agriculture

MDPI

Review

Application of Smart Techniques, Internet of Things and Data Mining for Resource Use Efficient and Sustainable Crop Production

Awais Ali [1], Tajamul Hussain [2], Noramon Tantashutikun [3], Nurda Hussain [2] and Giacomo Cocetta [1,*]

[1] Department of Agricultural and Environmental Sciences-Production, Landscape, Agroenergy, Università degli Studi di Milano, Via Celoria 2, 20133 Milano, MI, Italy
[2] Laboratory of Plant Breeding and Climate Resilient Agriculture, Agricultural Innovation and Management Division, Faculty of Natural Resources, Prince of Songkla University, Songkhla 90110, Thailand
[3] Prince of Songkla University, Hat Yai 90110, Thailand
* Correspondence: giacomo.cocetta@unimi.it

Abstract: Technological advancements have led to an increased use of the internet of things (IoT) to enhance the resource use efficiency, productivity, and cost-effectiveness of agricultural production systems, particularly under the current scenario of climate change. Increasing world population, climate variations, and propelling demand for the food are the hot discussions these days. Keeping in view the importance of the abovementioned issues, this manuscript summarizes the modern approaches of IoT and smart techniques to aid sustainable crop production. The study also demonstrates the benefits of using modern IoT approaches and smart techniques in the establishment of smart- and resource-use-efficient farming systems. Modern technology not only aids in sustaining productivity under limited resources, but also can help in observing climatic variations, monitoring soil nutrients, water dynamics, supporting data management in farming systems, and assisting in insect, pest, and disease management. Various type of sensors and computer tools can be utilized in data recording and management of cropping systems, which ensure an opportunity for timely decisions. Digital tools and camera-assisted cropping systems can aid producers to monitor their crops remotely. IoT and smart farming techniques can help to simulate and predict the yield production under forecasted climatic conditions, and thus assist in decision making for various crop management practices, including irrigation, fertilizer, insecticide, and weedicide applications. We found that various neural networks and simulation models could aid in yield prediction for better decision support with an average simulation accuracy of up to 92%. Different numerical models and smart irrigation tools help to save energy use by reducing it up to 8%, whereas advanced irrigation helped in reducing the cost by 25.34% as compared to soil-moisture-based irrigation system. Several leaf diseases on various crops can be managed by using image processing techniques using a genetic algorithm with 90% precision accuracy. Establishment of indoor vertical farming systems worldwide, especially in the countries either lacking the supply of sufficient water for the crops or suffering an intense urbanization, is ultimately helping to increase yield as well as enhancing the metabolite profile of the plants. Hence, employing the advanced tools, a modern and smart agricultural farming system could be used to stabilize and enhance crop productivity by improving resource use efficiency of applied resources i.e., irrigation water and fertilizers.

Keywords: smart farming; sensors; precision farming; yield prediction; IoT; vertical farming

Citation: Ali, A.; Hussain, T.; Tantashutikun, N.; Hussain, N.; Cocetta, G. Application of Smart Techniques, Internet of Things and Data Mining for Resource Use Efficient and Sustainable Crop Production. *Agriculture* **2023**, *13*, 397. https://doi.org/10.3390/agriculture13020397

Academic Editors: Paul Kwan and Wensheng Wang

Received: 17 January 2023
Revised: 2 February 2023
Accepted: 6 February 2023
Published: 8 February 2023

1. Introduction

Technological advancements have revolutionized almost all sectors, particularly agriculture, in the modern world. Likewise, the agricultural sector, which is a very risk-averse [1], has also been transforming over time, and is aiming at producing more yield and better quality food by establishing and maintaining better crops. In order to diversify and improve the natural population of crops and to enhance the genetic variability, techniques such as mutagenesis, traditional breeding, gene editing, and marker-assisted breeding has been under practice for years [2]. However, climate change has impacted the agriculture sector [3], whereas adaptations to climate change and advances in agricultural-related aspects, such as optimal natural resources usage and limiting the deteriorating environmental impacts altogether, have given the farming sector a new face and dimension. Efficiency of the agriculture sector is threatened due to world population pressure on global production systems, changing climate [4], and crops or food losses due to mishandling [5]. According to the United Nations prediction about the increase in population, a world population of 9.8 billion is expected by the year 2050, and this number may hit 11.2 billion after 70–80 years [6]. Keeping these stats in mind, food production must be increased up to 50% to meet the food demand of this increasing population and ensure food security.

Smart farming, often known as smart agriculture, is a farming practice that uses sustainable methods to meet the population's growing food needs while minimizing negative effects. The global community has embraced it and is supporting it. The fundamental tenet of this strategy is to effectively utilize the resources at hand for sustainable output while lowering the expenses of all activities associated with the agricultural industry [7]. Smart agriculture represents the use of technologies such as sensors; the internet of things (IoT) [8], which is a network of computing devices; artificial intelligence; and robotics [9] to assist traditional agriculture and convert it into a smart and sustainable agriculture [10]. In fact, the IoT is the combination of modern technologies that has the potential to provide modern solutions to agricultural problems [8]. Additionally, with the help of data mining technologies [11], a large number of datasets, either agronomical [12], genomics [13], or meteorological [14], are partitioned into useful information to make easy and efficient decision making [15] in order to make farming activities more precise and efficient. Climatic- or soil-related data in smart agriculture and farming is obtained using sensors [16], and then automatic processing of this big data is carried out with the help of modern methods and analysis tools, such as machine learning [17], spike and slab regression analysis, and time-series analysis [18]. This process gives the obtained data an easy, understandable, and knowledgeable form, which then warns the farmers about any upcoming climatic events, i.e., droughts or heavy rains, chances of insect or pest infestation, and the spread of infectious disease (i.e., fungal diseases) [19]. Following the warning alerts, this IoT based agriculture system blended with ecological sensing and assisted with image processing techniques [20] helps farmers in adopting precautionary measures and in customizing the planning of crop management practices, i.e., irrigation, fertilization, and pest management, with the help of modern digital and internet-assisted tools and smart applications as presented in the Figure 1.

The internet of things provides efficient ways to assist the farmers and researchers in the agricultural crop production sector. Moreover, it assists the decision making by making various information readily available when it comes to soil [16], water [21], pesticides [22], fertilizers [23], and manures [24]. Climate change and global warming are the burning issues of the world, with a lot of studies and resources being spent to ensure a better future for the coming generations. With the IoT availability [13], increased benefits [25,26] can be made available for this cause by concentrating on the sustainability of the resources and by protecting the earth with wise decision making [20]. Additionally, the IoT can help agriculturists and farmers to not only grow the crops smartly, but to effectively deal the post-harvesting and the end consumer's deals on the agricultural products [27]. In addition to this, IoT effectively contributes to precision farming with technologies including drones for agriculture [28], remote sensing [29], smart greenhouses [30], smart livestock management [31], computer imaging [32], and efficient climate monitoring [33] as indicated in the Figure 2. Data mining and simulation modeling of various crops [12], environmental situations, and their management [34] are receiving a lot of attention. Researchers are developing new algorithms to ensure more vigorous and detailed information [35] for better and improved decision making. These techniques have also been used in fertilizer application suggestions [36], i.e., timing and rate of applications, disease, yield predictions [37,38], soil moisture detection, and in scheduling irrigation [39]. Keeping in view the importance of smart techniques, the objectives of the study were to summarize the latest applications of smart techniques, including (i) yield estimation, (ii) irrigation and fertilizer management, and (iv) insect, pest, and disease monitoring and management in crop production, particularly under changing climate. Schematic diagrams and figures created and used in this review were prepared using the Canva software, Canva Pro version 4.49.0, Perth, Australia (https://www.canva.com/en_gb/, accessed on 24 June 2022).

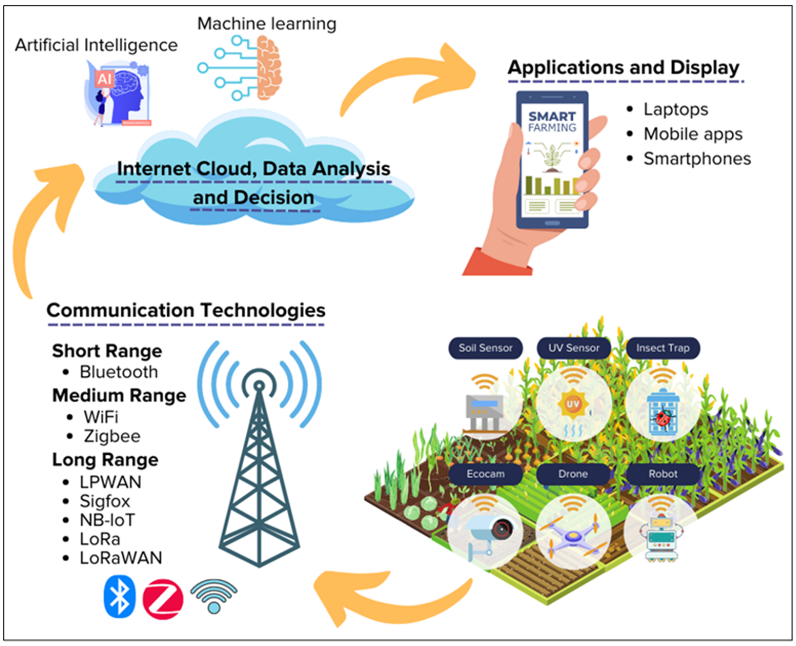

Figure 1. An architecture of smart farming components: Monitoring to end use applications.

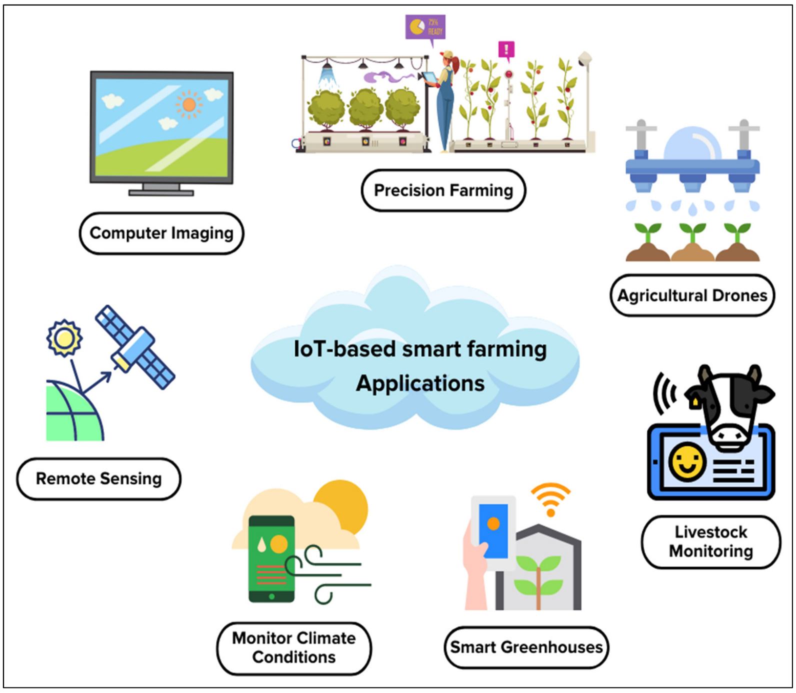

Figure 2. An exemplary hub of IoT based smart farming applications in smart agriculture.

2. Climate Change and Its Effects on Various Crops: A Need of Smart Crop Production

Climate change has severely impacted agriculture worldwide [40]. Rising temperature, fluctuations during day and night temperature, and seasonal variability in the rainfalls has increased the intensity of extreme weather events, i.e., droughts, flash floods [40–43], and incidence of disease occurrence have increased [44]. Efficiency of production systems has been affected, and the impact of climate change has triggered the need for and the adoption of climate-smart adaptation options to sustain productivity and availability throughout the year. Such adaptation options and technologies need to be adopted in almost all aspects related to agricultural crop production, such as soil–water dynamics, nutrients, and fertilizers [41,45] management, improvements in crop types and evaluations [46], applications of beneficial elements [47], organic amendments in soil [48], fisheries, livestock, and poultry, and farm mechanization, as indicated in Figure 3. Temperature is one of the critical factors in crop production.

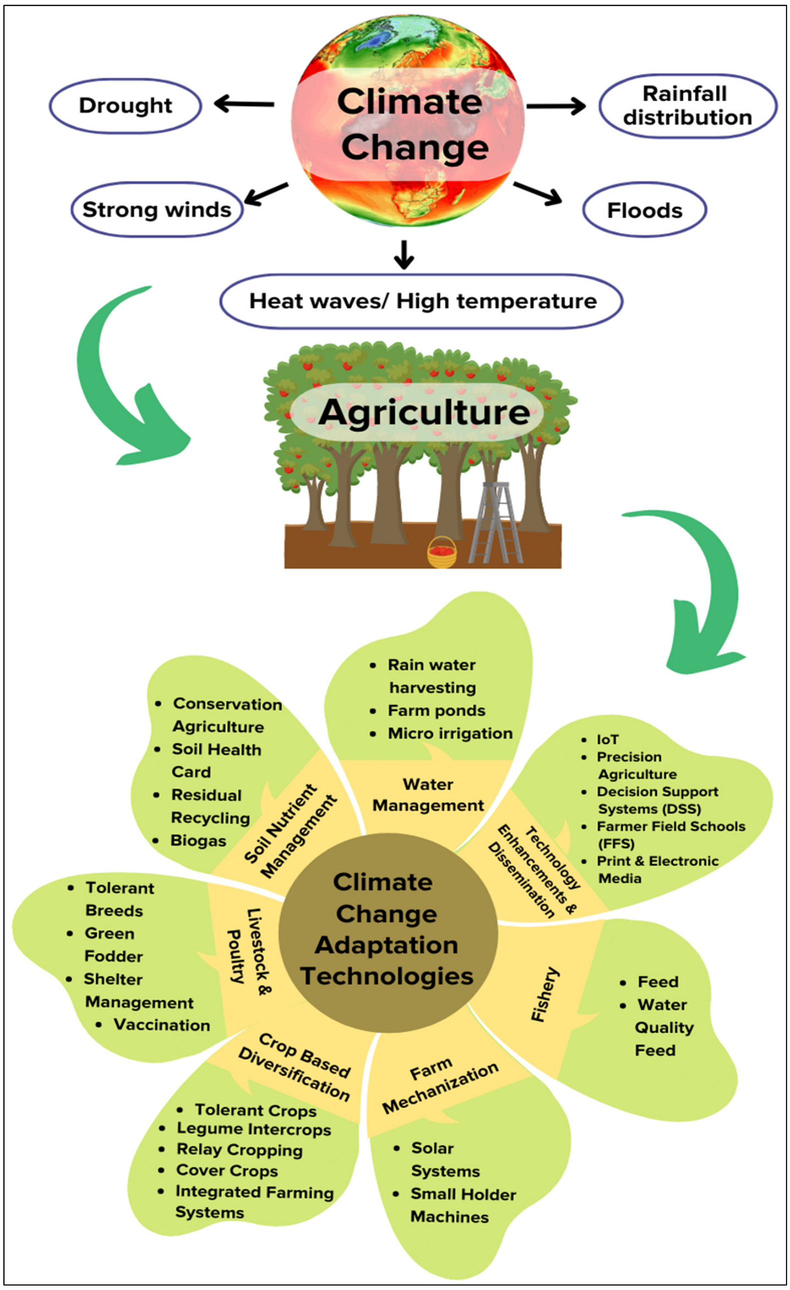

Figure 3. Climatic impacts on agriculture and adaptation technologies to combat climate change.

Numerous studies have been carried out regarding temperature and its effect on various vegetative and reproductive phases in crops [49,50]. A productivity decline has been observed in various crops, such as peaches and plums, which refers to a change in the temperature pattern of a low chilling zone [51]. Moreover, a shift has been observed due to an increase in temperature in the choices of different varieties in bananas, grapes, and other horticultural crops, which ultimately yield a better product to this changing climate. A periodic change in climate is inducing a significant impact on the production of certain spices such as cardamom and black pepper [52]. Biomass production and total yield of potato has been affected by the elevated temperature, and an effective decrease in gross photosynthesis has been noticed [53]. Despite increased biomass production, a 14% decrease in seed yield has been observed by Ruiz-Vera et al. [54] while growing maize at an elevated temperature of 25.4 ± 1.6 °C. Tip burn and leaf desiccation have been noticed in San Joaquin, Imperial, and Salinas Valley in the United States due to higher temperatures in lettuce, which eventually affected its growth and maturation [55]. Specific ranges of temperature are finalized for the effect of temperature on crop growth and productivity. However, an increase in temperature results bolting in cole crops, which is not a desirable attribute while growing it for vegetable purpose [56]. The temperature range 25–35 °C is considered as the moderate range for most crops, where they show the best thriving and productive attributes [41,57]. However, the temperature below the moderate range is the temperature where the growth is slow and unsteady. According to Ounlert and Sadoode [58] and Ounlert et al. [59], the temperature of 38–40 °C is quite high for most crops and their optimum production. Likewise, temperatures below 5 °C is where there is no production of fruit at all for different agronomic and horticultural crops, i.e., mangosteen. If the temperature exceeds 42 °C and 45 °C, it causes the suppression in the germination of cucumber and melon seeds, respectively, while the same trend has been observed at 42 °C in watermelon, summer squash, winter squash, and pumpkin seeds [60].

Dry periods are very important for fruit trees such as mangosteen to stimulate flowering, and various studies have observed the same trend. It is reported that a dry period of 15–20 days is required to induce the flowering in the mangosteen [61]. Moreover, it has been observed that, in case of mangosteen, flowering increased as the drought period before the flowering increased. Delayed curd initiation has been recorded in cauliflower when the daily temperature exceeded 30 °C [62]. Uneven head in broccoli and reduced tomato sizes were reported when the temperature increased above 25 °C for certain period, the traits of which are not very much liked by the end consumers. Rai et al. [63] reported that insufficient chilling is responsible for lowering fruit texture and taste, while high temperature and moisture stress bring cracking in fruit trees such as apple and apricot. Summarizing the various symptoms such as bud drop, abnormal flower development, poor pollen production, dehiscence, and, ultimately, yield losses has been reported by Hazra et al. [64] due to an increase in the temperature for tomato.

Climate change, variability, and its impact have some serious impacts on all the agricultural commodities. There is a change in phenology of crops and horticultural fruit trees with the observed changes in the rainfall pattern. Changes in rainfall and temperature affects the flowering dates of fruit trees [59]. Research had been carried out to investigate the minimum and maximum rainfall and its impact on crop production. If the rainfall received by the mangosteen is >2500 mm, then there is no need to irrigate it manually, while the range of 1270–2500 mm needs a checked irrigation to keep mangosteen hydrated and fit for growth and flowering [65]. Rainfall below the 1270 mm ultimately limits the growth and overall fruit and flower production. Humidity, like rainfall, plays a vital role in ensuring the best thriving fruit in mangosteen production, and it has been suggested that the humidity level of 75–80% is optimum for the mangosteen [65]. Optimum soil moisture levels should be maintained to keep the enough water available for the roots to absorb and transport it to the whole tree. Various management levels are required to meet the effective requirements of the crops, even within an irrigated area.

Soil moisture, irrigation, and rainfall are the pivotal entities to fulfill the net water requirements of a crop [66]. Based on water deficit analysis, Li et al. [66] suggested that rainfall, coupled with irrigation, proved an increased yield of sorghum, corn, and soybean in the Jilin region of China. In addition, rainfall is an indicator of the crop water requirement as well as an indicator of the irrigation requirement for all these crops. To measure the glucosinolates contents in variety of vegetables, such as cauliflower, cabbage, kale, reddish, turnips, and brussels sprouts, it has been found that climatic factors, including the varying rainfall, influence the accumulation of these secondary metabolites in vegetables. However, AZM et al. [67] reported that both soil and environmental factors are going to impact the production of winter vegetables. The rainfall patterns of 2000–2001 and 2002–2003 was the deciding factor for the reduction in the fresh pod weight of okra in the inland valley, and it played a significant role in pest development, disease onset, and in soil chemistry [68]. There is always a negative reaction of crops towards climate change, but vegetables are generally more prone to its adverse conditions [69]. Furthermore, climate change is also responsible for bringing strong winds, storms, hurricanes, and tornadoes to various parts of the world that are the foregrounds of agricultural productivities. When faced by these strong winds, the branches of trees and crops are prone to damage. Leaf tearing of broad leaves has also been observed in various crops, while difficulty in carrying out agricultural operations demands increased investment in agriculture. Keeping in view the climate change aspects, it becomes important to adopt modern techniques and methodologies to sustain the efficiency of farming systems, which ultimately leads to stable crop productivity under diverse environmental conditions and contributes to food security.

3. Yield Prediction in Smart Agriculture

Crop yield is an important entity, and yield prediction is a salient and challenging task in agriculture. Soil properties, meteorological data and seasonal fluctuations, seed quality, harvesting methods, monitoring of pests and diseases, managing nutrient deficiencies, and maintaining water requirements for the crops are all contributing factors for predicting the overall yield of a plant or crop. Precision agriculture has been used for years and now researchers are considering the use of variable rate technologies [70], sensor monitoring [16], and management systems to ensure better crop health [27], improved productivity [28], and better quality [71] of the produce. Sensor- and drone-assisted quality monitoring of horticultural crops [21], yield predicting sensors [72] on harvesters of various agronomic crops [73] (Figure 4), and use of the internet and real time data simulators [74] are receiving attention day by day, particularly for their use in large scale crop production.

Simulation models have been introduced for yield simulations which are assisting in understanding the behaviors of varying yield in relation to fluctuating environment, nutrient, water, pest, diseases, and other field conditions [38,75,76]. The CROPGRO model [77] was especially designed for simulating different grain legume crops such as soybean, groundnut, and common dry bean crops. In an experiment for predicting the yield of tomatoes in glasshouse, Qaddoum et al. [78] used an EFuNN (Evolving Fuzzy Neural Network) model which predicted fluctuations in the weekly yield of tomato with an average accuracy of 90%. Cropping system models, such as APSIM and ARMOSA, consider the soil physical and chemical conditions (i.e., water dynamics, nutrient cycling) and perform accurate predictions of products such as grain, biomass, or sugar yield in response to climate and management conditions [79,80]. These insights make the model a pivotal choice for the farmer's adaptation to the external changes, and allow simulations to understand the farmer's response to varying seasons and climate changes [81,82]. The Erosion Policy Integrated Climate (EPIC), currently known as Environmental Policy Inte-Climate, model is another comprehensive model which is under continuous improvements and has the capacity to simulate crop growth, heat and water balance, wind and water erosion, and nutrient cycling [83]. This model helps in understanding the soil dynamics and their relationship to crop management while keeping the soil erosion details in consideration.

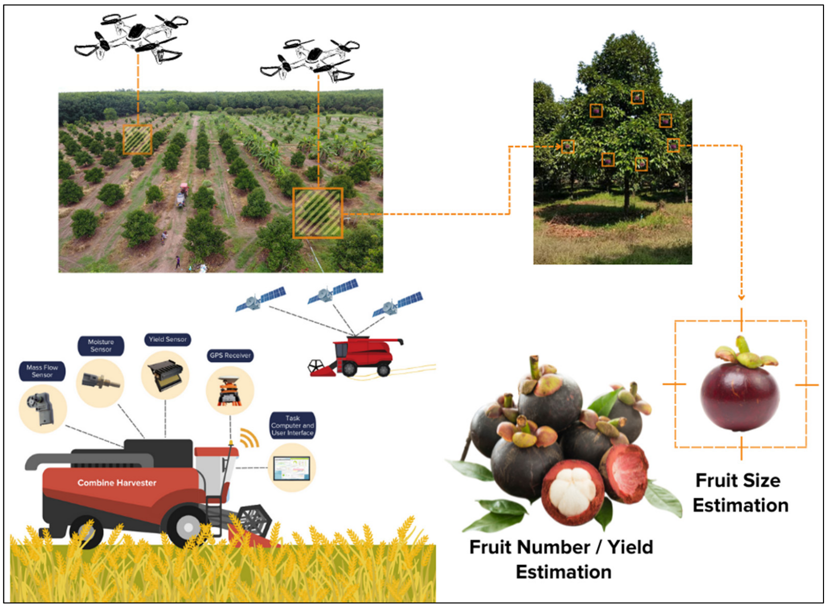

Figure 4. Sensors- and drones-assisted quality monitoring of horticultural crops and yield prediction during harvesting of crops.

Various environmental components are considered, and their impact on crop production have been evaluated using modern techniques. For example, soybean productivity was observed, and the influence of relative humidity, evapotranspiration, temperature, and precipitation over it was predicted by Veenadhari et al. [84]. Using ID3 algorithm, Veenadhari et al. [84] reported that humidity has the most prominent effect on yield, followed by temperature and precipitation. In another study, temperature and humidity sensors were used to suggest the appropriate crop and to carry out an effective irrigation control. Moreover, climatic parameters such as soil temperature, air temperature, and humidity were also considered. Varman et al. [85] discussed, in their research work, various machine learning models, such as Feed Forward Neural Network, Long Short-Term Memory (LSTM), and GRU, and concluded that LSTM was the most fit model for his research, in which they calibrated and proposed the best suitable crop for the next rotation. Sugarcane yield was forecasted by Suresh and Krishna Priya [86] after developing a statistical method for predicting the considerable amount of yield. Data in this research, which included temperature, relative humidity, and rainfall, was collected from weather stations. Conclusions of the model were entirely dependent on the condition of how precisely the input data was incorporated into model. Interestingly, the sugarcane yield was estimated successfully prior to the harvest. Soil moisture prediction in Cojocna was carried out by Matei et al. [39], using nine algorithms, namely: KNN, SVM, Logistic Regression, Neural Networks, Rule Induction, Decision Tree, Fast Large Margin, Random Forest, and Linear Regression. The accuracy of the results was high, and the findings assisted the farmers to decide and opt for the appropriate steps, which helped them to avoid future crop damage. Machine learning methods (RF, SVM, NN) and the regression method LASSO (Least Absolute Shrinkage and Selection Operator) were used to predict wheat yield based on the data obtained from satellite and climatic data by Cai et al. [87] in their research work. Additionally, data mining provides a way to analyze nonlinear relationships and capture complicated biological processes that underlie plant responses to stimuli, both of which are difficult to perform using simple statistics such as ANOVA and linear regression. Exploratory data analysis was performed before using the abovementioned machine learning methods, and it was concluded that the best performance was shown by integrating climate and satellite data. Blagojevic et al. [88] studied apricot in a research work where PDCA (Plan, Do, Check, Act) method was employed for predicting the yield. An Artificial Neural Network, as a machine learning method, was used for the abovementioned predictions that took as input: shoot length, fruit weight, shoot thickness, amount of fertilizer, and beginning of the harvest. A web application was developed considering the ease of displaying the predictions for the yield as a result output. Ravichandran and Koteeshwari [89] proposed a prediction system constructed on the ANN (Artificial Neural Network). Various parameters were determined by using this approach, namely pH, phosphate, potassium, nitrogen, depth, temperature, and precipitation, and the output was the adapted culture. This system appeared to be helpful in determining the productivity status for the crop. It assisted the farmers to select the best and most suitable crop for their land and gave options for the selection of mandatory fertilizers. The system manifested 92% accuracy in achieving the forementioned objectives. In another study carried out by Cillis et al. [90], several interactions were discussed (Table 1). The research work considered the interaction between soil–genotype, genotype–climate, climate, and management practices. The findings of the study comprehended the organic carbon storage of the soil and specifically monitored greenhouse gases emissions. Moreover, in order to determine the nutritional requirement of strawberries species, MARS (Multivariate Adaptive Regression Splines) has been successfully employed, which has aided in predicting the shoot quality as well as determining the leaf color responses of strawberries towards tissue culture nutrients [91]. In a similar study, minor nutrient requirements were assessed by using regression trees, and it was found that CART (Classification and Regression Tree) analysis was the better indicator of the nutrient requirements, such as B, Mo, Zn, and CU levels, for a better growth response in hazelnut [92]. The regression tree approach is exceptional at handling missing values and outliers. Additionally, crop yields were observed by noticing the management approaches and their long-term effects. Using the regression analysis approach, it confirmed the diminishing of soil organic carbon losses by practicing conservation tillage systems under actual climatic conditions.

Table 1. Yield prediction and climatic impression on overall yields of crops using smart agricultural data mining techniques.

Techniques Used	Data Used	Objectives	References
DT (Decision Tree)	Rainfall, temperature, and humidity	To study the influence of climatic factors on soybean yield	Veenadhari et al. [84]
NN (Neural Network)	Temperature and humidity data	Soil and air temperature prediction, humidity	Varman et al. [85]
Regression Model	Weather data	Sugarcane yield prediction	Suresh and Krishna Priya [86]
NN (Neural Network), SVM (Support Vector Machine), RF (Random Forest) and Linear Regression	Weather data	Soil moisture prediction	Matei et al. [39]
RF (Random Forest), SVM (Support Vector Machine), NN (Neural Network)	Climate data, satellite data	Wheat yield prediction	Cai et al. [87]
Artificial Neural Network	Shoot thickness and length, fruit size and fruit weight, harvest time	Apricot yield prediction	Blagojevic et al. [88]
ANN (Artificial Neural Network)	pH, phosphorus, and potassium along with weather data	Sowing time prediction	Ravichandran and Koteeshwari [89]
Regression Analysis	Weather data (Historical) and yield maps	Soil organic carbon storage, greenhouse gases emission, effect of long-term soil management on crop yield	Cillis et al. [90]

4. Smart Irrigation Techniques

The water cycle has been substantially altered by climate change, which has also increased the severity of droughts [93]. Hence, efficient water use in agricultural systems is a basic concern in the current scenario. The losses of water under limited water availability have gained a lot of interest in these days, when a major part of the world is susceptible to drought each year. Traditional and manual irrigation systems fail to accomplish water-saving goals, and are unable to supply water efficiently [22]. Smart irrigation is a technique which is countering this problem efficiently by not just providing efficient water use, but also saving it for the future [94]. Additionally, smart irrigation reduces the input costs, which provides relief to the farmers [95]. Manual irrigation requires manpower for daily observations and scheduling irrigations by observing plants or crops in fields, but a sensor-assisted irrigation system detects soil moisture available in the soil profile and initiates the irrigation, making irrigation control better than the manual [96], whereas a decision-support-system-assisted irrigation system integrates soil moisture sensors and climate sensors to observe water demand and control irrigation application for crops (Figure 5). The development of accurate and effective irrigation systems has been aided by the revolution in decision-support-assisted irrigation systems, brought about by advancements in technology [97]. This not only incorporated soil moisture and climate sensors, but also an internet-assisted cloud system for real-time data observation. Dynamic simulation models are linked to examine the effects of irrigation on crop growth and productivity estimation. Moreover, in accordance with data analysis and yield predictions, an irrigation quantity has been finalized and is supplied through an automatic irrigation control system. A remote control or mobile application [98] is also linked up with this system for easy understanding and usage of the modern irrigation hub. A scheme of an advanced irrigation hub is presented as of Figure 6.

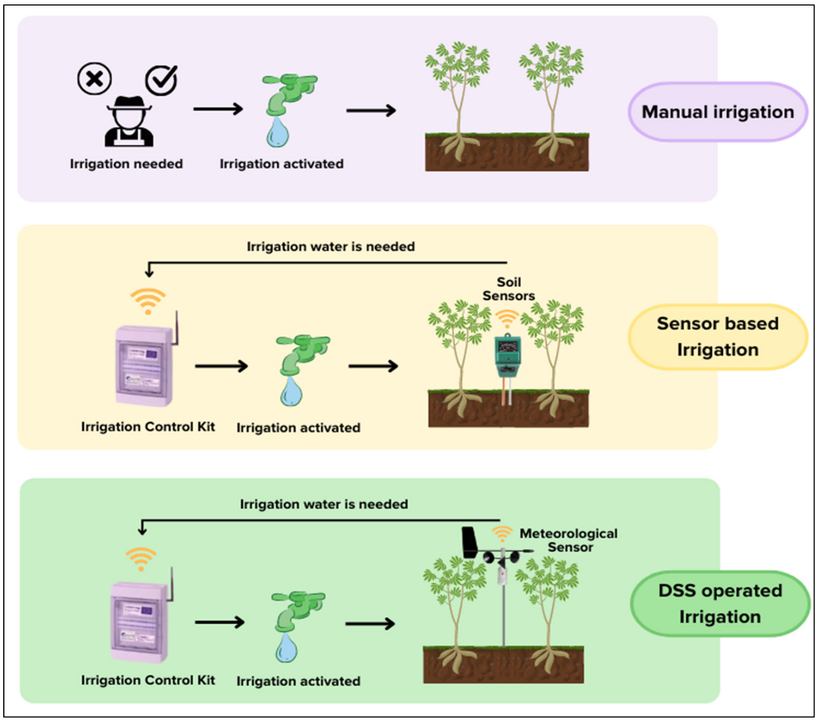

Figure 5. Manual versus smart-sensor-based and decision-support-system-assisted irrigation applications.

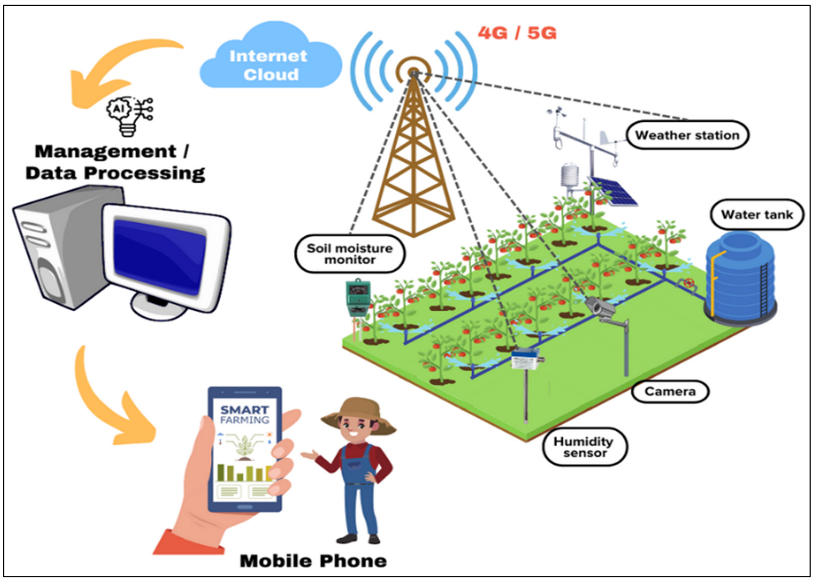

Figure 6. Advanced irrigation hub assisted with real time weather and moisture sensors and decision support systems.

Smart irrigation consists of various steps and schemes, which are illustrated in Figure 7, which, in combination, make this technique a revolution in agricultural production systems. Various techniques were developed and utilized to achieve efficient irrigation goals in smart agriculture systems. Automatic drip, sprinkler, real-time moisture-sensor-assisted, and predictive irrigation schemes are commonly being utilized [99]. Various advanced irrigation techniques haven been developed and improved with time, and some of those are indicated in Table 2 with their methods of data usage and objectives. Padalalu et al. [37] presented a control system for an automatic irrigation, aiming to record and control the irrigation needs of the crop. Several variables, such as humidity, soil temperature, and pH, were observed by installing sensors. Additionally, a Naive Bayes algorithm was applied to estimate the exact water demand of the crop. Weather forecasts were observed to monitor the quantity of applied water to crops and the model of this intelligent irrigation system assured the intuitive use of water. An irrigation system based on the Support Vector Regression method was developed and proposed by Xie et al. [100]. The system was composed of an irrigation demand estimation component to evaluate the energy and time needed for carrying out the subsequent operations. It was also composed of a solar energy prediction component for forecasting the solar energy.

Numerical Weather Prediction (NWP) and the Time of Use price model (TOU) were employed, which exhibited clearly that the water resources and the amount of energy can be saved was up to 7.97%. Following the forementioned findings, costs declined by an estimated 25.34% when subjected to a comparison with the soil-moisture-based irrigation system. To maximize crop yields and to conserve an excess of water, Goumopoulos et al. [101] devised a decision support system based on a Wireless Sensor/Actuator Network (WSAN). The system was positioned to observe irrigation in a greenhouse. Real-time monitoring for precision irrigation was provided by the developed system in it. Various sensors were considered, such as soil moisture sensors, humidity sensors, and temperature sensors, in strawberry field. The results from this research depicted a 20% decreased water consumption as compared to a traditional irrigation system. In another study, Zhang et al. [102] performed experiments in the laboratory and in the greenhouses. A Fuzzy Logic-based irrigation control system was developed, and information was gathered from soil moisture sensors to decide the irrigation application time. The system came out to be a successful one in tackling the uncontrolled lengthy irrigation schedules. Peng et al. [103] developed an irrigation system using WSN and Fuzzy Logic to save water. The system was composed of four parts: the cluster of sensor nodes, coordinator nodes, two variables as inputs (soil moisture error and the rate of change of the error), which provided watering time as an output. An irrigation controller was also used for automatic watering and monitoring of the pipe network, which eventually helped in precise and quick calculation of amount of water required in irrigation.

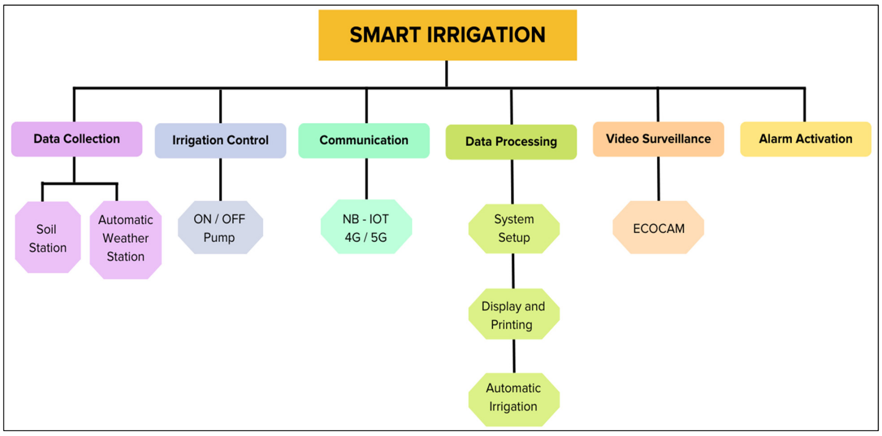

Figure 7. Flow diagram of various components and processes of smart irrigation systems.

An automatic irrigation system was developed by Anand and Perinbam [104] that consisted of four different parts. The first part was sensor nodes, which were collecting the temperature and moisture readings. The coordinator node, as a second part, the irrigation controller, as a third one, which was based on Fuzzy Logic to monitor the watering and the time of its application, and the irrigation pipe network, as the last component of their proposed system. The Fuzzy Logic-based controller was accounting for numerous activities in the automatic irrigation system. One such use was monitoring the water level in the tank. Likewise, it was also responsible for examining the amount of rain, the atmospheric temperature, and the wind speed. All the information which was under investigation, whether the field condition or the system itself, was collected and made available for the farmer through the GSM Module [105]. The Fuzzy Inference System, another smart irrigation system for monitoring the evapotranspiration (ET) and irrigation, was developed by Mousa et al. [106]. Goals were accomplished by using the specific algorithms such as the estimation of ET, soil moisture observations, required irrigation's estimation as per reference ET (ET0), monitoring irrigation schedule, and the time of irrigation. Drip and sprinkler irrigation systems can be linked and applied successfully using this system. Moreover, results indicated the fuzzy model as an intelligent and quick implementation for recording the evapotranspiration and water needs of the crop field.

Table 2. Techniques to achieve efficient irrigation goals in smart agriculture systems.

Techniques	Used Data	Objectives	References
Naive bayes algorithm	Soil, temperature, and humidity sensor data	Precision of water and fertilizers used	Padalalu et al. [37]
Optimization model and irrigation estimation algorithm	Soil moisture data, weather information data and solar energy data	Irrigation cost management	Xie et al. [100]
DM algorithms	Sensor's data (air, soil temperature, and humidity)	Zone specific irrigation management	Goumopoulos et al. [101]
Fuzzy logic	Sensor data (soil)	Irrigation management	Zhang et al. [102]
Fuzzy logic	Sensor data (soil)	Irrigation management	Peng et al. [103]
Fuzzy logic	Meteorological parameters	Irrigation management	Anand and Perinbam [104]
Fuzzy logic	Climatic parameters	Irrigation management	Mousa et al. [106]

5. Smart Monitoring of Insects and Pests

In modern agriculture production systems, modern techniques are being utilized for smart monitoring and control of insects and pests. To spot six parasites in an apple orchard, Boniecki et al. [107] suggested a neural classifier. The names of the parasites were apple blossom weevil, apple clearwing, codling moth, apple leaf sucker, apple aphid, and apple moth. The abovementioned classifier was established on 23 parameters, which included form and color characteristics. The former was 7 and latter was 16 in number. Decisive results were obtained by considering the Multi-Layer Perceptron Neural Network topology in the peach orchard. Rodrigues et al. [108] used an extension of Fuzzy Logic, named Interval Fuzzy Logic, to predict the appearance of the parasites. Data was captured using temperature and humidity sensors, and processed by Interval Fuzzy Logic, which ultimately provided the warning levels. Different hardware components, such as the Arduino platform and different sensors, were used to develop this system. A demonstration of a drone-assisted evaluation of insects and pests in enabling the timely implementation of actions to remove the high-risk infestations is presented in Figure 8. In addition, AgroDSS for agriculture, a new decision support system, was developed to learn the pest population by Rupnik et al. [109]. This system relied on data mining approaches, and the implemented tools used were supervised learning, unsupervised learning, and time series analysis. The data was gathered by Trap View and allowed an efficient pest observation by using insect traps in the vineyards and orchard. When it came to deal with the missing data, linear regression was used by Da Silva et al. [110], who also applied logistic regression while inspecting the results obtained from the land and the monthly surface temperature. They calculated "accumulated degree-day" by using a meteorological satellite to reduce disease risks by mapping the pests. A significant relationship was observed between the accumulated meteorological stations values and satellite values.

The crops lines algorithm, in association with the Convolutional Neural Network, was proposed by Bah et al. [111]. The aim was to pin down weeds in various crops, such as beet, spinach, and bean fields. The research work was also assisted by the drone images, which were taken about 20 m height. The best accuracy in results were achieved in beet field. However, the research work also mentioned a few hardships concerning the right detection of the weeds. This usually happened when the plants were at early growth stage or when there was a less distance between weeds and crop. Various techniques for smart pest monitoring and its related goals are described in Table 3. For an early alert and recommending necessary control measures, Tripathy et al. [112] presented a real-time Decision Support System. The main objective was observing and predicting the pest and disease status in the field. Furthermore, numerous DM techniques have been used in groundnut crops, which were based on some climatic and weather parameters. The experiment was using the Naive Bayes method with Gaussian distribution. Rapid Association Rule Mining, in conjunction with the aforementioned technique, was performed to search out the multiple weather correlations with other related parameters. Doses of pesticides are an important indicator for the betterment of the crop, and they were predicted by Viani et al. [113] by using Fuzzy Logic. Weather data (soil temperature and moisture) were considered, and the risk of infection was counted by examining developmental stages of the plant and the fluctuating environmental conditions. By combining hydroponics with IoT, Alipio et al. [114] developed an efficient hydroponic system, which assisted in providing the right nutrient's type and amount at the best suitable time. A Bayesian Network (BN) prediction algorithm was implemented to obtain the maximum of the right decisions to control the system. The three main components of the developed system were a data analysis module, a web interface, and sensors. The sensors used were controlling the electrical conductivity, managing pH, monitoring light intensity, recording humidity, and water temperature. For displaying the data and to control the system, there were two operational websites for this purpose. A clear increase in the yield obtained with the automatic control was observed as compared to the manual control system.

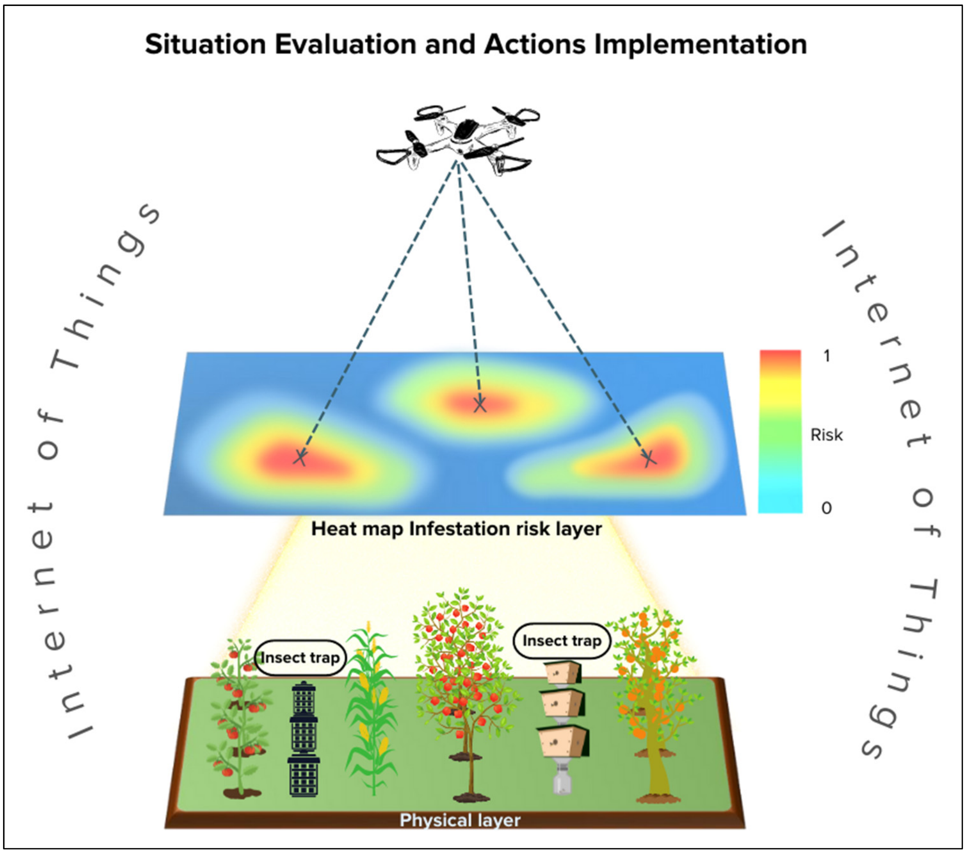

Figure 8. Evaluation of pests and encountering remedies in smart farming.

Table 3. Techniques and goals for monitoring pests and input management in smart agriculture.

Data Used for Analysis	Techniques	Goals	References
Digital image of pests	Neural Networks	Pest prediction in apple orchard	Boniechki et al. [107]
Temperature data and humidity data	Interval Fuzzy Logic	Prediction of pests and diseases	Rodrigues et al. [108]
Pest data	Random Forest	Pest dynamics and population prediction	Rupnik et al. [109]
Meteorological satellite data and in situ meteorological data	Linear and Logistic Regression	Pest and disease mapping and detection	Da Silva et al. [110]
Vegetable images taken by drones	Convolutional Neural Network	Weeds identification in crops such as spinach and beans	Bah et al. [111]
Temperature, humidity, and soil moisture data	Naive Bayes Method with Gaussian Distribution	Pest predictions	Tripathy et al. [112]
Soil moisture, leaf wetness and soil temperature data	Fuzzy Logic	Specific dose prediction for pests	Viani et al. [113]
Sensor data (pH level, electrical conductivity, light intensity, etc.)	Bayesian Network	Crop growth management in hydroponic farm	Alipo et al. [114]

6. Smart Disease Management

Diseases in crops are devastating in terms of yield and deteriorating the quality of the produce. Numerous solutions are out there in the market and industries [115,116], yet there is a need to think or perform smarter, to remove the excessive damage to the final product, and to enhance the outcome in terms of the revenue. In smart agriculture, the focus is on the classification of the diseases and its detection precisely at any stage [117], so that smart decision making can be conducted and the excessive failure in the yield and quality can be avoided. A modified model image of smart disease management using normalized difference vegetation index (NDVI), drone, and imaging techniques is presented in Figure 9. Singh et al. [118] opted for the image processing technique using a genetic algorithm. In his research work, he observed and managed several leaf diseases on various crops, achieving the precision percentage of 88.99%. Likewise, 89.56% precision was achieved by Warne and Ganorkar [119] while detecting the leaf diseases in cotton crop. They classified the diseases as red leaf spot and Alternaria leaf spot of cotton using a neural network algorithm. Similar research was performed by Revathi and Hemalatha [120] while working on a cotton crop. Image processing was assisted by the neural network to detect and classify cotton diseases. In this research work, they classified Fusarium wilt and leaf blight with the high precision of 98.1%. Image processing by employing Support Vector Machine was performed by Bhange and Hingoliwala [121], Yao et al. [122], Jian and Wei [123], and Dubey and Jalal [124] to target teyla in pomegranate, rice blast and rice sheath blight in rice, downy mildew and brown spot in cucumber, and apple rot, scab, and blotch in apple. The results from these research studies have indicated the precision percentages as high as 82%, 97.2%, 94% and 93%, respectively, as represented in Table 4.

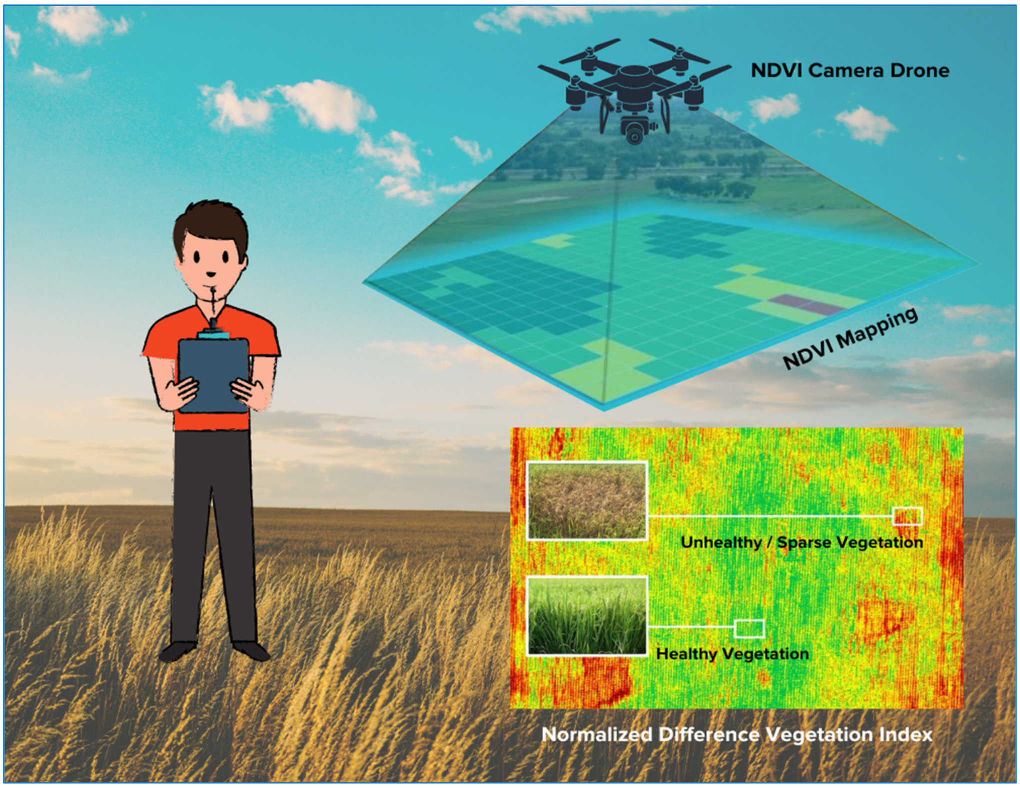

Figure 9. Smart disease management by using normalized difference vegetation index (NDVI), drone and imaging techniques. Modified figure where the drone mapping image on the top right was obtained from: https://www.futurefarming.com/tech-in-focus/pain-points-of-nitrogen-applications-how-drone-data-helps/, accessed on 14 June 2022.

Table 4. Methods and precision percentage for detecting and classifying diseases in smart agriculture.

Methods	Diseases	Precision	References
Image Processing + Genetic Algorithm	Leaf diseases on different crops	88.99%	Singh et al. [118]
Image Processing + Neural Networks	Cotton leaf diseases, red leaf spot, Alternaria leaf spot	89.56%	Warne and Ganorkar [119]
Image Processing + Neural Networks	Cotton leaf spot disease, Fusarium wilt and Leaf blight	98.1%	Revathi and Hemalatha [120]
Image processing + Support Vector Machine	Pomegranate disease: teyla	82%	Bhange and Hingoliwala [121]
Image Processing + Support Vector Machine	Rice blast and rice sheath blight	97.2%	Yao et al. [122]
Image Processing + Support Vector Machine	Cucumber disease, downy mildew and brown spot	-	Jian and Wei [123]
Image Processing + Support Vector Machine	Apple diseases such as apple rot, scab and blotch	93%	Dubey and Jalal [124]

7. Smart Indoor Farming/Vertical Farming

The amount of agricultural land has decreased as a result of the persistent trends of population growth, urbanization, water supply reduction, and ongoing climate change [125]. Numerous variables, including the rise in food prices, social tensions and land disputes, the severity of persevering climate change, and increased urbanization, contribute to the absence of effective planning for food security and sustainability. Contrary to old farming systems, a controlled, automated vertical farming model was introduced, which is an indoor based farm model constituting of an automatic air, temperature, and humidity control, solar panel lighting and heating, tunable 24 h LED illumination, and creative uses of recycled water supplemented by rainwater or water from a desalination facility [126]. The impacts of seasonality can be reduced or completely eliminated when performed in conjunction with temperature and humidity control. Two categories of this farming system have been used: those where the crop is produced on a vertical surface, and those that have several tiers of conventional horizontal growth platforms [127]. Leafy vegetables such as lettuce, peppers, tomatoes, and herbs have all been cultivated extensively in horizontal systems, which are sometimes stacked on top of one another to form vertical farms. These horizontal and stacked horizontal agricultural technologies make use of numerous glasshouses and plant factories [128]. Occasionally, for personal production, the use of balconies as an alternative to indoor horizontal farming has also been proven as an effective urban horticultural practice. For vertical farming, green walls [129] and cylindrical growth units [130] have been in practice, the former operated in facades of the buildings, while in the latter one, plants are connected with a nutrient medium source and are grown one above another. These farming systems are often assisted by an artificial lighting system to meet the adequate requirement of photosynthetic active radiation for a better growth and yield [131]. The carotenoids accumulation has been known to be increased by 15% in *Brassica rapa* under a blue and white LED recipe compared to only white LED [132]. Red LEDs alone are responsible for enhancing biomass accumulation, green LEDs for carbon assimilation, and blue LEDs are mainly helpful in photosynthetic processes in plants [133]. All these available LEDs not only provide better growth and development, but also cheaper and more reliable artificial lighting options compared to the high-pressure sodium (HPS), fluorescent tubes, and metal halides (MH) lights.

8. Major Obstacles for Implementation of IoT and Smart Techniques

Smart farming and IoT are considered as a blessing to the agricultural sector, yet it brought a series of various challenges to agriculturists, and farmers in particular [134,135]. If not overcome or addressed timely, those hurdles can reduce the feasibility and effectivity of this technology. Over time, numerous constraints have been reported [103,136] and efforts are being made to resolve the limitations [137,138]. Among the major problems to be remitted, one is the security of the big data [139–141]. IoT devices accumulate huge data from an agricultural IoT system, which can be viewed by an unauthorized access due to the paucity of the necessary security protocols by some of the IoT providers [142,143]. Hence, the data may suffer manipulation or other ownership problems. Another big problem is the lack of infrastructure for this technology. Infrastructure concerning internet access and remote field locations are the main issues for farmers who, even after adopting this technology, cannot achieve the maximum output. High costs of IoT systems are another hurdle which is being addressed by making available less costly wireless sensors in the market [144]. Still, a lot is in needed to minimize the costs of the whole system [145], after which one can expect that farmers will switch to IoT and smart farming.

Moreover, the majority of the farmers in various parts of the world are uneducated [146]. Smart farming and IoT demands a fair amount of knowledge to deal with the sensors, internet cloud, and end user applications [147]. Additionally, various countries pose a series of regulations and paperwork for the farmers who are willing to adopt new technologies. These tiresome regulations are another factor which is keeping farmers away from it. For example, there are numerous no fly zones for the drones in the agricultural fields near to airports, military zones, and other government properties [148,149]. Hence drone mapping is not feasible for those fields and farmers. Meanwhile, agricultural digitalization is engulfing a huge employment opportunity for the laborers and other farming-related professionals. On one hand, it is better for reducing the labor input and cost for the owner, but on the other hand, is depriving local workers of multiple job opportunities [150]. Keeping these constraints in mind, there arises an important question: Will this technology thrive more in the coming years?

9. Conclusions and Future Guidelines

The study provided a summary of the inventive strategies created and applied to combat the effects of climate change and maintaining a sustainable crop output. The recent smart strategies for various crop management approaches, as well as the technologies associated with yield predictions and enhancements, are explained. It has been shown that implementation of smart techniques and IoT is necessary to boost the productivity of crop production systems. It was found that various neural networks and simulation models could aid in yield prediction for better decision support, with an average simulation accuracy up to 92%. Numerous techniques have been presented for yield forecasting, pest management, smart irrigation, and disease classification and detection for efficient monitoring of crop health and water status. Different numerical models and smart irrigation tools help to save energy use by reducing it up to 8%, whereas advanced irrigation reduced the cost by 25.34% as compared to soil moisture-based irrigation system. Yield prediction under different predicted climatic conditions not only help to modify ongoing irrigation and fertilizer management practices, but ultimately lead to resource use efficiency and profitable agricultural productivity. Smart and precision disease management is an effective approach to control diseases and sustain yields. Several leaf diseases on various crops can be managed by using image processing techniques, such as by using a genetic algorithm with 90% precision accuracy. While aiding image processing techniques by neural networks, diseases can be detected and classified, and the research achieved precision up to 98% in detecting and classifying diseases in different crops. Vertical farming and its various methods of indoor production has been discussed in order to understand its impact on global food production, especially as an option to eradicate or minimize the effects of urbanization over global food productivity. The use of artificial lighting with a purpose of providing an effective photosynthetic photon flux density has been discussed for better growth and development of various horticultural produce. Moreover, the current review discussed the various effective tactics, important techniques, IoT-based smart technologies, and the application of sensors, in addition to the constraints that exist worldwide as restrictions to adopting these smart technologies in agriculture. Future work will go on to explain the new emerging challenges and constraints, to accept and adopt the modern advancements for smart farming.

Author Contributions: Conceptualization, A.A. and T.H.; methodology, A.A. and T.H.; writing—original draft preparation, A.A. Software, N.T.; writing—review and editing. G.C., N.H. and T.H.; supervision, G.C. All authors have read and agreed to the published version of the manuscript.

Funding: This article received no external funding.

Acknowledgments: Authors would like to acknowledge the efforts of editors and reviewers for valuable comments to improve the manuscript.

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

References

1. Komarek, A.M.; De Pinto, A.; Smith, V.H. A review of types of risks in agriculture: What we know and what we need to know. *Agric. Syst.* **2020**, *178*, 102738. [CrossRef]
2. Awais, A.; Nualsri, C.; Soonsuwon, W. Induced mutagenesis for creating variability in Thailand's upland rice (cv. Dawk Pa-yawm and Dawk Kha 50) using ethyl methane sulphonate (EMS). *Sarhad J. Agric.* **2019**, *35*, 293–301. [CrossRef]
3. Roy, T.; George, K.J. Precision farming: A step towards sustainable, climate-smart agriculture. In *Global Climate Change: Resilient and Smart Agriculture*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 199–220.
4. Agovino, M.; Casaccia, M.; Ciommi, M.; Ferrara, M.; Marchesano, K. Agriculture, climate change and sustainability: The case of EU-28. *Ecol. Indic.* **2019**, *105*, 525–543. [CrossRef]
5. Komarnytsky, S.; Retchin, S.; Vong, C.I.; Lila, M.A. Gains and Losses of Agricultural Food Production: Implications for the Twenty-First Century. *Annu. Rev. Food Sci. Technol.* **2022**, *13*, 239–261. [CrossRef] [PubMed]
6. United Nations. *Sources, Effects and Risks of Ionizing Radiation, United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR) 2016 Report: Report to the General Assembly, with Scientific Annexes*; United Nations: San Francisco, CA, USA, 2017.
7. Buckley, C.; Carney, P. The potential to reduce the risk of diffuse pollution from agriculture while improving economic performance at farm level. *Environ. Sci. Policy* **2013**, *25*, 118–126. [CrossRef]
8. Rehman, A.; Saba, T.; Kashif, M.; Fati, S.M.; Bahaj, S.A.; Chaudhry, H. A Revisit of Internet of Things Technologies for Monitoring and Control Strategies in Smart Agriculture. *Agronomy* **2022**, *12*, 127. [CrossRef]
9. Oliveira, L.F.P.; Moreira, A.P.; Silva, M.F. Advances in agriculture robotics: A state-of-the-art review and challenges ahead. *Robotics* **2021**, *10*, 52. [CrossRef]
10. An, C.; Sun, C.; Li, N.; Huang, B.; Jiang, J.; Shen, Y.; Wang, C.; Zhao, X.; Cui, B.; Wang, C. Nanomaterials and nanotechnology for the delivery of agrochemicals: Strategies towards sustainable agriculture. *J. Nanobiotechnol.* **2022**, *20*, 11. [CrossRef]
11. El Bilali, H.; Bottalico, F.; Ottomano Palmisano, G.; Capone, R. Information and communication technologies for smart and sustainable agriculture. In *Scientific-Experts Conference of Agriculture and Food Industry*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 321–334.
12. Saiz-Rubio, V.; Rovira-Más, F. From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy* **2020**, *10*, 207. [CrossRef]
13. Harper, L.; Campbell, J.; Cannon, E.K.S.; Jung, S.; Poelchau, M.; Walls, R.; Andorf, C.; Arnaud, E.; Berardini, T.Z.; Birkett, C. AgBioData consortium recommendations for sustainable genomics and genetics databases for agriculture. *Database* **2018**, *2018*, bay088. [CrossRef]
14. Parolini, G. Weather, climate, and agriculture: Historical contributions and perspectives from agricultural meteorology. *Wiley Interdiscip. Rev. Clim. Chang.* **2022**, *13*, e766. [CrossRef]
15. Deepa, N.; Ganesan, K. Decision-making tool for crop selection for agriculture development. *Neural Comput. Appl.* **2019**, *31*, 1215–1225. [CrossRef]
16. Menne, D.; Hübner, C.; Trebbels, D.; Willenbacher, N. Robust Soil Water Potential Sensor to Optimize Irrigation in Agriculture. *Sensors* **2022**, *22*, 4465. [CrossRef]
17. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [CrossRef]
18. Adebayo, T.S.; Akinsola, G.D.; Kirikkaleli, D.; Bekun, F.V.; Umarbeyli, S.; Osemeahon, O.S. Economic performance of Indonesia amidst CO2 emissions and agriculture: A time series analysis. *Environ. Sci. Pollut. Res.* **2021**, *28*, 47942–47956. [CrossRef]
19. Yashodha, G.; Shalini, D. An integrated approach for predicting and broadcasting tea leaf disease at early stage using IoT with machine learning–a review. *Mater. Today: Proc.* **2021**, *37*, 484–488. [CrossRef]
20. Saxena, L.; Armstrong, L. *A Survey of Image Processing Techniques for Agriculture*; Australian Society of Information and Communication Technologies in Agriculture: Perth, Australia, 2014.
21. Kamienski, C.; Soininen, J.-P.; Taumberger, M.; Dantas, R.; Toscano, A.; Salmon Cinotti, T.; Filev Maia, R.; Torre Neto, A. Smart water management platform: IoT-based precision irrigation for agriculture. *Sensors* **2019**, *19*, 276. [CrossRef]

22. Kanuru, L.; Tyagi, A.K.; Aswathy, S.U.; Fernandez, T.F.; Sreenath, N.; Mishra, S. Prediction of pesticides and fertilizers using machine learning and Internet of Things. In Proceedings of the 2021 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 27–29 January 2021; pp. 1–6.
23. Hegedus, P.B.; Maxwell, B.D.; Mieno, T. Assessing performance of empirical models for forecasting crop responses to variable fertilizer rates using on-farm precision experimentation. *Precis. Agric.* **2022**, 1–28. [CrossRef]
24. Ather, D.; Madan, S.; Nayak, M.; Tripathi, R.; Kant, R.; Kshatri, S.S.; Jain, R. Selection of Smart Manure Composition for Smart Farming Using Artificial Intelligence Technique. *J. Food Qual.* **2022**, *2022*, 4351825. [CrossRef]
25. Elijah, O.; Rahman, T.A.; Orikumhi, I.; Leow, C.Y.; Hindia, M.H.D.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]
26. Antony, A.P.; Leith, K.; Jolley, C.; Lu, J.; Sweeney, D.J. A review of practice and implementation of the internet of things (IoT) for smallholder agriculture. *Sustainability* **2020**, *12*, 3750. [CrossRef]
27. Ping, H.; Wang, J.; Ma, Z.; Du, Y. Mini-review of application of IoT technology in monitoring agricultural products quality and safety. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 35–45. [CrossRef]
28. Boursianis, A.D.; Papadopoulou, M.S.; Diamantoulakis, P.; Liopa-Tsakalidi, A.; Barouchas, P.; Salahas, G.; Karagiannidis, G.; Wan, S.; Goudos, S.K. Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet Things* **2022**, *18*, 100187. [CrossRef]
29. Khanal, S.; Kc, K.; Fulton, J.P.; Shearer, S.; Ozkan, E. Remote sensing in agriculture—Accomplishments, limitations, and opportunities. *Remote Sens.* **2020**, *12*, 3783. [CrossRef]
30. Mellit, A.; Benghanem, M.; Herrak, O.; Messalaoui, A. Design of a novel remote monitoring system for smart greenhouses using the internet of things and deep convolutional neural networks. *Energies* **2021**, *14*, 5045. [CrossRef]
31. Kim, M.-J.; Mo, C.; Kim, H.T.; Cho, B.-K.; Hong, S.-J.; Lee, D.H.; Shin, C.-S.; Jang, K.J.; Kim, Y.-H.; Baek, I. Research and Technology Trend Analysis by Big Data-Based Smart Livestock Technology: A Review. *J. Biosyst. Eng.* **2021**, *46*, 386–398. [CrossRef]
32. Ouhami, M.; Hafiane, A.; Es-Saady, Y.; El Hajji, M.; Canals, R. Computer vision, IoT and data fusion for crop disease detection using machine learning: A survey and ongoing research. *Remote Sens.* **2021**, *13*, 2486. [CrossRef]
33. Marwa, C.; Othman, S.B.; Sakli, H. IoT based low-cost weather station and monitoring system for smart agriculture. In Proceedings of the 2020 20th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), Monastir, Tunisia, 20–22 December 2020; pp. 349–354.
34. Sunhare, P.; Chowdhary, R.R.; Chattopadhyay, M.K. Internet of things and data mining: An application oriented survey. *J. King Saud Univ.-Comput. Inf. Sci.* **2020**, *34*, 3569–3590. [CrossRef]
35. Roy, S.K.; De, D. Genetic algorithm based internet of precision agricultural things (IopaT) for agriculture 4.0. *Internet Things* **2022**, *18*, 100201. [CrossRef]
36. Padalalu, P.; Mahajan, S.; Dabir, K.; Mitkar, S.; Javale, D. Smart water dripping system for agriculture/farming. In Proceedings of the 2017 2nd International Conference for Convergence in Technology (I2CT), Mumbai, India, 7–9 April 2017; pp. 659–662.
37. Hussain, T.; Anothai, J.; Nualsri, C.; Soonsuwon, W. Application of CSM-CERES-Rice in scheduling irrigation and simulating effect of drought stress on upland rice yield. *Indian J. Agric. Res.* **2018**, *52*, 140–145. [CrossRef]
38. He, L.; Fang, W.; Zhao, G.; Wu, Z.; Fu, L.; Li, R.; Majeed, Y.; Dhupia, J. Fruit yield prediction and estimation in orchards: A state-of-the-art comprehensive review for both direct and indirect methods. *Comput. Electron. Agric.* **2022**, *195*, 106812. [CrossRef]
39. Matei, O.; Rusu, T.; Petrovan, A.; Mihuţ, G. A data mining system for real time soil moisture prediction. *Procedia Eng.* **2017**, *181*, 837–844. [CrossRef]
40. Ali, A.; Altaf, M.T.; Nadeem, M.A.; SHAH, A.N.; Azeem, H.; Baloch, F.S.; Karaköy, T.; Hussain, T.; Duangpan, S.; AASIM, M. Recent Advancement in OMICS approaches to enhance abiotic stress tolerance in Legumes. *Front. Plant Sci.* **2022**, *13*. [CrossRef]
41. Hussain, T.; Gollany, H.T.; Hussain, N.; Ahmed, M.; Tahir, M.; Duangpan, S. Synchronizing Nitrogen Fertilization and Planting Date to Improve Resource Use Efficiency, Productivity, and Profitability of Upland Rice. *Front. Plant Sci.* **2022**, *13*, 895811. [CrossRef]
42. Hussain, T.; Hussain, N.; Ahmed, M.; Nualsri, C.; Duangpan, S. Responses of lowland rice genotypes under terminal water stress and identification of drought tolerance to stabilize rice productivity in southern Thailand. *Plants* **2021**, *10*, 2565. [CrossRef]
43. Hussain, N.; Ahmed, M.; Duangpan, S.; Hussain, T.; Taweekun, J. Potential impacts of water stress on rice biomass composition and feedstock availability for bioenergy production. *Sustainability* **2021**, *13*, 10449. [CrossRef]
44. Haldhar, S.M.; Kumar, R.; Corrado, G.; Berwal, M.K.; Gora, J.S.; Thaochan, N.; Samadia, D.K.; Hussain, T.; Rouphael, Y.; Kumar, P.; et al. A Field Screening of a Pomegranate (*Punica granatum*) Ex-Situ Germplasm Collection for Resistance against the False Spider Mite (*Tenuipalpus punicae*). *Agriculture* **2022**, *12*, 1686. [CrossRef]
45. Hussain, T.; Hussain, N.; Ahmed, M.; Nualsri, C.; Duangpan, S. Impact of nitrogen application rates on upland rice performance, planted under varying sowing times. *Sustainability* **2022**, *14*, 1997. [CrossRef]
46. Hussain, T.; Anothai, J.; Nualsri, C.; Soonsuwon, W. Evaluating performance of sixteen upland rice genotypes under field conditions for further breeding process. *J. Agric. Sci* **2018**, *10*, 144.
47. Duangpan, S.; Tongchu, Y.; Hussain, T.; Eksomtramage, T.; Onthong, J. Beneficial Effects of Silicon Fertilizer on Growth and Physiological Responses in Oil Palm. *Agronomy* **2022**, *12*, 413. [CrossRef]
48. Ali, M.F.; Ali, U.; Bilal, S.; Zulfiqar, U.; Sohail, S.; Hussain, T. Response of sorghum and millet to poultry and farmyard manure—Based biochar treatments. *Arab. J. Geosci.* **2022**, *15*, 1592. [CrossRef]

49. Hussain, S.; Huang, J.; Huang, J.; Ahmad, S.; Nanda, S.; Anwar, S.; Shakoor, A.; Zhu, C.; Zhu, L.; Cao, X. Rice production under climate change: Adaptations and mitigating strategies. In *Environment, Climate, Plant and Vegetation Growth*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 659–686.
50. Shahzad, A.; Ullah, S.; Dar, A.A.; Sardar, M.F.; Mehmood, T.; Tufail, M.A.; Shakoor, A.; Haris, M. Nexus on climate change: Agriculture and possible solution to cope future climate change stresses. *Environ. Sci. Pollut. Res.* **2021**, *28*, 14211–14232. [CrossRef] [PubMed]
51. Hazarika, T.K. Climate change and Indian horticulture: Opportunities, challenges and mitigation strategies. *Int. J. Environ. Eng. Manag* **2013**, *4*, 629–630.
52. Murugan, M.; Shetty, P.K.; Ravi, R.; Anandhi, A.; Rajkumar, A.J. Climate change and crop yields in the Indian Cardamom Hills, 1978–2007 CE. *Clim. Chang.* **2012**, *110*, 737–753. [CrossRef]
53. Fleisher, D.H.; Timlin, D.J.; Reddy, V.R. Temperature influence on potato leaf and branch distribution and on canopy photosynthetic rate. *Agron. J.* **2006**, *98*, 1442–1452. [CrossRef]
54. Ruiz-Vera, U.M.; Siebers, M.H.; Drag, D.W.; Ort, D.R.; Bernacchi, C.J. Canopy warming caused photosynthetic acclimation and reduced seed yield in maize grown at ambient and elevated [CO_2]. *Glob. Chang. Biol.* **2015**, *21*, 4237–4249. [CrossRef]
55. Lafta, A.; Turini, T.; Sandoya, G.V.; Mou, B. Field evaluation of green and red leaf lettuce genotypes in the Imperial, San Joaquin, and Salinas Valleys of California for heat tolerance and extension of the growing seasons. *Hort Sci.* **2017**, *52*, 40–48. [CrossRef]
56. Thamburaj, S.; Singh, N. *Textbook of Vegetables, Tuber Crops, and Spices*; Indian Council of Agricultural Research: New Delhi, India, 2001.
57. Vietmeyer, N. Underexploited tropical plants with promising economic value: The last 30 years. *Trees Life J.* **2008**, *3*, 1–13.
58. Ounlert, P.; Sdoodee, S. The effects of climatic variability on Mangosteen flowering date in southern and eastern of Thailand. *Res. J. Appl. Sci. Eng. Technol.* **2015**, *11*, 617–622. [CrossRef]
59. Ounlert, P.; Sdoodee, S.; Tongkhow, P. The mangosteen flowering date model in Nakhon Si Thammarat province, southern Thailand. *J. Cent. Eur. Agric.* **2017**, *18*, 176–184. [CrossRef]
60. Kurtar, E.S. Modelling the effect of temperature on seed germination in some cucurbits. *Afr. J. Biotechnol.* **2010**, *9*, 1343–1353.
61. Makhonpas, C.; Kunjet, S. Study on Flowering of Mangosteen Tree as Induced by Water Stress. In *Management of Land Use Systems for Enhanced Food Security: Conflicts, Controversies and Resolutions*; Tropentag: Berlin, Germany, 2015; pp. 16–18.
62. Singh, H. Impacts of climate change on horticultural crops. In *Challenges of Climate Changes in Indian Horticulture*; Singh, H., Singh, J., Lal, S., Eds.; Westville Publishing House: New Delhi, India, 2010; pp. 1–8.
63. Rai, R.; Joshi, S.; Roy, S.; Singh, O.; Samir, M.th; Chandra, A. Implications of changing climate on productivity of temperate fruit crops with special reference to apple. *J. Hortic.* **2015**, *2*, 135–141.
64. Hazra, P.; Samsul, H.A.; Sikder, D.; Peter, K. V Breeding tomato (*Lycopersicon esculentum* Mill) resistant to high temperature stress. *Int. J. Plant Breed.* **2007**, *1*, 31–40.
65. Bin Osman, M.; Milan, A.R. *Mangosteen: Garcinia mangostana L.*; University of Southampton, International Centre for Underutilised Crops: Southampton, UK, 2006; ISBN 0854328173.
66. Li, F.M.; Wang, P.; Wang, J.; Xu, J.Z. Effects of irrigation before sowing and plastic film mulching on yield and water uptake of spring wheat in semiarid Loess Plateau of China. *Agric. Water Manag.* **2004**, *67*, 77–88. [CrossRef]
67. AZM, S.P.; Md, S.I.; Md, M.I.; Md, N.H.; Islam, M. Effect of soil and environment on winter vegetables production. *MOJ Food Process. Technol.* **2018**, *6*, 384–389. [CrossRef]
68. Adigbo, S.O. Effect of low land rice-upland rice-vegetables/cowpea sequence on vegetable and cowpea rainfed inland valley. *Agric. Trop. Subtrop.* **2009**, *42*, 105–109.
69. Abewoy, D. Review on impacts of climate change on vegetable production and its management practices. *Adv. Crop. Sci. Technol.* **2018**, *6*, 330. [CrossRef]
70. Singh, N. An IoT Based Soil Analysis System for Variable Rate Application. *Int. J. Recent Adv. Multidiscip. Top.* **2021**, *2*, 255–257.
71. Witjaksono, G.; Rabih, A.A.S.; bt Yahya, N.; Alva, S. IOT for agriculture: Food quality and safety. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2018; Volume 343, p. 12023.
72. Reshma, R.; Sathiyavathi, V.; Sindhu, T.; Selvakumar, K.; SaiRamesh, L. IoT based classification techniques for soil content analysis and crop yield prediction. In Proceedings of the 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), Palladam, India, 7–9 October 2020; pp. 156–160.
73. Sharma, H.; Haque, A.; Jaffery, Z.A. Maximization of wireless sensor network lifetime using solar energy harvesting for smart agriculture monitoring. *Ad Hoc Netw.* **2019**, *94*, 101966. [CrossRef]
74. Wiangsamut, S.; Chomphuwiset, P.; Khummanee, S. Chatting with Plants (Orchids) in Automated Smart Farming using IoT, Fuzzy Logic and Chatbot. *Adv. Sci. Technol. Eng. Syst. J.* **2019**, *4*, 163–173. [CrossRef]
75. Hussain, T.; Anothai, J.; Nualsri, C.; Ata-Ul-Karim, S.T.; Duangpan, S.; Hussain, N.; Ali, A. Assessment of CSM–CERES–Rice as a Decision Support Tool in the Identification of High-Yielding Drought-Tolerant Upland Rice Genotypes. *Agronomy* **2023**, *13*, 432. [CrossRef]
76. Aslam, M.A.; Ahmed, M.; Hassan, F.-U.; Afzal, O.; Mehmood, M.Z.; Qadir, G.; Asif, M.; Komal, S.; Hussain, T. Impact of temperature fluctuations on plant morphological and physiological traits. In *Building Climate Resilience in Agriculture*; Springer: Cham, Switzerland, 2022; pp. 25–52.

77. Boote, K.J.; Jones, J.W.; Hoogenboom, G. Simulation of crop growth: CROPGRO model. In *Agricultural Systems Modeling and Simulation*; Marcel Dekker: New York, NY, USA, 1998.
78. Qaddoum, K.; Hines, E.L.; Iliescu, D.D. Yield Prediction for Tomato Greenhouse Using EFuNN. *ISRN Artif. Intell.* **2013**, *2013*, 430986. [CrossRef]
79. Keating, B.A.; Carberry, P.S.; Hammer, G.L.; Probert, M.E.; Robertson, M.J.; Holzworth, D.; Huth, N.I.; Hargreaves, J.N.G.; Meinke, H.; Hochman, Z. An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.* **2003**, *18*, 267–288. [CrossRef]
80. Perego, A.; Giussani, A.; Sanna, M.; Fumagalli, M.; Carozzi, M.; Alfieri, L.; Brenna, S.; Acutis, M. The ARMOSA simulation crop model: Overall features, calibration and validation results. *Ital. J. Agrometeorol.* **2013**, *3*, 23–38.
81. Hochman, Z.; Horan, H.; Reddy, D.R.; Sreenivas, G.; Tallapragada, C.; Adusumilli, R.; Gaydon, D.S.; Laing, A.; Kokic, P.; Singh, K.K.; et al. Smallholder farmers managing climate risk in India: 2. Is it climate-smart? *Agric. Syst.* **2017**, *151*, 61–72. [CrossRef]
82. Holzworth, D.P.; Huth, N.I.; deVoil, P.G.; Zurcher, E.J.; Herrmann, N.I.; McLean, G.; Chenu, K.; van Oosterom, E.J.; Snow, V.; Murphy, C.; et al. APSIM—Evolution towards a new generation of agricultural systems simulation. *Environ. Model. Softw.* **2014**, *62*, 327–350. [CrossRef]
83. Wang, X.C.; Li, J. Evaluation of crop yield and soil water estimates using the EPIC model for the Loess Plateau of China. *Math. Comput. Model.* **2010**, *51*, 1390–1397. [CrossRef]
84. Veenadhari, S.; Mishra, B.; Singh, C.D. Soybean productivity modelling using decision tree algorithms. *Int. J. Comput. Appl.* **2011**, *27*, 11–15. [CrossRef]
85. Varman, S.A.M.; Baskaran, A.R.; Aravindh, S.; Prabhu, E. Deep learning and IoT for smart agriculture using WSN. In Proceedings of the 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), Coimbatore, India, 14–16 December 2017; pp. 1–6.
86. Suresh, K.K.; Krishna Priya, S.R. A study on pre-harvest forecast of sugarcane yield using climatic variables. *Stat. Appl.* **2009**, *7&8*, 1–8.
87. Cai, Y.; Guan, K.; Lobell, D.; Potgieter, A.B.; Wang, S.; Peng, J.; Xu, T.; Asseng, S.; Zhang, Y.; You, L. Integrating satellite and climate data to predict wheat yield in Australia using machine learning approaches. *Agric. For. Meteorol.* **2019**, *274*, 144–159. [CrossRef]
88. Blagojević, M.; Blagojević, M.; Ličina, V. Web-based intelligent system for predicting apricot yields using artificial neural networks. *Sci. Hortic.* **2016**, *213*, 125–131. [CrossRef]
89. Ravichandran, G.; Koteeshwari, R.S. Agricultural crop predictor and advisor using ANN for smartphones. In Proceedings of the 2016 International Conference on Emerging Trends in Engineering, Technology and Science (ICETETS), Pudukkottai, India, 24–26 February 2016; pp. 1–6.
90. Cillis, D.; Maestrini, B.; Pezzuolo, A.; Marinello, F.; Sartori, L. Modeling soil organic carbon and carbon dioxide emissions in different tillage systems supported by precision agriculture technologies under current climatic conditions. *Soil Tillage Res.* **2018**, *183*, 51–59. [CrossRef]
91. Akin, M.; Eyduran, S.P.; Eyduran, E.; Reed, B.M. Analysis of macro nutrient related growth responses using multivariate adaptive regression splines. *Plant Cell Tissue Organ Cult.* **2020**, *140*, 661–670. [CrossRef]
92. Akin, M.; Hand, C.; Eyduran, E.; Reed, B.M. Predicting minor nutrient requirements of hazelnut shoot cultures using regression trees. *Plant Cell Tissue Organ Cult.* **2018**, *132*, 545–559. [CrossRef]
93. Hussain, T.; Hussain, N.; Tahir, M.; Raina, A.; Ikram, S.; Maqbool, S.; Ali, M.F.; Duangpan, S. Impacts of Drought Stress on Water Use Efficiency and Grain Productivity of Rice and Utilization of Genotypic Variability to Combat Climate Change. *Agronomy* **2022**, *12*, 2518. [CrossRef]
94. Bwambale, E.; Abagale, F.K.; Anornu, G.K. Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review. *Agric. Water Manag.* **2022**, *260*, 107324. [CrossRef]
95. Karpagam, J.; Merlin, I.I.; Bavithra, P.; Kousalya, J. Smart irrigation system using IoT. In Proceedings of the 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 6–7 March 2022; pp. 1292–1295.
96. Ragab, M.A. IOT based smart irrigation system. *Int. J. Ind. Sustain. Dev.* **2022**, *3*, 76–86. [CrossRef]
97. Valsan, V.; Rajesh, K.; Santhoshlal, N.M.; Pradeep, V. Smart Irrigation Monitoring System for Multipurpose Solutions. In *Ubiquitous Intelligent Systems*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 461–473.
98. Muangprathub, J.; Boonnam, N.; Kajornkasirat, S.; Lekbangpong, N.; Wanichsombat, A.; Nillaor, P. IoT and agriculture data analysis for smart farm. *Comput. Electron. Agric.* **2019**, *156*, 467–474. [CrossRef]
99. García, L.; Parra, L.; Jimenez, J.M.; Lloret, J.; Lorenz, P. IoT-based smart irrigation systems: An overview on the recent trends on sensors and IoT systems for irrigation in precision agriculture. *Sensors* **2020**, *20*, 1042. [CrossRef]
100. Xie, T.; Huang, Z.; Chi, Z.; Zhu, T. Minimizing amortized cost of the on-demand irrigation system in smart farms. In Proceedings of the 3rd International Workshop on Cyber-Physical Systems for Smart Water Networks, Pittsburgh, PA, USA, 21 April 2017; pp. 43–46.
101. Goumopoulos, C.; O'Flynn, B.; Kameas, A. Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support. *Comput. Electron. Agric.* **2014**, *105*, 20–33. [CrossRef]

102. Zhang, Q.; Wu, C.-H.; Tilt, K.M. Application of fuzzy logic in an irrigation control system. In Proceedings of the IEEE International Conference on Industrial Technology (ICIT'96), Shanghai, China, 2–6 December 1996; pp. 593–597.
103. Peng, X.; Mo, Z.; Xiao, L.; Liu, G. A water-saving irrigation system based on fuzzy control technology and wireless sensor network. In Proceedings of the 2009 5th International Conference on Wireless Communications, Networking and Mobile Computing, Beijing, China, 24–26 September 2009; pp. 1–4.
104. Anand, J.; Perinbam, J.R.P. Automatic irrigation system using Fuzzy Logic. *AE Int. J. Multidiscip. Res.* **2014**, *2*, 1–9.
105. Ragavi, B.; Pavithra, L.; Sandhiyadevi, P.; Mohanapriya, G.K.; Harikirubha, S. Smart agriculture with AI sensor by using Agrobot. In Proceedings of the 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 11–13 March 2020; pp. 1–4.
106. Mousa, A.K.; Croock, M.S.; Abdullah, M.N. Fuzzy based decision support model for irrigation system management. *Int. J. Comput. Appl.* **2014**, *104*, 14–20.
107. Boniecki, P.; Koszela, K.; Piekarska-Boniecka, H.; Weres, J.; Zaborowicz, M.; Kujawa, S.; Majewski, A.; Raba, B. Neural identification of selected apple pests. *Comput. Electron. Agric.* **2015**, *110*, 9–16. [CrossRef]
108. Rodrigues, L.M.; Dimuro, G.P.; Franco, D.T.; Fachinello, J.C. A system based on interval fuzzy approach to predict the appearance of pests in agriculture. In Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, AB, Canada, 24–28 June 2013; pp. 1262–1267.
109. Rupnik, R.; Kukar, M.; Vračar, P.; Košir, D.; Pevec, D.; Bosnić, Z. AgroDSS: A decision support system for agriculture and farming. *Comput. Electron. Agric.* **2019**, *161*, 260–271. [CrossRef]
110. Da Silva, J.R.M.; Damásio, C.V.; Sousa, A.M.O.; Bugalho, L.; Pessanha, L.; Quaresma, P. Agriculture pest and disease risk maps considering MSG satellite data and land surface temperature. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *38*, 40–50.
111. Bah, M.D.; Dericquebourg, E.; Hafiane, A.; Canals, R. Deep learning-based classification system for identifying weeds using high-resolution UAV imagery. In *Intelligent Computing. SAI 2018. Advances in Intelligent Systems and Computing*; Springer: Cham, Switzerland, 2018; pp. 176–187.
112. Tripathy, A.K.; Adinarayana, J.; Merchant, S.N.; Desai, U.B.; Ninomiya, S.; Hirafuji, M.; Kiura, T. Data mining and wireless sensor network for groundnut pest/disease precision protection. In Proceedings of the 2013 National Conference on Parallel Computing Technologies (PARCOMPTECH), Bangalore, India, 21–23 February 2013; pp. 1–8.
113. Viani, F.; Robol, F.; Bertolli, M.; Polo, A.; Massa, A.; Ahmadi, H.; Boualleague, R. A wireless monitoring system for phytosanitary treatment in smart farming applications. In Proceedings of the 2016 IEEE International Symposium on Antennas and Propagation (APSURSI), Fajardo, PR, USA, 26 June 2016–1 July 2016; pp. 2001–2002.
114. Alipio, M.I.; Dela Cruz, A.E.M.; Doria, J.D.A.; Fruto, R.M.S. A smart hydroponics farming system using exact inference in Bayesian network. In Proceedings of the 2017 IEEE 6th Global Conference on Consumer Electronics (GCCE), Nagoya, Japan, 24–27 October 2017; pp. 1–5.
115. Lindsey, A.P.J.; Murugan, S.; Renitta, R.E. Microbial disease management in agriculture: Current status and future prospects. *Biocatal. Agric. Biotechnol.* **2020**, *23*, 101468. [CrossRef]
116. He, D.; ZHAN, J.; XIE, L. Problems, challenges and future of plant disease management: From an ecological point of view. *J. Integr. Agric.* **2016**, *15*, 705–715. [CrossRef]
117. Pang, H.; Zheng, Z.; Zhen, T.; Sharma, A. Smart farming: An approach for disease detection implementing IoT and image processing. *Int. J. Agric. Environ. Inf. Syst. (IJAEIS)* **2021**, *12*, 55–67. [CrossRef]
118. Singh, D.; Wang, X.; Kumar, U.; Gao, L.; Noor, M.; Imtiaz, M.; Singh, R.P.; Poland, J. High-throughput phenotyping enabled genetic dissection of crop lodging in wheat. *Front. Plant Sci.* **2019**, *10*, 394. [CrossRef]
119. Warne, P.P.; Ganorkar, S.R. Detection of diseases on cotton leaves using K-mean clustering method. *Int. Res. J. Eng. Technol. (IRJET)* **2015**, *2*, 425–431.
120. Revathi, P.; Hemalatha, M. Classification of cotton leaf spot diseases using image processing edge detection techniques. In Proceedings of the 2012 International Conference on Emerging Trends in Science, Engineering and Technology (INCOSET), Tiruchirappalli, India, 13–14 December 2012; pp. 169–173.
121. Bhange, M.; Hingoliwala, H.A. Smart farming: Pomegranate disease detection using image processing. *Procedia Comput. Sci.* **2015**, *58*, 280–288. [CrossRef]
122. Yao, Q.; Guan, Z.; Zhou, Y.; Tang, J.; Hu, Y.; Yang, B. Application of support vector machine for detecting rice diseases using shape and color texture features. In Proceedings of the 2009 International Conference on Engineering Computation, Hong Kong, China, 2–3 May 2009; pp. 79–83.
123. Jian, Z.; Wei, Z. Support vector machine for recognition of cucumber leaf diseases. In Proceedings of the 2010 2nd international Conference on Advanced Computer Control, Shenyang, China, 27–29 March 2010; Volume 5, pp. 264–266.
124. Dubey, S.R.; Jalal, A.S. Detection and classification of apple fruit diseases using complete local binary patterns. In Proceedings of the 2012 Third International Conference on Computer and Communication Technology, Allahabad, India, 23–25 November 2012; pp. 346–351.
125. Pandey, B.; Seto, K.C. Urbanization and agricultural land loss in India: Comparing satellite estimates with census data. *J. Environ. Manag.* **2015**, *148*, 53–66. [CrossRef] [PubMed]
126. Beacham, A.M.; Vickers, L.H.; Monaghan, J.M. Vertical farming: A summary of approaches to growing skywards. *J. Hortic. Sci. Biotechnol.* **2019**, *94*, 277–283. [CrossRef]

127. Eigenbrod, C.; Gruda, N. Urban vegetable for food security in cities. A review. *Agron. Sustain. Dev.* **2015**, *35*, 483–498. [CrossRef]
128. Agrilyst. State of Indoor Farming. 2017. Agrilyst Brooklyn, NewYork, USA. Available online: http://artemisag.com/ (accessed on 1 January 2023).
129. Takatsuji, M. Present status of completely-controlled plant factories. *J. Sci. High Technol. Agric.* **2010**, *22*, 2–7. [CrossRef]
130. Song, X.P.; Tan, H.T.; Tan, P.Y. Assessment of light adequacy for vertical farming in a tropical city. *Urban For. Urban Green.* **2018**, *29*, 49–57. [CrossRef]
131. Touliatos, D.; Dodd, I.C.; McAinsh, M. Vertical farming increases lettuce yield per unit area compared to conventional horizontal hydroponics. *Food Energy Secur.* **2016**, *5*, 184–191. [CrossRef]
132. Frede, K.; Baldermann, S. Accumulation of carotenoids in Brassica rapa ssp. chinensis by a high proportion of blue in the light spectrum. *Photochem. Photobiol. Sci.* **2022**, *21*, 1947–1959. [CrossRef]
133. Ouzounis, T.; Heuvelink, E.; Ji, Y.; Schouten, H.J.; Visser, R.G.F.; Marcelis, L.F.M. Blue and red LED lighting effects on plant biomass, stomatal conductance, and metabolite content in nine tomato genotypes. In Proceedings of the VIII International Symposium on Light in Horticulture, East Lansing, MI, USA, 22–26 May 2016; Volume 1134, pp. 251–258.
134. Idoje, G.; Dagiuklas, T.; Iqbal, M. Survey for smart farming technologies: Challenges and issues. *Comput. Electr. Eng.* **2021**, *92*, 107104. [CrossRef]
135. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [CrossRef]
136. Memarbashi, P.; Mojarradi, G.; Keshavarz, M. Climate-Smart Agriculture in Iran: Strategies, Constraints and Drivers. *Sustainability* **2022**, *14*, 15573. [CrossRef]
137. Quy, V.K.; Van Hau, N.; Van Anh, D.; Quy, N.M.; Ban, N.T.; Lanza, S.; Randazzo, G.; Muzirafuti, A. IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges. *Appl. Sci.* **2022**, *12*, 3396. [CrossRef]
138. Zerssa, G.; Feyssa, D.; Kim, D.-G.; Eichler-Löbermann, B. Challenges of smallholder farming in Ethiopia and opportunities by adopting climate-smart agriculture. *Agriculture* **2021**, *11*, 192. [CrossRef]
139. Sandal, Y.S.; Pusane, A.E.; Kurt, G.K.; Benedetto, F. Reputation based attacker identification policy for multi-access edge computing in internet of things. *IEEE Trans. Veh. Technol.* **2020**, *69*, 15346–15356. [CrossRef]
140. Wang, J.; Hao, S.; Wen, R.; Zhang, B.; Zhang, L.; Hu, H.; Lu, R. IoT-praetor: Undesired behaviors detection for IoT devices. *IEEE Internet Things J.* **2020**, *8*, 927–940. [CrossRef]
141. Jia, Y.; Zhong, F.; Alrawais, A.; Gong, B.; Cheng, X. Flowguard: An intelligent edge defense mechanism against IoT DDoS attacks. *IEEE Internet Things J.* **2020**, *7*, 9552–9562. [CrossRef]
142. Neshenko, N.; Bou-Harb, E.; Crichigno, J.; Kaddoum, G.; Ghani, N. Demystifying IoT security: An exhaustive survey on IoT vulnerabilities and a first empirical look on Internet-scale IoT exploitations. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 2702–2733. [CrossRef]
143. Chaterji, S.; DeLay, N.; Evans, J.; Mosier, N.; Engel, B.; Buckmaster, D.; Ladisch, M.R.; Chandra, R. Lattice: A vision for machine learning, data engineering, and policy considerations for digital agriculture at scale. *IEEE Open J. Comput. Soc.* **2021**, *2*, 227–240. [CrossRef]
144. Cucho-Padin, G.; Loayza, H.; Palacios, S.; Balcazar, M.; Carbajal, M.; Quiroz, R. Development of low-cost remote sensing tools and methods for supporting smallholder agriculture. *Appl. Geomat.* **2020**, *12*, 247–263. [CrossRef]
145. Rodríguez-Robles, J.; Martin, Á.; Martin, S.; Ruipérez-Valiente, J.A.; Castro, M. Autonomous sensor network for rural agriculture environments, low cost, and energy self-charge. *Sustainability* **2020**, *12*, 5913. [CrossRef]
146. Kassim, M.R.M. Iot applications in smart agriculture: Issues and challenges. In Proceedings of the 2020 IEEE conference on open systems (ICOS), Kota Kinabalu, Malaysia, 17–19 November 2020; pp. 19–24.
147. Li, D.; Nanseki, T.; Chomei, Y.; Kuang, J. A review of smart agriculture and production practices in Japanese large-scale rice farming. *J. Sci. Food Agric.* **2022**, *103*, 1609–1620. [CrossRef] [PubMed]
148. Reger, M.; Bauerdick, J.; Bernhardt, H. Drones in Agriculture: Current and future legal status in Germany, the EU, the USA and Japan. *Landtechnik* **2018**, *73*, 62–79.
149. Ayamga, M.; Tekinerdogan, B.; Kassahun, A. Exploring the challenges posed by regulations for the use of drones in agriculture in the African context. *Land* **2021**, *10*, 164. [CrossRef]
150. Regan, Á. 'Smart farming'in Ireland: A risk perception study with key governance actors. *NJAS-Wagening. J. Life Sci.* **2019**, *90*, 100292.