**, *5*, 1531–1533.
147. Shanmugapriya, P.; Rathika, S.; Ramesh, T.; Janaki, P. Applications of remote sensing in agriculture-A Review. *Int. J. Current Microbiol. Appl. Sci.* **2019**, *8*, 2270–2283. [CrossRef]

148. Gafesa, F.E. Aggregation for Sustainable Traceability in Smallholder Coffee Producers: Cases of Ethiopia. *RAIS Collect. Vol. –Econ. Sci.* **2018**, *2*, 47–71.
149. Hameed, A.; Hussain, S.A.; Ijaz, M.U.; Ullah, S.; Pasha, I.; Suleria, H.A.R. Farm to consumer: Factors affecting the organoleptic characteristics of coffee. *Ii Postharvest Process. Factors. Compr. Rev. Food Sci. Food Saf.* **2018**, *17*, 1184–1237. [CrossRef]
150. Di Donfrancesco, B.; Guzman, N.G.; Chambers, I.V.E. Comparison of Results from Cupping and Descriptive Sensory Analysis of C olombian Brewed Coffee. *J. Sens. Stud.* **2014**, *29*, 301–311. [CrossRef]
151. Ferguson, J.E. Coffee Quality, Land Use, and Processing in the Cajamarca Region of Peru, USA. 2017. Available online: https://www.semanticscholar.org/paper/COFFEE-QUALITY%2C-LAND-USE%2C-AND-PROCESSING-IN-THE-OF-Ferguson/c658054cab699b3db7f5b6f0585746bd043266ce#paper-header (accessed on 10 February 2021).
152. Kamilaris, A.; Fonts, A.; Prenafeta-Boldύ, F.X. The rise of blockchain technology in agriculture and food supply chains. *Trends Food Sci. Technol.* **2019**, *91*, 640–652. [CrossRef]
153. Hackett, R. How this startup plans to use blockchain to revolutionize the coffee supply chain. *Fortune*, 24 October 2017.
154. Nguyen, G.N.T.; Sarker, T. Sustainable coffee supply chain management: A case study in Buon Me Thuot City, Daklak, Vietnam. *Int. J. Corp. Soc. Responsib.* **2018**, *3*, 1. [CrossRef]
155. Van der Vossen, H. A critical analysis of the agronomic and economic sustainability of organic coffee production. *Exp. Agric.* **2005**, *41*, 449–473. [CrossRef]
156. Kilcher, L. How organic agriculture contributes to sustainable development. *J. Agric. Res. Trop. Subtrop. Suppl.* **2007**, *89*, 31–49.
157. D'Souza, M. Soil acidity and its management (liming). *Indian Coffee* **2011**, *75*, 12–14.
158. Bacon, C.M.; Méndez, V.E.; Fox, J.A. Cultivating sustainable coffee: Persistent paradoxes. In *Confronting the Coffee Crisis: Fair Trade, Sustainable Livelihoods and Ecosystems in Mexico and Central America*; MIT Press: Cambridge, MA, USA, 2008; pp. 337–372.
159. Kilian, B.; Jones, C.; Pratt, L.; Villalobos, A. Is sustainable agriculture a viable strategy to improve farm income in Central America? A case study on coffee. *J. Bus. Res.* **2006**, *59*, 322–330. [CrossRef]
160. Coradi, P.C.; de Oliveira, M.B.; de Carneiro, L.; de Souza, G.A.C.; Elias, M.C.; Brackmann, A.; Teodoro, P.E. Technological and sustainable strategies for reducing losses and maintaining the quality of soybean grains in real production scale storage units. *J. Stored Prod. Res.* **2020**, *87*, 101624. [CrossRef]
161. Eswaran, H.; Lal, R.; Reich, P. Land degradation: An overview. *Response Land Degrad.* **2019**, 20–35. [CrossRef]
162. Fereres, E.; Orgaz, F.; Gonzalez-Dugo, V. Reflections on food security under water scarcity. *J. Exp. Bot.* **2011**, *62*, 4079–4086. [CrossRef] [PubMed]
163. Diao, X.; Pratt, A.N. Growth options and poverty reduction in Ethiopia–An economy-wide model analysis. *Food Policy* **2007**, *32*, 205–228. [CrossRef]
164. Horrigan, L.; Lawrence, R.S.; Walker, P. How sustainable agriculture can address the environmental and human health harms of industrial agriculture. *Environ. Health Perspect.* **2002**, *110*, 445–456. [CrossRef] [PubMed]
165. Pearson, T. Hardware-based image processing for high-speed inspection of grains. *Comput. Electron. Agric.* **2009**, *69*, 12–18. [CrossRef]
166. Tippayawong, N.; Tantakitti, C.; Thavornun, S. Energy efficiency improvements in longan drying practice. *Energy* **2008**, *33*, 1137–1143. [CrossRef]
167. Tippayawong, N.; Tantakitti, C.; Thavornun, S. Performance Enhancement of Traditional Unpeeled Longan Dryers with Design Modification. *Ama Agric. Mech. Asia Afr. Lat. Am.* **2009**, *40*, 56.
168. Pintana, P.; Thanompongchart, P.; Phimphilai, K.; Tippayawong, N. Combined effect of air temperature and velocity on drying of Thai rice cracker. *Eng. Appl. Sci. Res.* **2016**, *43*, 244–246.
169. Pintana, P.; Thanompongchart, P.; Phimphilai, K.; Tippayawong, N. Improvement of Airflow Distribution in a Glutinous Rice Cracker Drying Cabinet. *Energy Procedia* **2017**, *138*, 325–330. [CrossRef]
170. Patelli, N.; Mandrioli, M. Blockchain technology and traceability in the agrifood industry. *J. Food Sci.* **2020**, *85*, 3670–3678. [CrossRef]
171. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.-J. Big data in smart farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
172. El Bilali, H.; Allahyari, M.S. Transition towards sustainability in agriculture and food systems: Role of information and communication technologies. *Inf. Process. Agric.* **2018**, *5*, 456–464. [CrossRef]
173. Basso, B.; Shuai, G.; Zhang, J.; Robertson, G.P. Yield stability analysis reveals sources of large-scale nitrogen loss from the US Midwest. *Sci. Rep.* **2019**, *9*, 1–9. [CrossRef]
174. Wiseman, L.; Sanderson, J.; Zhang, A.; Jakku, E. Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. *Njas-Wagening. J. Life Sci.* **2019**, *90*, 100301. [CrossRef]
175. Pretty, J.; Bharucha, Z.P. Sustainable intensification in agricultural systems. *Ann. Bot.* **2014**, *114*, 1571–1596. [CrossRef] [PubMed]