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Incorporating Artificial Intelligence Technology in Smart Greenhouses: Current State of the Art

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Abstract: This article presents the current state-of-the-art research on applying artificial intelligence (AI) technology in smart greenhouses to optimize crop yields, water, and fertilizer use efficiency, to reduce pest and disease, and to enhance agricultural sustainability. The key technologies of interest were robotic systems for pesticide application, irrigation, harvesting, bio-inspired algorithms for the automation of greenhouse processes, energy management, machine path planning and operation of UAVs (unmanned aerial vehicles), resolution of scheduling problems, and image signal processing for pest and disease diagnosis. Additionally, the review investigated the cost benefits of various energy-management and AI-based energy-saving technologies, the integration of photovoltaics and dynamic pricing based on real-time and time-of-use metrics, and the cost benefits of LoRa, Wi-Fi, Bluetooth, ZigBee, mobile, and RFID (radiofrequency identification) technologies. The review established that commercially viable AI technologies for agriculture had increased exponentially. For example, AI-based irrigation and soil fertilizer application enabled farmers to realize higher returns on investment on fertilizer application and gross returns above the fertilizer cost, higher yields, and resource use efficiency. Similarly, AI image detection techniques led to the early diagnosis of powdery mildew. The precise operation of agricultural robots was supported by the integration of light imaging, detection, and ranging (LIDAR) optical and electro-optical cameras in place of the traditional GPS (geographic positioning systems) technologies, which are prone to errors. However, critical challenges remained unresolved, including cost, disparities between research and development (R&D) innovations and technology commercialization, energy use, the tradeoff between accuracy and computational speeds, and technology gaps between the Global North and South. In general, the value of this review is that it surveys the literature on the maturity level of various AI technologies in smart greenhouses and offers a state-of-the-art picture of how far the technologies have successfully been applied in agriculture and what can be done to optimize their usability.

Keywords: greenhouses; agriculture; artificial intelligence; intelligent; algorithms; robotics

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1. Introduction

The AI systems of interest include bio-inspired ecological and swarm intelligence algorithms, unmanned UAVs (Unmanned aerial vehicles) for pesticide application, and robotic systems for harvesting, irrigation, soil treatment, fertilizer application, and seeding [1,2]. In addition, the study critiques the role of swarm intelligence (genetic optimization algorithms and related algorithms) in agricultural parameter optimization, machinery path planning, robotic flight, resolution of scheduling problems, system identification, power systems, and image and signal processing [1,2]. The multidimensional view of AI (artificial intelligence) technologies in smart greenhouses would provide a nuanced understanding of the recent milestones in research and development and their implications for commercial and smallholder agriculture in the developed global north (North America, Western Europe, Mediterranean region, China, Japan, and South Korea) and underdeveloped global south (Africa, Latin America, and South Asia) [3].

Emerging technology companies, such as Blue River Technology, Harvest CROO Robotics, Trace Genomics, and Autonomous Tractor Corp were leading in the commercial deployment of self-driving agricultural tractors, AI-based weed control systems, pest diagnostics, soil analysis, and crop health monitoring [4,5]. In line with [4,5], Karnawat et al. [6] acknowledged the immense role played by Blue River Technology in the advancement of robotics and AI systems in agriculture in California and the US in general. These emerging trends of AI and machine learning (ML) in agriculture need to be summarized to provide a comprehensive overview of the state of the art (i.e., maturity levels of various AI applications in agriculture, including barriers and facilitators) and insights into future developments [7].

Many factors dictate the need to review the maturity levels of various AI applications in agriculture. First, there is increasing demand for technological solutions to address global food insecurities, especially in the Global South. Currently, at least 810 million people are food insecure. The actual ratio would increase over time in line with the global population growth. By 2050, the global population will surpass 9 billion [8,9]. The higher population growth within a generation would strain the already fragile agricultural systems and ecosystems that are being gradually destroyed to create additional land for farming. Iddio et al. argued that controlled environment agriculture (CEA) using greenhouses might help to offset the pressing concerns about agricultural sustainability [10]. The case for greenhouse-based CEA was validated by the fact that greenhouse crop cultivation improves yields and reduces the need for excess pesticides, water, land, and transportation of crops over extended distances. The case for CEA advanced by [10] was in tandem with Afzali et al. [11], who supported the intensification of agricultural technologies. The need for a paradigm shift in agricultural cultivation was premised on the increasing risk of global starvation [12]. The AI-mediated improvements in crop yields may help avert the forecasted global food crises.

Second, a large body of knowledge, including the evidence presented by Senavirathne et al. [13] and Haque et al. [12], suggested that the satisfaction of future food needs would be achieved by optimizing the existing crop production technologies, given there was limited arable land for agricultural expansion [14]. In line with [14], Lakshmi and Corbett [15] estimated that smart technology in agriculture may help boost yields by 60% before 2030. Conservative estimates indicate the EU market for precision agriculture systems will surpass 11.8 billion by 2025 [16]. The projected market growth and higher yields catalyzed the current greenhouse boom. As of 2020, there were 3.6 million hectares of greenhouse crops globally [17–22].

Third, current climate projection models forecast suppressed rainfall, land degradation, desertification, flooding, and other weather phenomena triggered by climate change and increased release of greenhouse gases [23,24]. The projections documented by [23,24] reflected the current realities in Sub-Saharan Africa [25]. The expansion of open-field agriculture to offset climate-related challenges is no longer a viable option. The European Commission Joint Research Centre estimated that three-quarters of the useful land on earth was already degraded, and the proportion of degraded land would surpass 90% by 2050 [26]. The challenge is most pronounced in developing countries that experienced the highest dryland desertification rate between 1982 and 2015. During this period, at least 5.4 million km^2 of land was degraded [27]. In theory, losing traditional farming dryland was a sufficient motivational factor for transitioning to smart greenhouses powered by AI technologies. However, the contrary phenomenon is true for climate-smart agriculture worldwide [28]. The current pace of transition does not match the challenges. On a positive note, the transition to precision agriculture would enable farmers to optimally use water, soil, and energy resources to minimize the negative effects of climate change on farming [29]. The rational use of agricultural resources would reduce the pressure on the natural environment, resulting in higher sustainability.

The article critiques recent research on smart greenhouses and artificial intelligence technologies, including the favorable factors and the challenges that have impeded the growth of AI and smart greenhouse technologies. The study emphasized smart farming technologies, mechanization of farms, smart micro-irrigation, rapid soil analysis, pest prediction, and autonomous modification of the greenhouse microclimate, and LIDAR (light Imaging, detection, and ranging), optical and electro-optical cameras for robotic system motion and object identification (see Figure 1) [30]. The specific scope was supported by the gaps in research and the breadth of information relating to the impact of AI and IoT (Internet of Things) and data-driven agriculture, intelligent crop planning, and farm gate-to-fork systems [31,32]. More particularly, no review has so far comprehensively mapped the state of AI and IoT application in smart greenhouse farming to help researchers and farmers of plant factories to solve the imminent problems related to global food insecurities and climate change, despite the fact that technological innovations have been centrally placed in the development of effective and sustainable solutions to these challenges. Thus, this review will enable farmers of factory plants to understand the extent to which AI and IoT can be combined to improve farming efficiency and productivity and will enable researchers to advance knowledge on this subject domain by building on the research achieved so far.

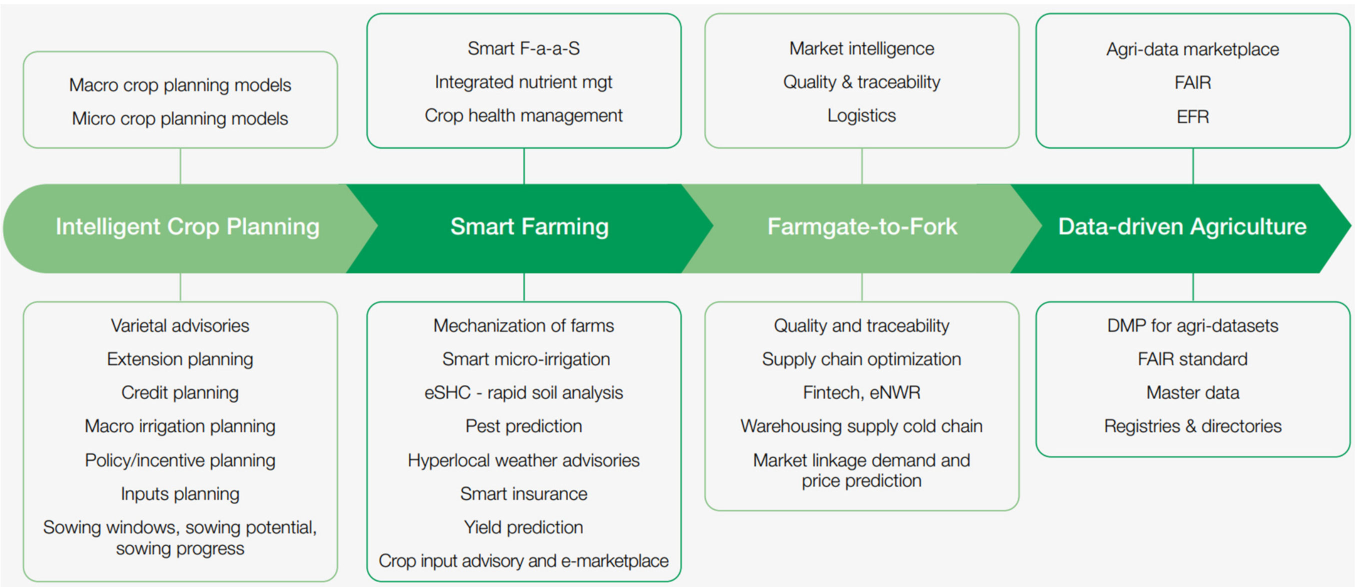

Figure 1. Smart farming and other emerging innovations in the agricultural sector [30].

Method for Systematic Review

The review of Incorporating Artificial Intelligence Technology in Smart Greenhouses was aligned with the PRISMA guidelines for systematic reviews and meta-analyses (see Figure 2). PRISMA Flowchart shown in Figure 2 below provides detailed information about how the 174 articles cited in this review were identified and selected. All data were sourced from published articles. The peer-reviewed data were sourced from the following primary databases: MDPI, Elsevier, Springer (including Nature Springer) and Taylor and Francis, Scopus, and Google Scholar. More databases would have been searched, but a quick literature survey revealed that that they mostly publish duplicated content, such as between Frontiers and Springer.,Emphasis was given to literature published after 2019, since technological advancements, especially AI and IoT, are rapidly evolving. The choice of articles published from 2019 onwards was therefore motivated by the need to review only recent studies in this field. This motivation was also appraised as valid owing to the many research studies on the application of AI in agriculture that have been published within the past three years. The primary keywords were AI, greenhouses, smart, IoT, and agriculture. The inclusion and exclusion criteria were characterized by a title and abstract screening, followed by a full-text and abstract screening process, which focused on the subject's relevance. Articles were excluded if they did not discuss the role of various AI technologies in agriculture. Studies were also excluded if they did not use any methodological approach to analyze and synthesize data before making conclusions. Studies published in non-English languages were also excluded to avoid translation errors and associated financial costs and factual consequences. The research design of the studies did not matter, but primary studies with experimental design were given priority over others during the selection process.

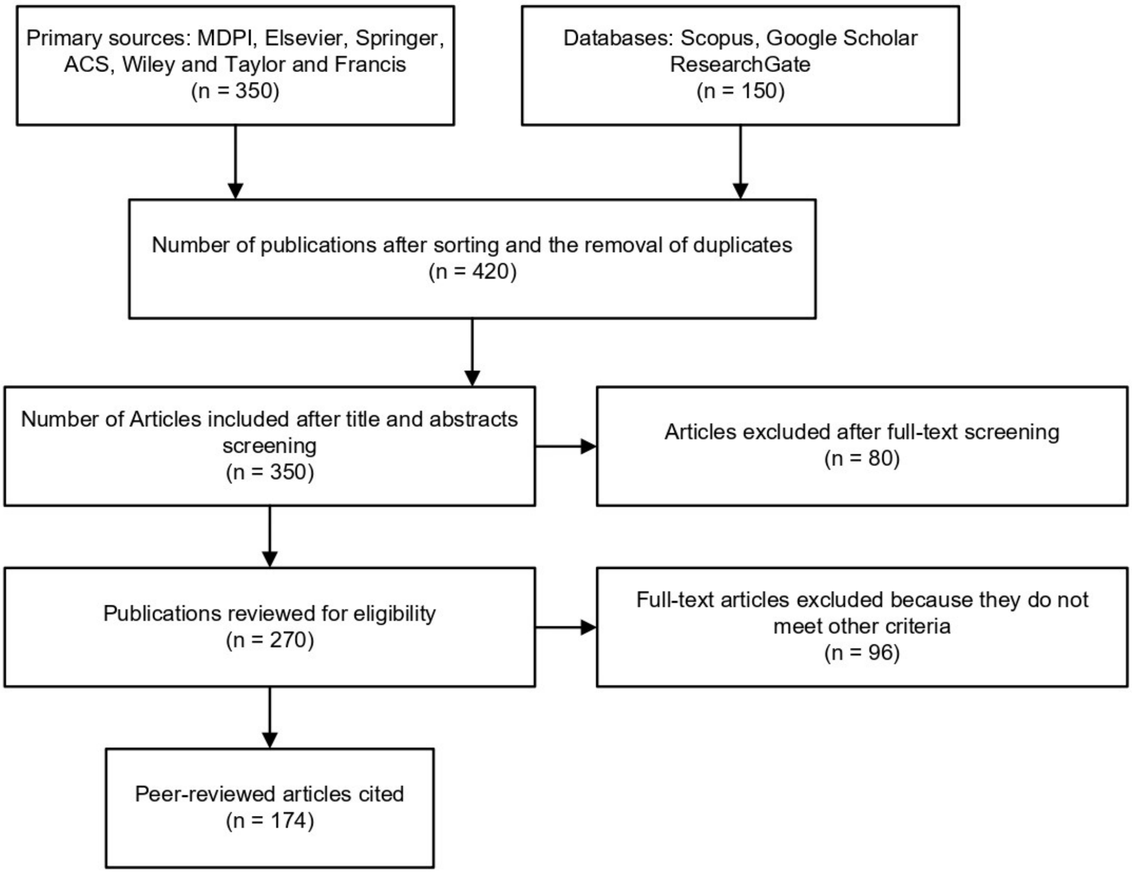

Figure 2. PRISMA diagram.

2. Artificial Intelligence Technologies for Smart Greenhouses

2.1. Historical Background of AI and ICTs in Agriculture

Using AI and ICT in precision agriculture is not a new phenomenon. Rao et al. [33] traced the use of ICTs in precision agriculture back to the 20th century. In 1958, psychologist Frank Rosenblatt first formulated and proposed artificial neural networks as mathematical models of artificial intelligence whose mathematical structure attempted to mimic the functionality of biological neurons [34]. More specifically, in this first work, the well-known mathematical simulant of Perceptron, which is the first structure of the artificial neural network, was successfully employed to simulate how the human brain processes optical data and learns to recognize objects. The first structure of Perceptron is the main basis and architecture of the neural networks that have been extensively used in precision agriculture and other disciplines.

Perception marked a historic key point in artificial intelligence research and commercial adoption with the coining of a phrase that embodied an entire field within AI. AI techniques have developed because of the complexity of the technological era, where a plethora of complex problems with a strongly non-linear nature cannot be solved using classical deterministic techniques, such as regression analysis and least-squared methods. Despite their novelty, it took four decades (until the early 1990s) for artificial neural networks to be used widely in medical applications [35–42], computational engineering [43–53], and precision agriculture.

The historical analysis of ICTs in agriculture by Rao et al. [33,43–53] aligns with the broader trends in the global demand for AI, ML, and IoT, as noted by Misra et al. [33]. On the downside, the true potential of AI and ICTs has not been fully exploited. The observation was validated by the fact that the transition of ICT technologies from computing to agriculture was delayed, considering the field of artificial intelligence was first proposed in 1955 and expanded in subsequent years [8]. During the early phases of precision agriculture, the key focus was improving crop yields and productivity by monitoring soil nutrients. However, the scope of precision agriculture has broadened to encompass artificial pollination using robot bees, autonomous operation of farm equipment, and optimization of different agricultural processes using bio-inspired algorithms [1,54,55]. The technology patterns demonstrate a peak in AL technologies from 2016 onwards. The convergence of new technologies in precision agriculture ushered in the Industry 4.0 revolution and the Internet of Plants (IoP) [56] (see Figure 3). The figure demonstrates how the availability of digital sensors and IoT can be used to collect environmental data, such as light, temperature, humidity, nutrition, and water, and then be stored in a cloud-based server, which can supply information for various farm work operations. However, there is growing criticism of AI technologies in agriculture due to their higher energy demand, high initial capital outlay, and variable accuracy [17]. These concerns have been discounted in view of the immense benefits of AI systems, including better crop yields, lower labor costs, and improved efficiency [57].

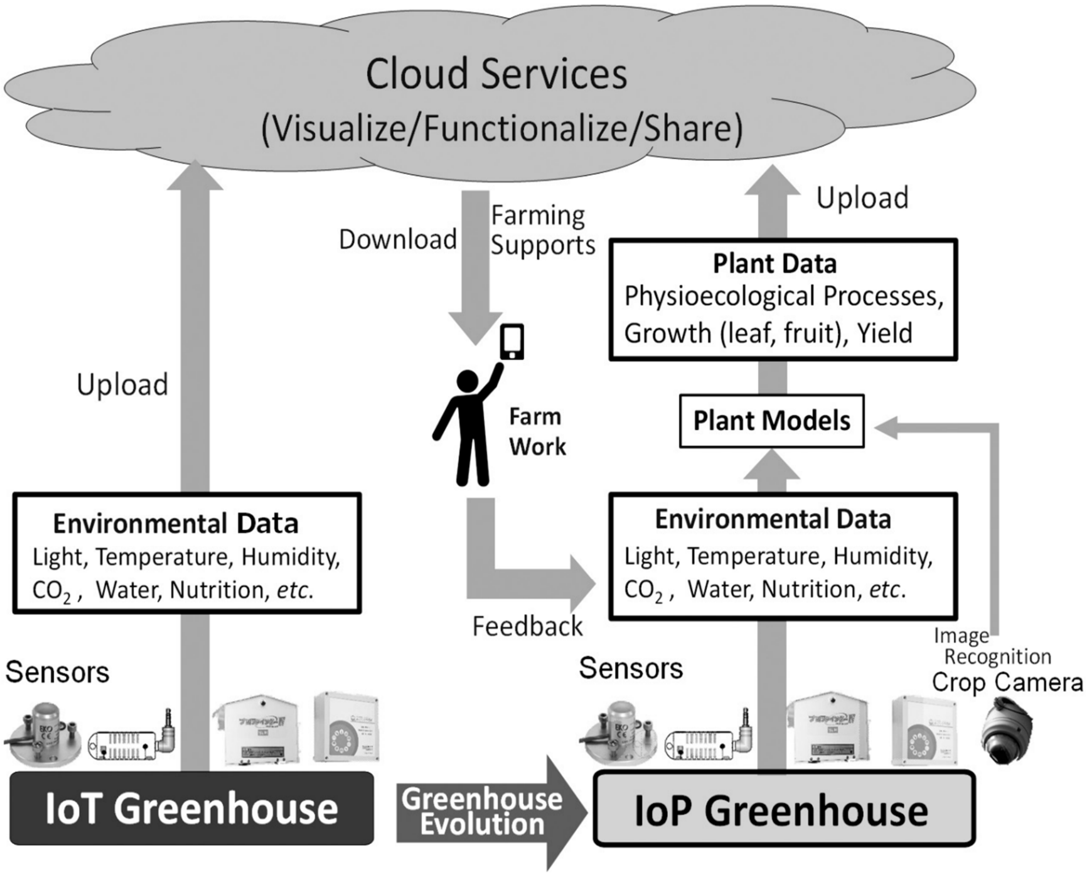

Figure 3. Core attributes and the link between IoP and IoT [56].

The current scope of AI and IoT in smart greenhouses encompasses artificial lighting using LEDs [58], air ventilation, water and nutrition pumps, plant nutrition, humidity control, moisture control, and temperature control subsystems with a unique combination of sensors and controls with distinct attributes [13]. The impact of weeds, pests, diseases, and water stress on crop yields validated the broadening scope of AI in precision agriculture. Egorov et al. [59] noted that livermore was a pervasive weed across the US, impacting the germination and growth of plants. In line with Egorov et al., [8,59] noted that improper management of weeds could potentially reduce crop yields by 48–60%. However, the projected reduction in crop yields due to pest infestation observed by [8] contrasts with Raatz et al., who reported up to 60% losses in harvests due to pest infestation [60], but attributed the phenomena to biotic culprits, including weed growth. Despite the contrasting observations made by Raatz et al. [60] and [8], poor management of crop pests and diseases had a detrimental effect on crop yields. The devastating impact of South American tomato pinworm on sweet pepper and tomato in Almería, Southeastern Spain, was a case in point [61]. In the latter case, the Spanish farmers had to rely on toxic pesticides, such as Chlorpyrifos-methyl, to manage the pests [61,62]. Reducing human exposure to toxic pesticides through the mechanization of greenhouse spraying activities yielded significant benefits in the long term [63]. Additionally, intelligent IPM (Integrated pest management) practices may offset the emerging pesticide resistance threats.

2.2. Current AI Technologies for Agriculture

The AI technologies available for smart greenhouses and precision agriculture are diverse, ranging from ecological bio-inspired algorithms, such as Adaptive Neuro-Fuzzy Inference System–Particle Swarm Optimization (ANFIS-PSO), ANFIS-GA (ANFIS with Genetic Algorithm) and ANFIS-ACO (ANFIS with Ant Colony Optimization), swarm intelligence algorithms (Artificial Bee Colony (ABC), Flower Pollination algorithm (FPA), Firefly algorithm, Krill Herd algorithm, and genetic optimization algorithms) [64] to UAV (drones) pesticide application and robotic systems for harvesting [9], irrigation, soil treatment, seeding, fertilizer application, seeding, and other tasks [1,2]. The current body of knowledge linked the demand for robotics, UAVs, and bio-inspired algorithms in agriculture to distinct factors. On the one hand, scholars argued that the growth was catalyzed by the need to enhance yields and operational efficiency and reduce costs [8,29,33]. In line with [5,29,33], Cao et al. reported a 10% improvement in tomato yields with the iGrow intelligent greenhouse system and 92% higher profits [18]. On the other hand, AI assimilation in smart agriculture was triggered by natural events, including higher levels of pesticide resistance and forest fires, which compromised agricultural production [65,66]. The following sections critiqued the two worldviews to yield better insights into the favorable factors and barriers to AI-system adoption in smart greenhouses and precision agriculture at large.

2.2.1. Cost Benefits of AI Technologies for Agriculture

The focus on the role of AI systems in smart greenhouses and the agricultural sector, in general, was validated by the unique challenges and the enormous contribution in terms of Gross Value Added (GVA). Agriculture provided direct employment to approximately 4.4% of the population in Europe, and its GVA exceeded €181 billion [67]. The scenario was not specific to the EU; at least 70% of the Indian population depended on agriculture for employment and sustenance [68]. Despite the enormous contribution, the future of agriculture in Europe and across the world is threatened by population dynamics; most European farmers are older (>80%), while a minority are below 40 years [67]. In contrast to the European Economic and Social Committee's report [67] on the impact of demographics on agricultural technology adoption, Loudjani et al. [69] argued that the primary barriers were time and costs.

The average cost of installing AI systems on farms was enormous and beyond the reach of smallholder farmers [70]. The contrary was true for large commercial farms with a higher capacity to absorb costs and risks and a higher tendency to allocate resources for capital-intensive investments [71]. The concerns raised by Kendall et al. [70] were supported by the Cisco and the International Telecommunication Union (ITU) report [72], which noted that agricultural sensors for AI systems with greater functionality are expensive ($150–$1000+

per sensor). The initial capital outlay was a key impediment to technology adoption, considering that multiple sensors are required for monitoring greenhouse microclimate (humidity, temperature, soil nutrient, water levels, and pH). From another dimension, the expenses were relative, given that local production of smart greenhouse components may offset costs [73]; this view was corroborated by Chung's study [73] on South Korean companies Hyundai Metal Farming Company, Sewoon, DaeSungHione, and Dae Ryun and local production of precision farming systems, such as sensors, actuators, fans, heaters, dehumidifiers, and window motors. In contrast, there was insufficient production capacity in developing countries.

The cost-centric worldview advanced by Kendall et al. [70] and Loudjani et al. [69] negated the role of externalities. Lakshmi and Corbett [18] argued that the effectiveness of AI systems was largely dependent on the willingness of the local stakeholders to "modify, generate, and extend their operational capabilities to improve efficiency" (p. 5209). Additionally, the processes, AI resources, and tools (including drones, sensors, and robots) employed by commercial farms profoundly impacted the effectiveness of AI systems. Drawing from Lakshmi and Corbett's study [18], the cost was not a primary barrier to AI technology adoption.

2.2.2. Water and Fertilizer Use Efficiency and Crop Yields with AI Systems

The success of the GOSSYM (a combined simulation model for plant growth and decision) aid for cotton crop management mode influenced the iterative development of other AI systems, including the HortiMED-AI-powered Decision Support Systems (DSSs) [74]. On a positive note, the barriers to the transition from labor- and input-intensive agriculture to knowledge-based farming would be eliminated over time; this is evident with the recent innovations in AI systems for smart/precision agriculture. In 2022, Otazua reported the successful development of the HortiMED-AI-powered decision support systems (DSSs) that facilitated autonomous greenhouse control using sensors, "multilayer hierarchical control architecture," smart algorithms, "hybrid modeling combining well-known mechanistic models with AI techniques," IoT, and machine learning (p. 1) [74]. The HortiMED-DSS was capable of facilitating cost-effective automation of greenhouse heating, ventilation, and fertigation, and providing expert services relating to nutrient, crop, and climatic conditions (fertilizer and water application rates and timelines).

The observations made by [74] regarding the benefits of automating greenhouse were in tandem with Cui et al. [75]; precision irrigation and fertilizer application led to higher nitrogen use and water use efficiency, and in turn, a lower risk of pests and diseases in greenhouse cucumbers in China's Yangling region. The observations made by Cui et al. [75] about AI-mediated water-use efficiency corroborated the study by Lin et al., which noted that AI technologies provided water to crops within their demand ranges [76]. From a theoretical point of view, Cui et al. [75] and Lin et al. [76] advanced a simplistic view of sensor operation, which did not align with Briciu-Burghina et al. [77]. In the latter case, Briciu-Burghina et al. [77] argued that the accuracy of the soil moisture sensors was dependent on hardware components and environmental degradation of the sensor components. In line with Briciu-Burghina et al. [77], there were cases when the dielectric soil moisture sensors failed to accurately measure periodic changes in the soil moisture levels; this had a negative domino effect on demand irrigation. The faulty measurements were linked to either corrosion or hardware malfunction. The outcome reported by Briciu-Burghina et al. [77] negated the impact of soil type on sensor malfunction—an issue that was extensively investigated by Shamshiri et al. [78]. The study confirmed that the "resistive sensor operates defectively in sandy loam and clay loam soils owing to low bulk density and high organic matter" (p. 5) Emerging research recommended the adoption of capacitive soil moisture sensors to counteract the limitations of the resistive sensors.

From the researcher's perspective, the risk of corrosion was disproportionately higher, considering the dielectric sensors were buried in situ and the soils were humid [77]. The risk of sensor malfunction highlights the potential drawbacks and limits of demand-driven agriculture. Despite the mounting evidence on the risk of a sensor malfunction, the technology issues are often disregarded due to cost considerations and the anticipated cost savings. Cui et al. [75] reported a 17.5% higher cucumber yield following the introduction of AI-based irrigation, while the partial factor productivity of applied nitrogen increased by 29%. Similarly, with AI-based systems, Sharma et al. [79] reported a 17% improvement in wheat grain yields. Considering the outcomes were statistically significant ($p < 0.005$), AI-based irrigation and fertilizer application yielded tangible benefits compared to traditional drip irrigation and manual soil fertilization. The positive outcomes reported by Cui et al. [75] were consistent with the Sharma et al. case study in Saudi Arabia, where superior partial factor productivity of applied nitrogen with ANN (Artificial neural network) models was established [79]. Since no experimental data contradicted the positive findings made by Cui et al. [75] and Sharma et al. [79], it appears that the AI technologies were cost-effective and may enable farmers to achieve higher returns on investment on fertilizer application and gross returns above the fertilizer cost.

The use-efficiency-related benefits that emerged from applying fertilizers were comparable to pesticide-use efficiency. Facchinetti et al. [80] reported a 50% reduction in the use of pesticides based on an initial theoretical mixture of 1000 L/ha. The introduction of computational algorithms helped to reduce the demand for pesticides to 470 L/ha. The study confirmed that the pesticide application rates could be further reduced to 300 L/ha [80]. Facchinetti et al. hypothesized a 33% reduction in pesticide use [80], which does not match Claver's research, which noted it was possible to reduce pesticide usage by up to 78% using the state-of-the-art algorithm systems developed by Israel-based Greeneye Technology [81]. Similarly, Shankar et al. postulated that intelligent technologies enabled farmers to practice variable rate application (VAR), which provided real-time data on the areas most infested with pests and diseases [82]. The utility of the VAR was further reinforced by the xarvio Spray Timer and SprayWeather, which enabled farmers to establish the most appropriate window for spraying. Drawing from the empirical data provided by [82], VAR eliminated the need to apply excessive fertilizers in areas least affected by pesticides, and was an ideal alternative compared to the system proposed by Facchinetti et al. [80]. The use of fewer pesticides in the production of freshly cut salads had a beneficial effect on human health, considering pesticide residues in foods were risk factors for myriad non-communicable diseases.

On the downside, the benefits that accrue from DSS, VAR for pesticides, xarvio Spray Timer and SprayWeather, AI-based fertilizer, irrigation, and other systems may be less relevant to remote areas with limited IT infrastructure and technical expertise [8]. However, these challenges may not persist in the long term, considering the high pace of IT infrastructure deployment in rural and urban areas, previously classified as unprofitable for such ventures [83]. From another perspective, the deployment of IT infrastructure would only provide a partial solution, given the aging of the population was also a major issue of concern.

2.3. AI Systems for Integrated Pest Management

Despite the concerns raised about the prohibitive costs, the proponents of AI argue that the long-term benefits outweigh the short-term costs [84,85]. The reliable use of AI systems to predict rice production was a case in point [85]. Beyond the prediction of crop production, AI systems facilitated the development of intelligent IPM systems capable of detecting early infestation of white flies (*Trialeurodes vaporariorum* and *Bemisia argentifolii*) and thrips (*Thrips tabaci*, *Frankliniella intonsa*, *Thrips hawaiiensis*, and *Thrips tabaci*) [57]. The observations made by Rustia et al. [57] reinforce earlier observations made by Karar et al. [14] on the suitability of deep learning systems in the management of pests and diseases. From a commercial perspective, the findings reported by Rustia et al. [57] and Karar et al. [14] were compelling, but inadequate for catalyzing a paradigm shift in the market; this view was reinforced by the fact that the existing stock of Al systems for pest identification and management focused on insect pheromone identification [86]. The pheromone-centric ANN and wireless sensor network (WSN) technology cannot control all insect types, considering there is a limited number of commercially available pheromones for IPM [86].

Despite the reservations reported by Singh et al. [86], the ANN–WSN system for pest identification accurately categorized harmful and beneficial insects; these data guided the calculation of the volume of pesticides for IPM. The limits of WSN technology highlighted by [86] were in tandem with [87], who noted that variable monitoring ranges, complex typologies, and environmental conditions compromised the operation of WSN systems. However, recent R&D evidence suggests otherwise. The shortcomings of WSN identified by [86,87] negate recent milestones achieved by Sacaleanu et al. [88] with wireless sensors and actuators networks (WSAN). WSAN is an upgrade of WSN developed to resolve most of the limitations of WSN using actuators for better monitoring and control.

The advances made using WSAN have not been accompanied by greater market adoption, owing to the newness of the technology; most studies still focus on WSN technologies for smart greenhouses [19,89]. Beyond the concerns about the pace of market adoption, the body of knowledge, including Rustia et al. [57], Singh et al. [86], and Karar et al. [14], was informed by small-scale experiments under controlled conditions. Real-life applications of AI systems (IRIS scout robots and robot scouts) in identifying pests and diseases in agriculture yielded false positive data after analyzing pheromone trap images and powdery mildew [90]. Since the latter findings were based on market data, the IRIS scout robots and robot scouts were not ready for market adoption. Inaccurate assessment of pests and disease infestation using AI and ML (machine learning) image analysis techniques would result in the excessive application of pesticides. Further research and development efforts were necessary to minimize false positive rates.

2.4. Robotics and Algorithms for Precision Agriculture and Smart Greenhouses

Recently, commercial farms have deployed robotic systems to selectively harvest fragile fruits and vegetables such as broccoli and tomatoes [91]. The findings by [91] were in agreement with Lee et al. [92], who documented the increased use of robotic systems to sort tomatoes based on color, size, shape, and mass and to identify all defects during the harvesting process. The case for AI robotic systems in smart farming advanced by Kootstra et al. [91] was corroborated by Vidwath et al. [93] and Navas et al. [94], who highlighted the benefits of soft robotic grippers in fruit and vegetable harvesting. In contrast to Vidwath et al. [93] and Navas et al. [94], Tianhua et al. [95] argued that AI robotic systems could perform a wide range of unsafe greenhouse tasks beyond harvesting. Such applications include pesticide spraying and UV-C treatment of crops to mitigate the spread of powdery mildew. From a human health perspective, Tianhua et al. [95] perspective on the use of robotic systems for pesticide application was validated by pesticide toxicity studies [61,62,96]. For example, Chlorpyrifos-methyl, a common pesticide employed in integrated pest management of the South American tomato pinworm, caused cholinesterase inhibition in humans and death in severe cases [62]. In other studies, mechanical AI systems enabled farmers to reduce their labor requirements by up to 90% [13]. However, the actual reduction rates can be contested, considering robots cannot entirely replace human labor.

Empirical data supported the arguments concerning costs and operational efficiency of AI systems in farms. Hou et al. [97] used Dynamic Artificial Bee–Ant Colony algorithm (DABACA) to optimize agricultural machinery plant operational cycle and route planning. The study reported better optimization, convergence accuracy (>90%), and reduced operational cycles, which translated to significant cost savings. The observations made by Hou et al. [97] using DABACA were in line with Cao et al. [98], whose bio-inspired algorithm-mediated task assignment of agricultural machinery, which employed ant colony algorithm-based B-patterns to improve the operational efficiency of agricultural equipment, including the fuel used and non-working distance covered during routine farm operations. However, critics argue that the positive outcomes drawn from experimental studies, such as the observations made by Hou et al. [97] and Cao et al. [98], did not justify the widespread adoption of AI systems in greenhouses. The concerns were premised on the following factors. First, AI systems in agriculture lacked standardized accuracy rates. The system accuracy varied depending on the local environmental conditions and operational factors. Second, the risk of error remained regardless of the algorithm's robustness [99,100]. However, the higher risk of errors was not ubiquitous. Proietti et al. established that RNN (Recurrent neural network)-based decoder–encoder systems exhibited great potential in the early detection of anomalies [101]. Similarly, Aytenfsu et al. noted that Elman Recurrent Neural Network (ERNN) was 98% accurate in predicting greenhouse temperature and humidity levels. The case-specific error theory provided better context concerning the benefits and limits of AI systems in smart greenhouses. Even though [99,100] raised valid concerns about the constraints, commercial adoption should be encouraged.

The positive assessment of AI systems in commercial agriculture was validated by successful commercial adoption. For example, Gao et al. [102] used an ANN model to quantify crop evapotranspiration rates in Saudi Arabia. The ANN model yielded better estimates than traditional approaches to estimating evapotranspiration. Accurate determination of the plant evapotranspiration rates provided useful data for automated irrigation algorithms. Beyond the estimation of the crop evapotranspiration rates, the ANN and WDNN algorithms were equally proven useful in predicting the photosynthetic rates of plants, among other physiological indices that predict plant growth rates and yield [103]. In other cases, hybrid algorithms were proven reliable in weed prediction/optimization [104,105], and the determination of the soil cation exchange capacity [106]. The positive assessment of ANN technologies reinforces earlier observations by Proietti et al. [101] on the fusion of deep learning and artificial intelligence (RNN encoders and LSTM (Long Short-Term Memory)) to facilitate learning patterns in time series and modeling data sequences using monitored parameters to predict crop growth indicators in greenhouses. The case for RNN advanced by Proietti et al. [101] negated critical shortcomings identified by Codeluppi et al. [107]; NN systems were inferior to LSTM owing to the long time series and vanishing gradient problem, which made it difficult to train the model on long-term dependencies. The latter findings validate the emerging transition from LSTM to RNN.

Gao et al. [102] and Hu et al.'s [103] bias toward new algorithms for greenhouses was validated by the following considerations. First, modern greenhouses are complex; there are dynamic relationships between different greenhouse parameters, and the data mining ability of traditional models is insufficient to facilitate the extraction of all useful information. Second, the traditional models' low precision and convergence speeds made them incompatible with modern intelligent greenhouses. On the downside, the research of Gao et al. [102] and Hu et al. [103] negated the fact that the transition from traditional to modern algorithms does not automatically translate to higher prediction accuracy and sensitivity. The hybrid algorithms must be combined with the appropriate classifiers to yield better accuracy and specificity [105]. For example, Tao and Wei achieved a 92% accuracy with the CNN (Convolutional Neural Network)-Support Vector Machine (SVM) algorithm for weed recognition [104]. However, SVM coupled with the ANN algorithm proved inferior compared to the emerging class of deep learning models. CNN was paired with SVM because the former exhibited satisfactory results in computer pattern recognition, but unsatisfactory results in artificial differentiation of weeds. The SVM model helped to address this challenge [104]. In contrast to Tao and Wei [104], Emamgholizadeh et al. [106] proposed a three-model algorithm integrating particle swarm, integrated invasive weed optimization, and support vector for accurate weed recognition.

Drawing from the latter study, the development of algorithms for evaluating greenhouse parameters should be customized to match local conditions and requirements. The findings of Emamgholizadeh et al. [106] were corroborated by Ibrahim et al., who noted that the integrated particle swarm algorithm was ideal for selecting discriminant features [108]. On the downside, widespread adoption is constrained by a paucity of temporal data for precise predictions and training of AI and ML systems. Karnawat et al. argued that the lack of suitable historical data would be a critical impediment to the adoption of AI systems in agriculture. The latter findings contradict the positive narratives advanced by

Emamgholizadeh et al. [106] and Ibrahim et al. [108] concerning the immense potential of CNN and ANN algorithms in intelligent farming. The increased reliance on bio-inspired algorithms in crop irrigation is justified, given traditional irrigation methods resulted in a 60% waste of water resources [38]. The suitability of different algorithms in predicting the evapotranspiration rates is depicted in Table 1. The data show that ELM-GA, ELM-CSA, ELM-ACO, and ELM PFA were ideal models for determining the evapotranspiration rates, since the R^2 (coefficient of determination) values were close to unity. In addition, the relative mean, standard error, and mean of absolute value of errors (MAE) values were within the acceptable range [109]. The performance of ELM-GA/CSA/CSO/PFA raises questions on whether bio-inspired algorithms are better than traditional ones. Such concerns were informed by the study of Chahidi et al., which achieved comparable R^2, RSME (Relative Standard Mean Error), and MAE values using ANN, SVM, and Gaussian process regression techniques [110]. Following the comparison of the validation and test performance, it was deduced that the choice of ANN/SVM, GPR vis-à-vis ELM-GA/CSA/CSO/PFA should consider other variables beyond R^2, RSME, and MAE. The observations were justified by the model-specific training time and performance in the validation phase [110]. The selection of the appropriate algorithm is key to collecting reliable real-time data using sensors to help eliminate excessive waste of water, pesticides, and fertilizers.

Table 1. Evapotranspiration data collected using ELM statistical methods and bio-inspired algorithms [109].

Station/Model	Training				Validation				Testing			
	R2	RMSE	NRMSE (%)	MAE	R2	RMSE	NRMSE (%)	MAE	R2	RMSE	NRMSE (%)	MAE
		(mm d^{-1})		(mm d^{-1})		(mm d^{-1})		(mm d^{-1})		(mm d^{-1})		(mm d^{-1})
ELM	0.995	0.150	5.020	0.122	0.994	0.189	6.332	0.132	0.988	0.288	9.532	0.200
ELM-GA	0.995	0.149	4.983	0.117	0.995	0.176	5.882	0.125	0.988	0.281	9.280	0.193
ELM-ACO	0.995	0.149	4.981	0.117	0.996	0.166	5.575	0.122	0.988	0.279	9.256	0.191
ELM-CSA	0.996	0.148	4.981	0.117	0.996	0.159	5.320	0.121	0.988	0.274	9.232	0.191
ELM-FPA	0.996	0.144	4.967	0.116	0.996	0.155	5.189	0.119	0.989	0.272	9.112	0.190

AI-based irrigation techniques offer additional benefits, including reduced risk of powdery mildew and Botrytis and fungal pathogen spores caused by excess humidity in greenhouses (due to inadequate regulation of water molecule condensation during sunrise and sunset and on cold, cloudy days) [111]. Proactive prevention of crop pests and disease directly impacts crop yields, considering powdery mildew and Botrytis limit chlorophyll formation through conidia and conidiophores on the leaf surfaces. Recent advances in AI technology for agricultural production facilitated autonomous monitoring of chlorophyll formation using the SPAD value, which is a proxy measure for wavelength absorbance [112]. However, the reliability of the measurements is contingent on the chloroplast movements and light intensity.

Liu et al. [111] employed long short-term memory neural network systems to effectively manage powdery mildew in greenhouse structures. The findings reported by Liu et al. [111] were in line with the research of Abdulridha et al. [113] and other experimental studies, which supported using AI technology to prevent pests and diseases in greenhouses. In particular, Abdulridha et al. relied on UAV-based hyperspectral imaging and artificial intelligence to accurately diagnose the presence of powdery mildew [113] (see Figure 4). However, the case made by Abdulridha et al. [113] and Liu et al. [111] was not aligned with Pane et al. [114], who noted that machine learning techniques were equally effective in the management of powdery mildew.

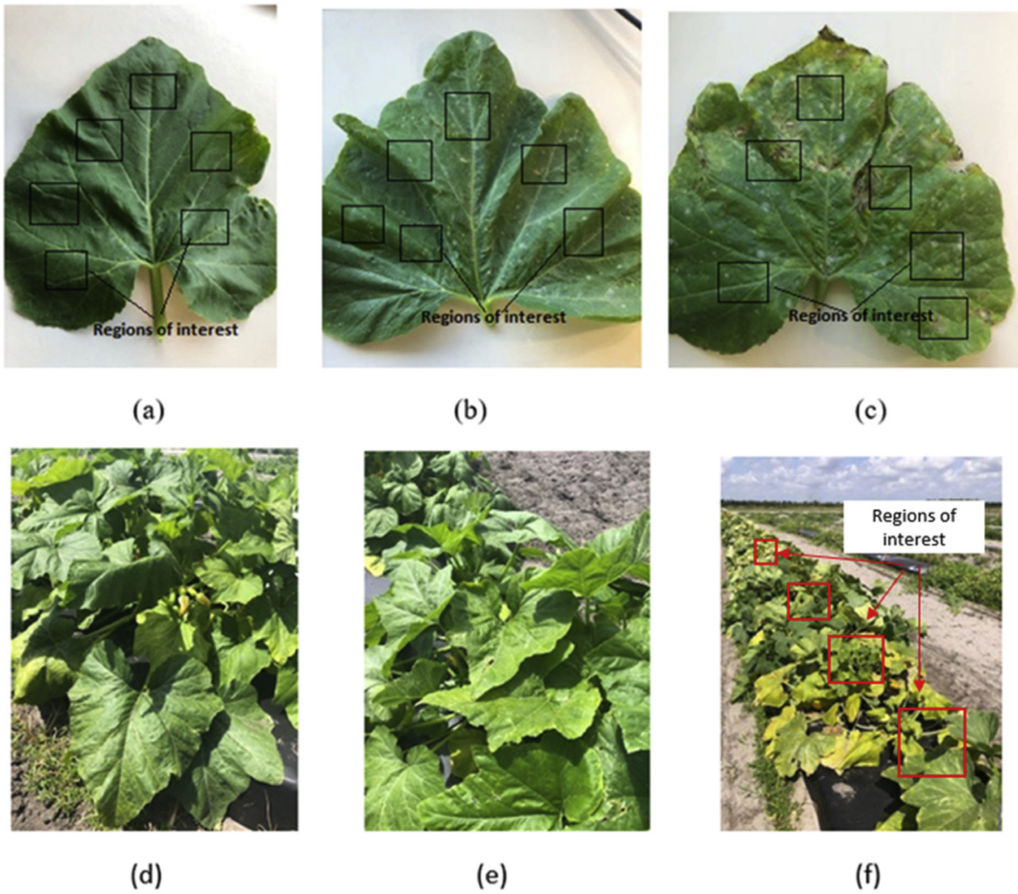

Figure 4. Hyperspectral imaging and artificial intelligence detection of powdery mildew in squash plant leaves. Images labeled (**a**–**c**) demonstrate different developmental stages of the powdery mildew disease in in-house leaves; (**e**,**f**) represent disease severity in outdoor squash plants. (**a**) Powdery mildew was not detected in the regions of interest. (**b**) Low severity of the powdery mildew disease (in-house photos). (**c**) High severity of the powdery mildew disease. (**d**) Powdery mildew was not detected in the regions of interest (outdoor plants). (**e**) Low severity of the powdery mildew disease (outdoor plants). (**f**) High severity of the powdery mildew disease (outdoor plants) [113].

The concerns raised by Abdulridha et al. [113], Liu et al. [111], and Pane et al. [114] about the reliability of the algorithms for powdery mildew diagnosis are but a microcosm of the limits of image detection techniques. Future R&D is anticipated to resolve these challenges.

2.4.1. Role of AI Technologies and Biological Pesticide Compounds in IPM

The use of AI technologies in place of chemical products (including Prestop®, Microflora PRO™, and Active Flower™) and biological powdery mildew management techniques was validated by ecological and cost considerations [115] and the mixed benefits of bio-pesticide formulations (such as succinic acid and methanolic extract of *Rosmarinus officinalis*) [96]. The case for the biological control interventions by Homayoonzadeh et al. [96] was in line with the research of Arnaouty et al. [116], which affirmed that biological control agents were effective compared to the traditional chemical agents (including Radiant 12% SC, Kanemite 15% SC and Actra 25% WG) in the management of pests, including whitefly, *Frankliniella occidentalis*, and flower thrips [116]. In addition to the superior efficacy of the biological control agents, the sweet pepper plants exhibited superior yields (35% better) following treatment with the biological control agents. Despite the positive observations made by Homayoonzadeh et al. [96] and Arnaouty et al. [116], one must acknowledge that the effectiveness of the biological control agents is contingent on the seasons and the intensity of the pests and disease. The biological control agents might be less effective if there is a high intensity of pests and diseases. Other major issues of concern with biological control agents include the mixed performance of the biological control agents.

Despite the reservations, the emphasis on biological rather than commercial IPM technicals by Homayoonzadeh et al. [96] and Arnaouty et al. [116] represents an emerging pattern in commercial agriculture, guided by the need to conserve the environment and reduce pesticide resistance—a phenomenon that is most common with commercial pesticides [75]. For example, studies conducted in the Russian Federation established that mites gradually became resistant to avermectin pesticides in the past 20 years [117]. The observations made by [117] in the Russian Federation were comparable to the research of Kirisik and Dagli's [118] and Solmaz et al. [66] in Turkey, where farmers recorded higher *Tetranychus Urtic* resistance to Bifenazate and Abamectin. The observations made by Kirisik and Dagli [118] and Solmaz et al. [66] concerning the growing pesticide resistance in Turkey were affirmed by Alpkent et al. [119], who attributed the arrhenotokous reproduction and high fecundity of *Tetranychus urticae* populations in greenhouses to acaricide resistance. However, in the latter case, the pesticides were resistant to a wide range of pesticides, bifenthrin, and hexythiazox. From a globalist perspective, *Tetranychus urticae* resistance to pesticides would create a monumental challenge for Turkey and the larger EU. Acaricides purchases represented 14% of the pesticide expenditure in the continent [120]. Higher expenditure on acaricides denotes greater dependence, which has catastrophic effects on crop yields if widespread pesticide resistance is documented.

Even though there was compelling evidence to catalyze the industry transition to biopesticides and intelligent IPM, the rate of biological agent adoption was inadequate [121]; this was despite favorable legislation and regulations, including Regulation (EC) No. 1107/2009 and 2016/2903 (RSP) [122]. Current research does not provide clear-cut reasons why biological agents have not outpaced chemical control agents in the market. On the one hand, Liu et al. attributed the phenomenon to risk aversion among farmers coupled with an unfavorable marketing environment for biological pesticides in China [121]. On the other hand, the low adoption was linked to the variable effectiveness of the biological control agents relative to chemical pesticides, and the longer duration needed to secure financial returns following years of R&D investment [123]. The operational challenges highlighted by leading biological pesticide manufacturers supported this narrative.

From another dimension, the limited uptake of biological pesticides could be linked to adopting a wide range of complementary interventions, including crop diversification and growing advocacy for pesticide-free agriculture [124,125]. Statistics compiled by the EU confirmed that farmers were assimilating pesticide-free agriculture policies; this was evident from the consistent reduction in the level of pesticide dependence—the most notable improvement was observed in the Czech Republic, where pesticide use reduced by 38% between 2011 and 2020. A similar downward trend was observed in Denmark, Portugal, and Romania, with each country recording a 20% drop in pesticide demand [120]. The pesticide use patterns documented by [120] were in agreement with Facchinetti et al. [80], who documented a marginal change in pesticide use from the 1990s to the late 2000s as a result of the stringent regulatory measures imposed by the EU, including Directive 2009/128/CE.

A contrary trend was observed in Latvia and Austria, where pesticide demand increased by 77% and 61%, respectively. In contrast to the statistics provided by Eurostat [120], Neumeister noted that EU farmers were locked into pesticide use [126], creating an eternal lose–lose situation for all stakeholders. The lose–lose situation was evident from the declining genetic diversity, impaired crop yields due to lower insect-assisted pollination, and the destruction of local ecosystems. The contrasting observations about pesticide use and the rates and barriers to biopesticide market entry affirm the complexity of phasing out chemical pesticides from the market. On a positive note, the scenario is forecasted to change with the gradual introduction of AI technologies in pest management.

Karar et al. deployed cloud-based solutions and CNN networks to target red spider, flax budworm, cicadellidae, aphids, and flea beetles [14]. Early detection of pesticides using

AI technologies would facilitate timely responses using AI and IoT infrastructure. The observations made by Karar et al. [14] were corroborated by Rustia et al., who integrated both AI and IoT systems in developing a new and intelligent system of IPM (see Figure 5). The IPM system shown in Figure 5 shows the use of sensors and image data during the data collection phase, which are then stored in a database and processed within the same server, using analytics to provide useful outputs, such as hotspot detection and other models that can aid decision-making on the farm. The system was > 90% effective in managing thrips and whitefly [57]. In both cases, intelligent IPM techniques had the potential to reduce pesticide usage, resulting in significant cost savings. However, the short-term investment costs are a major impediment [121,123]. The observations made by [60,62] reflect the broader concerns about the future of Al in agriculture highlighted by Karnawat et al. [6]. However, in the latter case, the researchers argued the challenge might be addressed by developing affordable interventions in open-source platforms to ensure higher penetration among farmers.

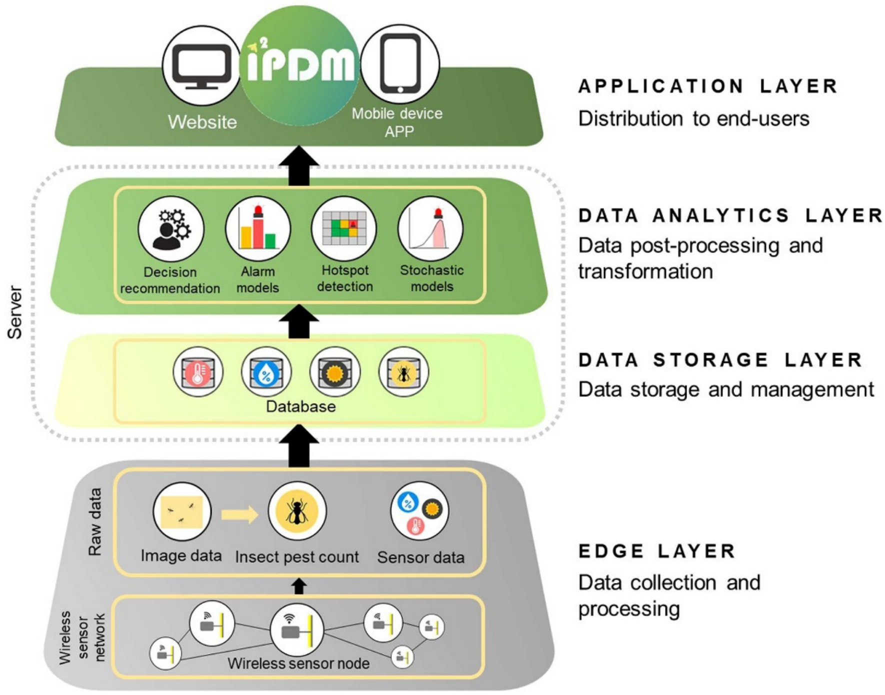

Figure 5. Key attributes of the intelligent IPM system [14].

The proponents of intelligent IPM coupled with biopesticides argue that there were immediate short-term benefits. For example, the crop yield was higher with intelligent and biological IPM compared to traditional chemical pesticides [116]. Moreover, the domino health benefits for humans and cost savings in commercial farming are unquantifiable. The latter evidence affirms there were justifiable grounds for the transition from traditional to intelligent IPM methods. The paradigm shift would benefit global agriculture, considering that pests and diseases accounted for up to 40% of global crop losses [14].

In contrast to the cost-related issues highlighted by Ni and Punja [115], continuous and excessive pesticide use has a detrimental impact on pest management, given the high risk of pesticide resistance. Pesticide resistance and incompatibility have partly led to the spread of the South American tomato pinworm *Tuta absoluta* [61] and mites. The current strains of the South American tomato pinworm can only be eradicated using strong and toxic pesticides, such as chlorpyrifos-methyl and Spinosad [61]. Even though pesticide toxicity and resistance risk can be mitigated with biopesticide formulations, adoption has remained low owing to their variable effectiveness across different classes of pests and diseases. For example, succinic acid and methanolic extract of *Rosmarinus officinalis* were only proven effective against *Aphis gossypii* in cucumber grown in greenhouses [96]. The lack of broad-spectrum biopesticides may partly explain why the demand for chemical pesticides remained unchanged; this phenomenon introduced new constraints, considering industrial greenhouses cannot be used in isolation. Glinushkin et al. proposed an alternative approach, focusing on less-potent chemical pesticides, such as Confidor Extra and Nocturne. On the downside, these pesticides were only effective against the phytoseiid mite *Neoseiulus barkeri* Hughes, and their efficacy was limited to approximately 25% [117]. According to the data in Table 2, the mortality rate for the mites was notably higher for avermectin pesticide (>93%) (see Table 2). The application of Confidor, Actellic, Scelta, and malathion did not yield mortality rates comparable to avermectin. The data suggested that pest mortality rates were proportional to the strength of the pesticides [117]. The estimates provided by [117] were comparable to experimental data drawn from Turkey [118,119]. Turkish farmers had recorded high levels of red spider mite (*Tetranychus Urtica*) resistance to Bifenazate and Abamectin (acaricides) [118,119]. Higher mite mortality rates (>90%) were observed with the adoption of aggressive pest management techniques, including mite-dipping and leaf dipping. The widespread pesticide resistance further validates the need for intelligent IPM systems.

Table 2. Potency of different classes of pesticides against mites [117].

Pesticides and Active Ingredients (AI)	Field Recommended Rates	Content of Active Ingredient, mcg/mL	Original Number Experiences (N0)	Cumulative Dead Mites (N1)	Mortality Rate (Xcp ± St), %
Pesticides used in greenhouses					
Fitoverm EC (avermectin C, 2 g/L)	1.0	20	146	9	93.7 ± 6.7
	0.2	10	208	68	33.1 ± 8.8
	0.1	5	154	27	16.3 ± 3.2
Confidor Extra, WDP 700 (imidacloprid, g/kg)	0.015	105	102	23	21.7 ± 4.0
	0.0075	525	89	16	18.2 ± 3.7
Actellic, EC (pirimiphos-methyl 500 g/L)	0.2	1000	217	86	39.5 ± 4.7
	0.1	500	260	65	24.8 ± 5.4
Novaction, WE (malathion, 440 g/L)	0.15	660	66	49	42.1 ± 7.3
	0.075	330	172	38	20.7 ± 11.5
Promising pesticides for use in greenhouses					
Scelta SC 20 (cyflumetofen, g/L)	0.2	40	104	7	6.9 ± 3.1
	0.1	20	106	7	4.4 ± 0.8
	0.05	10	79	4	5.4 ± 3.8
Nocturne, SC (pyridalyl, 100 g/L)	0.1	100	404	86	23.0 ± 8.3
	0.05	50	319	48	16.9 ± 8.2
Proclaim, WSP (emamectin benzoate, 50 g/kg)	0.2	100	158	111	70.5 ± 3.1
	0.1	50	151	62	40.7 ± 4.0
	0.05	25	68	7	9.3 ± 1.4
Oberon, SC 240 (spiromesifen, g/L)	0.05	120	136	55	42.2 ± 9.8
	0.025	60	74	18	25.9 ± 9.2
Control (water)	-	-	352	20	6.3 ± 5.3

Drawing from the IPM management practices for *Aphis gossypii* and phytoseiid mite *Neoseiulus barkeri* Hughes reported by [96,117], farmers with commercial greenhouses were faced with a dilemma. On the one hand, law regulations advocated using less toxic pesticides [127]. However, ecologically benign biopesticides were not broad-acting. On the other hand, chemical pesticides with broad-spectrum activity against pests and diseases were toxic to the environment [117,121,122,124]. In light of the critical shortcomings of traditional pesticides in greenhouse agriculture, the proactive management of powdery mildew and *Aphis gossypii*, among other pests and diseases, using AI and other smart technologies might yield enormous benefits to farmers.

Complementary techniques for disease detection are needed, considering that the research of Abdulridha et al. [113], Liu et al. [111], and Pane et al. [114] confirmed that AI-based disease detection systems had critical shortcomings. For example, the detection of powdery mildew was impacted by the UV wavelength, the camera properties, and the location of the infected leaves in relation to the non-infected leaves. The shortcomings of AI-based disease detection systems in greenhouse and open-field agriculture raise pertinent questions about sustainable IPM practices. Two theories were advanced in the literature. On the one hand, proponents of the current status quo supported the continued use of pesticides to manage aggressive pests and diseases, including *Orius laevigatus*, *Nesidiocoris tenuis*, *Tuta absoluta*, and *Amblyseius swirskii* [61]. However, persistent pesticide use increased the risk of crop pesticide resistance [61,113]. Moreover, the concentration of pesticides diminished over time, contributing to the resurgence in the population of *Nesidiocoris tenuis* (see Figure 6); this phenomenon informed the need for frequent pesticide applications.

On the other hand, the proponents of smart farming advocated using Al and IoT-based solutions in pest management. The high detection accuracy validated the case for AI in pest management. The UAV-based hyperspectral imaging and artificial intelligence system had 82% and 99% classification accuracy for the asymptomatic and late development of powdery mildew [113,127]. Asymptomatic detection was critical to the early management of crop diseases and the improvement of crop yields. In line with Abdulridha et al. [113], Pane et al. [114] demonstrated the utility of intelligent solutions in managing pests and diseases. Following delineating the cost-benefits of traditional pesticides versus smart farming solutions, the latter was encouraged despite the significant capital requirements in the short term.

In light of the unique benefits and constraints of AI-based IPM techniques, complementary solutions were needed moving forward; this view was corroborated by Agarwal and Verma's [128] assessment of pest behavior-modifying chemicals; genetic engineering and plant immunization; CRISPR-based genetic manipulation of pest populations; controlled introduction of predators, parasites, and diseases to reduce the population of plant pests and diseases; and microbial pesticides. Even though RNA interference and genome editing were supported by Agarwal and Verma [128], the gene editing of crops has not gained traction, and there is strong opposition from bioethicists [129]. The ethical concerns are valid, since CRISPR-based gene manipulation may trigger undesirable changes in the crop genome; these shortcomings validate the emphasis on AI in IPM.

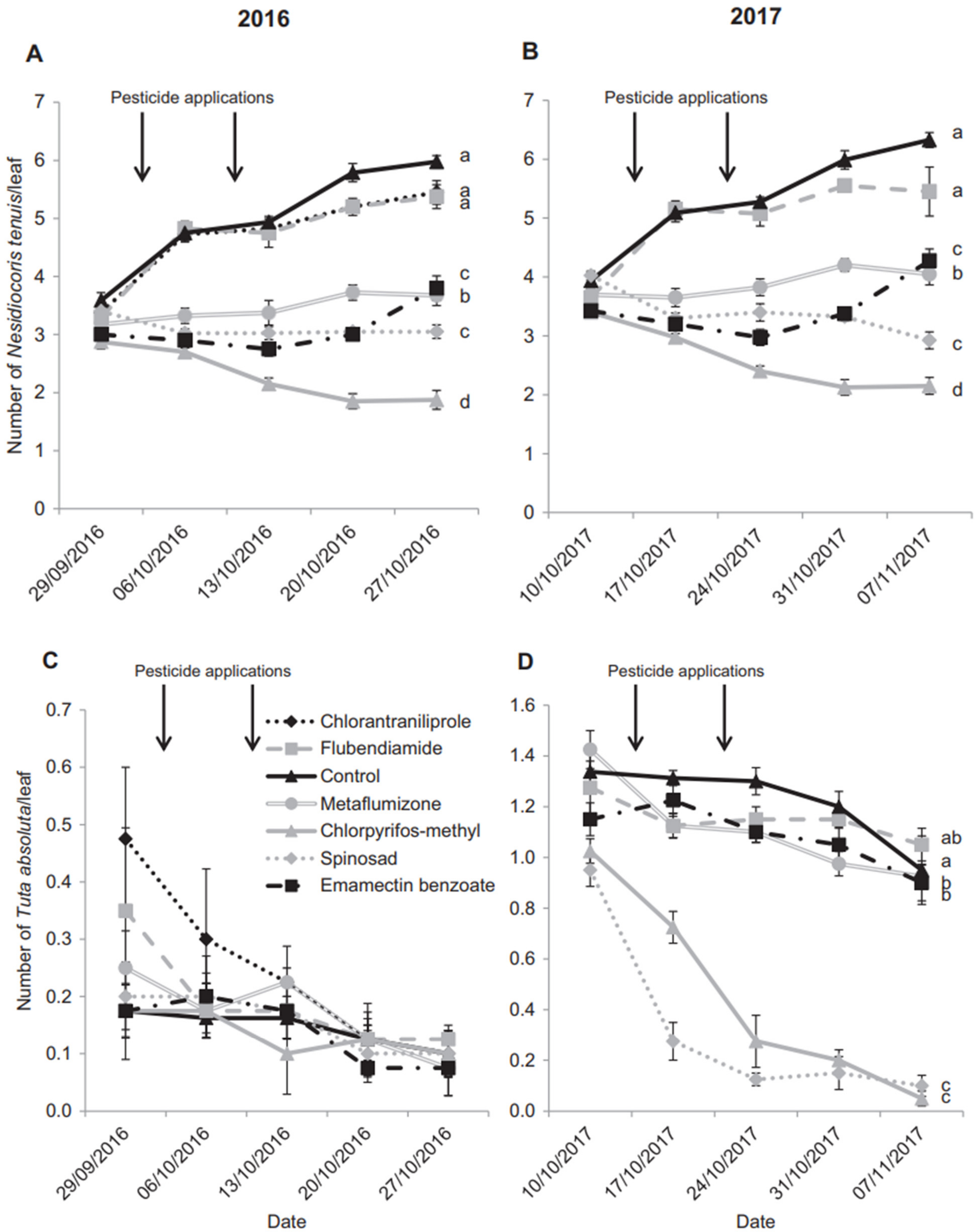

Figure 6. (**A**,**C**) show the average population of *Nesidiocoris tenuis* and *Tuta absoluta* per leaf inside a commercial greenhouse in 2016, and (**B**,**D**) show the average population of the same pests in 2017 after the pesticide was applied twice in 2016 [61].

2.4.2. Commercial Development of Robotic Systems for Smart Agriculture (Inhouse and Outdoors)

In 2022, John Deere Company (one of the world's leading farm machinery manufacturers) released fully autonomous tractors for precision agriculture featuring the next generation optical and electro-optical cameras. The cameras helped to detect obstacles and calculate distances in real time [130]. The utility of advanced computer vision systems in robotics was affirmed by Beloev et al. [131]. However, in the latter case, performance was augmented by the integration of image processing algorithms. The robotic system accurately distinguished tomatoes, leaves, and wood support structures (see Figure 7).

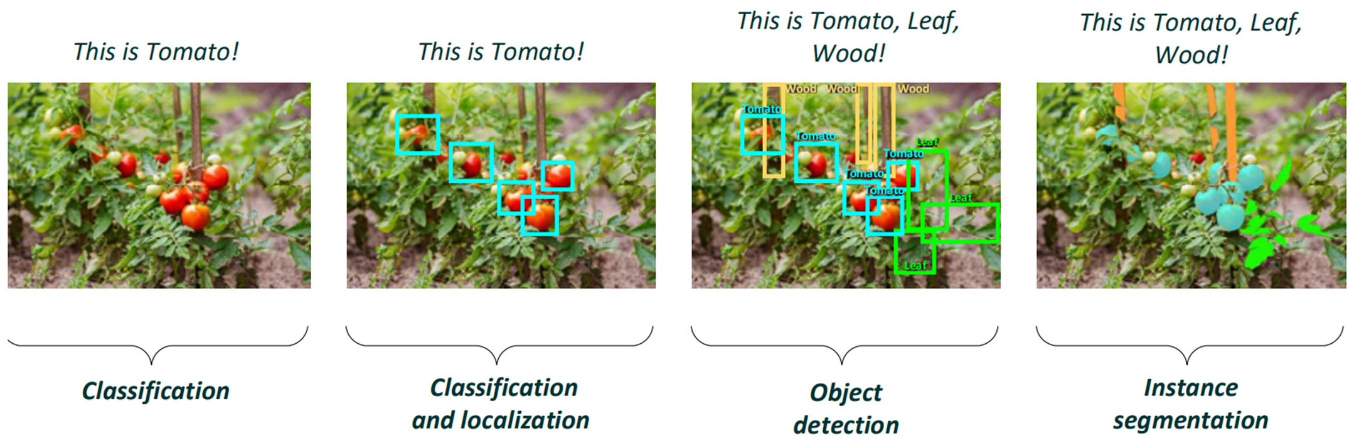

Figure 7. Object classification, localization, detection, and instance segmentation using image processing algorithms in agricultural robots [131].

Despite the milestones recorded in recent years, a major concern was the lack of consensus on the most effective method for robotic automation and mobility. Drawing from Beloev et al. [131] and John Deere [130], LIDAR and optical cameras yielded superior outcomes. However, not all scholars support the case for LIDAR and optical cameras. For example, Rahmadian and Widyartono [132] argued that satellite-differential GPS (geographic positioning systems) (S-DGPS) connected to a John Deere tractor (ground station) proved to be reliable and accurate in facilitating autonomous mobility. The John Deere-S-DGPS system had an accuracy of up to 2 cm from the target. In other cases, the robotic systems achieved an accuracy of less than a centimeter [132]. In contrast to other AI and ML systems, which recorded variable results under different environments and operating conditions, the G-DGPS had consistent accuracy in Israel, Georgia, and the US (California) [132]. The mixed observations of Rahmadian and Widyartono [132] and Beloev et al. [131] about the utility of GPS systems in agricultural robots show that contextual factors and technological improvements were important moderating factors. Additionally, one cannot disregard the legitimate concerns raised about robotic system accuracy.

The issues raised by Zha [8] concerning the inconsistent accuracy of AI systems in smart greenhouses were in agreement with Aghelpour, Bahrami-Pichaghchi, and Kisi's [133] research, which reported a low prediction accuracy for the Adaptive Neuro-Fuzzy Inference System (ANFIS) coupled with bio-inspired optimization algorithms. However, Aghelpour, Bahrami-Pichaghchi, and Kisi [133] and Zha [8] contradict Soheli et al. [134], who reported a >93.6% prediction accuracy using ANFIS and IoT. The higher accuracy reported by Soheli et al. [134] reinforces the perspectives of Howard et al. on achieving an optimal balance between scalability, computational speed, and accuracy of the AI systems.

The inconsistencies in the accuracy of ANFIS-AI systems with bio-inspired algorithms can be partly linked to the distinct operational parameters and optimum operational conditions. The later claims aligned with the research of Salam et al. [135] on optimal target identification using multiple unmanned UAVs guided by bio-inspired algorithms to identify crop diseases. On a positive note, the lower prediction accuracy reported by Aghelpour et al. [133] and Zha [8] could be resolved using digital models based on model predictive control. Howard et al. confirmed that the MPC (model predictive control) digital models improved accuracy without compromising the computational speed [136]. On the downside, the positive assessment of MPCs by Howard et al. [136] negated the fact that the classical controller systems had critical shortcomings and accurate operations depended on the mathematical models' accuracy [10]. In most cases, closed-loop control algorithms, such as MPC, may impose new constraints on manipulating variables and often on computational resources [10]. Despite the strain on computational resources, the continued use of MPC was validated by unique benefits and capabilities, including rolling optimization, which provided the operators with sufficient time to initiate inverse responses, address sensor failure, change the computing objectives, and address time delays between sensors.

The MPC system could help streamline the performance and accuracy of the UAV systems, which are affected by light intensity, soil moisture, relative humidity, pH, and the concentration of nitrogen, phosphorous, and potassium [103,113,135]. The observations made by [103,113,135] concerning the regulation of the greenhouse microclimate were in agreement with the research of Jiang et al. [137] on the factors predicting the economic return and fruit quality of greenhouse-grown-table grapes in Northern China. Proper regulation of greenhouse parameters was a key prerequisite for higher table grape yields and profit margins. The observations reinforce current research on the benefits of greenhouse microclimate control. For example, the DynaLight system and dynamic climate control in InfoGrow improved the quality of greenhouse crops [136]. Similarly to [136], Afzali et al. [11] confirmed that predictive modeling for greenhouse light management could yield significant cost savings. In contrast to [136] and Afzali et al. [11], Bersani et al. noted that cost savings in predictive modeling were largely dependent on the choice of the algorithm and MPC [138]. The latter study preferred particle swarm algorithms. On the downside, the selection of bio-inspired algorithms may not suffice to offset the existing challenges.

Even in cases where the dynamic climate control in InfoGrow was present, and it was challenging to mitigate the impact of local environmental conditions, the benefits associated with timely detection of powdery mildew and management of pests outweighed the drawbacks [13,103,111,113,135]. The variable test set accuracy (85–90%) of the Adam, RMSprop, Adamax, and Nadam optimizers depicted in Table 3 should not be perceived as a major impediment to the adoption of algorithms for smart farms [69]. The test accuracy can be improved in subsequent training of the algorithms. Moreover, new computational approaches have been employed to enhance the training and test set accuracy.

Table 3. Relationship between optimizers, learning rates, the training set accuracy, and test set accuracy [111].

Optimizers	Learning Rates	Training Set Accuracy (%)	Test Set Accuracy (%)
Nadam	0.001	96	89
Adamax	0.001	93	89
RMSprop	0.001	95	89
Adam	0.001	96	90
Adam	0.0001	89	86
Adam	0.01	91	85

3. Digital AI Models for Energy Management in Greenhouses

3.1. Energy Demand in Smart Greenhouses and Energy Optimization Algorithms

The adoption of digital models (such as MATLAB/Simulink) to regulate the insulated and transparent greenhouse microclimate is an emerging area of research [139]. The materials for greenhouse structures, such as fiberglass, PVC, polycarbonate, and reinforced plastics, had a domino effect on energy use [140]. Intelligent greenhouse structures are energy-intensive—a factor that may impede commercial adoption of AI technologies [141,142]. The claims made by [77,78] concerning the energy-intensive nature of greenhouse cultivation were in tandem with Iddio et al., who noted that energy costs accounted for 25% of the greenhouse overhead costs [10]. Energy is needed to heat and cool greenhouse structures and regulate light, humidity, and soil moisture. The disproportionate use of energy in greenhouses relative to other sectors in the agricultural industry may explain why there was renewed interest in developing the next generation of AI-based energy-saving technologies to reduce energy expenditure and improve yields.

Nguyen et al. documented various bio-inspired interventions for energy optimization in smart grids, smart homes, and the internet of energy [55]. The study suggested that swarm and evolutionary-based optimization algorithms were ideal for optimizing the use of traditional and renewable energy sources to achieve higher user comfort and energy demand aligned with the production capacity and grid demand. In contrast to Nguyen et al. [55], Zhang et al. [142] proposed an AI-based mode based on a particle swarm optimization (PSO) scheme. The latter reduced the cost of greenhouse energy through integrating photovoltaics and dynamic pricing (real-time and time-of-use). The algorithm enabled seamless communication between the external power grid (EPG) and the PV system. For example, the supply of power from the external power grid was only required when sunlight was low. If there was sufficient light and load, the EPG supply was disconnected.

In real-life greenhouse operations, the proposals made by Nguyen et al. [55] and Zhang et al. [142] may be relevant or less relevant depending on the local operating conditions, energy sources, the scale of greenhouse agriculture, and specific circumstances; this is in line with Iddio et al. who recommended the use of evolutionary algorithms to address the shortcomings associated with proportional–Integral–derivative (PID) control of greenhouse structures. Traditionally, PID was preferred owing to its great performance, simplicity, and flexibility [10]. However, there were certain tradeoffs, including time-consuming computing and the inability to handle abrupt and external disturbances [10]. The case for the PID greenhouse control strategy advanced by [10] corroborates [20], who noted it was a low-cost alternative. However, there were alternative systems with comparable performance, including GA-based model predictive control systems. The PID-related shortcomings partly explain why AI bio-inspired algorithms, such as EA (Evolutionary Algorithm), were used to modify PID controllers in greenhouses.

Similarly to Iddio et al. [10] and Zhang et al. [142], Jia et al. [143] confirmed that bio-inspired algorithms, particularly adaptive chaotic ACO algorithms, could achieve significant energy savings. However, the use of bio-inspired algorithms to reduce energy demand in isolation would not suffice, considering energy expenditure in greenhouses was a complex non-linear, multi-input and output process; this may explain why CFD (computational fluid dynamics) modeling coupled with mathematical transformations and systematization of greenhouse design parameters were appealing alternatives [144–146]. Rasakhodzhaev et al. employed mathematical models in the design of adjustable solar greenhouse structures with optimal height for better regulation of heating and cooling. In contrast to Zhang et al. [142] and Jia et al. [143], Chen et al. [144] employed computational fluid dynamics to regulate surplus air thermal energy in greenhouses. The data were employed in the operation of the fan-pad evaporative cooling system. Even though the latter system did not rely on bio-inspired algorithms, it demonstrated the effectiveness of modeling and simulations in regulating greenhouse cooling. In line with Chen et al. [144], Mirzamohammadi et al. demonstrated the effectiveness of mathematical simulations using the Monte Carlo model. However, the effectiveness of the modeling system was largely dependent on the level of uncertainty.

The ACOA proposed by Jia et al. [143] regulated energy demand in smart sensor networks. However, it remained unclear whether the optimal performance of the bio-inspired algorithms in controlled environments would yield satisfactory performance in real-world scenarios. Such concerns were premised on the fact that the performance of the bio-inspired algorithm was influenced by the dynamic relationship between biological interactions and physical conditions (atmospheric, weather, soil, and humidity). The concerns raised by Jia et al. [143] were partly in agreement with the assessment by An et al. [147] of system optimization under non-deterministic weather conditions. The unpredictable weather patterns impaired the performance of sensors and actuators for heating, lighting, and CO_2 dosing and the development of a climate and irrigation strategy.

3.2. Alternative Energy Saving Measures—LoRa Transmission, PCOA-Lighting Management, PCMs, and LEDs

Drawing from earlier case study data, the pilot experiments may not be practical for regions with diverse climatic conditions and unique energy requirements. The above concerns partly contributed to the diversification of AI approaches for energy management. In the meantime, the researcher posits that it would be prudent for smallholder farmers to make incremental changes for better energy management; these may include selecting connectivity technologies with lower energy requirements. For example, a comparison of LoRa, Wi-Fi, Bluetooth, ZigBee, mobile, and RFID technologies established the following. Leading connectivity technologies for AI systems with higher transmission ranges (20–100 m) had higher energy input requirements; Wi-Fi is a case in point. In contrast, LoRa had very low energy requirements and high transmission ranges (<30 km) [148]. The claims made by Bersani et al. [148] on the low energy requirements were in tandem with Placidi et al. [84], who noted that the system's typology reduced the energy demand while enhancing data transmission over long distances. Beyond the selection of communication channels, Bersani et al. [138] reported 54% to 83% energy savings in incandescent and fluorescent lamps after incorporating a parallel particle swarm algorithm for optimal location of lighting.

The case for LoRa networks in agriculture made by Bersani et al. [148] and Placidi et al. [84] aligned with the research of Chen et al. [149] on the market integration of LoRa technology in greenhouses. In one case, the LoRa transmission module was used to transfer data collected from sensors to the Raspberry Pi (single-board computer). In contrast to Chen et al. [149], Henningson [150] observed that the accuracy of the Raspberry Pi system was higher when paired with Canon camera systems to improve the resolution of the images detected. After integrating the two systems, each plant had a resolution of 0.006 pixels. On the downside, farm-based data show that high transmission ranges and low energy requirements of LoRa did not automatically translate to greater commercial adoption in relation to -Fi, Bluetooth, ZigBee, mobile, and RFID. For example, Siskandar et al. [151] preferred fuzzy-guided RFID-based communication channels for smart greenhouses featuring DHT22/ DS18B20 sensors for temperature and humidity regulation. In contrast to Chen et al. [149], Bersani et al. [148], and Placidi et al. [84], Mu et al. [152] and Elsayed et al. [153] recommended alternative methods for managing energy resources, including the use of phase change materials for energy conservation and agricultural residue to generate biofuels and energy. However, the application of PCMs recommended by Mu et al. [152] represents but a tiny fraction of the potential applications in smart farming. For example, Kong et al. [154] noted that PCMs were appropriate materials for cold chain logistics [154]. However, not all scholars support the use of PCMs in greenhouses and related applications due to the high risk of leakage during the phase change process [155]. The researcher supports the use of PCMs, considering they can be coupled with solar systems for maximum energy saving.

On the downside, incremental changes, such as selecting less energy-intensive communication systems, cannot suffice; they must be paired with other interventions, including the adoption of renewable energy systems in greenhouses [156,157]. Solar and geothermal energy are the most viable renewable energy systems [158]. Even though the transition to renewable energy was widely encouraged, the reliability of the energy source was not guaranteed, especially in regions with intermittent solar radiation [159]. Even in regions where the supply of solar energy was guaranteed, mass utilization of renewable energy resources was a challenge, owing to the significant disconnect between the use of AI in the greenhouse and the deployment of AI in energy saving; this was a paradoxical phenomenon, considering smart greenhouses (featuring predictive light control systems) could reduce energy expenditure by 14–33.85% [11]. The improvements in lighting achieved by [11] were in tandem with [58], who documented a 19.4% cost saving following the introduction of a predictive control strategy and innovative greenhouse lighting system. The light prediction model is illustrated in Figure 8.

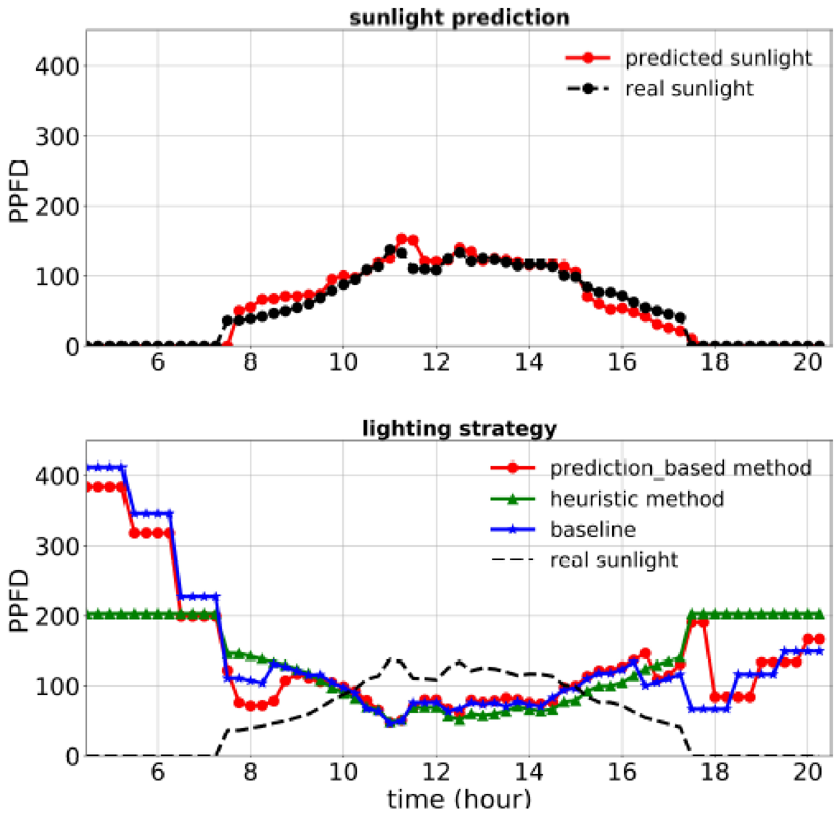

Figure 8. Sunlight prediction models and lighting strategies for the predictive light control systems [11]. PPFD was measured with units of μmoL m^{-2} s^{-1}.

Following the comparison of the heuristic versus application-specific models, the former yielded accurate predictions with minimal variations from the baseline. Beyond the lower prediction accuracy, the case against the heuristic systems was further corroborated by the high cost of heuristic-based predictions compared to the prediction-based method (PBM). On average, the heuristic-based predictions cost \$5.96/m^2, while the PBM cost \$0.73/m^2 per day [11]. The notable disparities in the cost validate the PBM approaches.

Proper energy management in greenhouse structures remained a priority, considering that the current rates of energy expenditure were unsustainable in the long term. For example, US-based greenhouse operators utilize \$600 million worth of electricity per year [160]. Regulating energy use using AI was a practical option, since small-scale and large commercial farms had to spend additional resources on IPM. On average, US farmers spend \$1 billion on pesticides per year. Similarly, commercial farming in Europe was pesticide intensive—farmers utilized an estimated 346,000 tons of pesticides in 2020 alone [120]; nearly half of the expenses were on fungicides and bactericides.

4. Barriers to Incorporating Artificial Intelligence Technology in Smart Greenhouses

Current research on AI and IoT in agriculture advances distinct claims on the potential barriers to incorporating AI technology in smart greenhouses. One school of thought claimed that the inconsistent adoption of AI could be linked to the slow commercialization of R&D innovations, barriers to technology acceptance, and information asymmetry. This school of thought was corroborated by Zha [8] and Senavirathne et al. [13]. The second school of thought suggested that demographics were a major determinant. Research from Europe suggested that demographics directly affect progressiveness and technology adoption in agriculture [67,161]. Younger generations are more highly motivated to adopt new farming technologies than older generations. In contrast to the scenario observed by [67,161] in Europe, Asian studies highlighted the aging of the population as a barrier [162]. Drawing from the latter studies, each continent had unique barriers and drivers for precision technology adoption in greenhouses.

The issues raised by Zha [8] and Senavirathne et al. [13] concerning the pace of technology adoption were discounted by emerging research on the immense benefits of augmented reality, such as the GRETA application in promoting technology adoption among hobby farmers, and those with limited knowledge about farming technologies, and even professional farmers using unique human-computer interactions [24]. The case for AR advanced by [24] corroborates Yaqot and Meneses's study [163], which noted AR would help transform rural and novice farmers into experts while providing agronomists with a real-time and holistic view of farm and crop health. The benefits afforded by AR-based systems such as GRETA suggest that poor understanding of technology should not be an impediment to the automation of greenhouse operations.

The low pace of AI technology adoption in the global agricultural sector has remained unresolved. For example, the first AI-powered system for agriculture was the GOSSYM cotton crop simulation model developed in 1985 to regulate water and fertilizer application, weed control, and local climate for better cotton yields [8]. The GOSSYM model was key to developing the Artificial Intelligence Automated Greenhouse System (AIAGS), processing systems, and web applications [13]. On the downside, there was limited R&D in the subsequent years to build on the GOSSYM model. In 1996, researchers developed an autonomous AURORA greenhouse robot to replace manual labor. The historical slow adoption of precision farming technologies documented by [8,13] was in line with Maloku's appraisal of precision farming technology integration in the US and EU [71]. Until the late 2000s, only 22% of the farmers had integrated precision farming technologies in the West [71]. On a positive note, there was a notable improvement in the pace of technology adoption post-2013. In the past two years, researchers have developed multi-application AI systems for intelligent IPM [15,86,128], seeding and harvesting, and weed recognition [104,105], and digital twins for autonomous greenhouse operation using traditional sensor data, IoT, big data analytics, and AI [136]. However, the pace of R&D innovations does not match commercial adoption—the digital twin-based GHI4.0 project in the Danish horticultural industry was in the pilot phase. On a positive note, 80% of Danish farmers attempted to integrate precision farming technologies in the production of maize and barley crops [71].

Presently, it is challenging to determine the cost-benefits of technological innovation and underlying motives for the transition to AI in agriculture [18]. For example, even though digital twins offer immense potential to balance accuracy, accuracy, and computational speeds in agriculture, there are limited data on their applications. Howard et al. noted that "state-of-the-art for DTs is limited to specific sub-processes modeled with highly specialized models" [136] (p. 7). Further experimental data on the cost-benefits of digital twins was needed before deploying the systems in greenhouses to simulate and optimize production. The issues relating to digital twins are but a microcosm of the broader gaps in the body of knowledge, which does not sufficiently delineate the impacts of AI and IT in agriculture. Drawing from experimental data compiled by researchers in Europe, North America, and Asia [86,90,104,105,108], there were region-specific barriers and enablers for AI integration in agriculture depending on the pace of knowledge and technology transfer.

The intermittent integration of R&D innovations could be due to the higher costs, knowledge and resource gaps between advanced and developing countries, the inability to entirely replace human labor on farms with robots, and variations between the simulated and actual outcomes in the field/smart greenhouses [8]. The criticism of AI systems in smart greenhouses and farms by [8] was corroborated by Beloev et al. [131], who claimed that mechanical robots were unreliable because they relied on satellite triangulation to guide movement—this technology was less reliable compared to LIDAR and camera sensor innovations. On a positive note, the constraints associated with satellite triangulation have been addressed using light imaging, detection, and ranging (LIDAR) optical and electro-optical cameras [131]. The advances highlighted by [131] were consistent with [162], which noted that algorithm systems had led to the development of advanced sensor systems, including fusion algorithms that facilitated the separation of colors into the hue, saturation, and value formats. However, the case for electro-optical cameras made by [131,162] was not in line with the research of Saddik et al. on latency issues in an image collection using multispectral cameras [164]. The latter concerns reinforced the case for LIDAR systems in agricultural robots [162]. The technology milestones in robotics shaped industry trends in the adoption of robotics for harvesting and greenhouse management.

4.1. Training and Test Accuracy of AI Systems in Smart Greenhouses and Precision Agriculture

The inclusion of different computational methods to attain higher accuracy rates was confirmed by Siskandar et al. in their assessment of the fuzzy logic system's accuracy (~95%) in smart greenhouses (see Table 3) [151]. Even though the observations of Siskandar et al. were specific to the long short-term memory neural network for predicting the occurrence and development of powdery mildew in greenhouse cucumber plants, they were relevant to other AI systems for greenhouses. On the downside, these claims contrast with Lakshmi and Corbett [15], who argued the current barriers to technology adoption must be resolved.

Traditionally, it was challenging for Al systems to reconcile the images and measurements taken under controlled conditions with those in the field due to variations in the background complexity, imaging angle, and interferences in the natural environment. The constraints have been partly resolved with bio-inspired algorithms customized for fault prediction, image recognition, and pest identification [165,166]. The use of AI to prevent root rot diseases and fusarium wilt among cucumber plants in greenhouses was a case in point [167]. The broad application of IoT, machine learning (ML), and artificial intelligence (AI) in agriculture can be partly linked to technological advances in computing.

4.2. Impact of Demographics and Socioeconomic Factors on AI Technology Adoption in Agriculture

The shortage of young, progressive EU farmers raises legitimate concerns regarding the actualization of Eurozone agricultural innovation policies, and by extension, the ability to sustain higher food demands [67]. The issues raised in the European Economic and Social Committee's report [67] were partly in line with Mohr and Kühl's research in Germany, where age predicted technology adoption [161]. For example, smartphone use and access decreased with age among the German farmers sampled. Similarly to Mohr and Kühl [161], Maloku [71] noted that less educated and older farmers were less inclined to adopt precision farming technologies. However, the observations by Mohr and Kühl [161] concerning the rate of technology acceptance in agriculture were not aligned with the European Economic and Social Committee's report [67]. Most of the sampled German farmers were young (mean age = 33 years), and there was more than an 80% assimilation of smart farming technologies among old and young farmers. The contrasting observations from Mohr and Kühl and the European Economic and Social Committee's report raise fundamental questions on whether demographics were a barrier to adopting AI on smart farms across Europe and the world.

In contrast to the European Economic and Social Committee's report [67] and Mohr and Kühl [161], Maloku [71] claimed multiple externalities aided and impeded smart farming technology adoption; these variables included farm size, financial status, technology factors, information resources, social, economic issues (age, experience, and education), and farm size. The latter argument provides a more representative picture of the dynamics that led to higher or lower technology adoption that is more applicable to developing and developed countries in the North and the South [137]. Further research on the role of demographics, farm size, financial status, technology factors, and information resources was necessary, considering achieving and sustaining exponential growth in AI technology adoption in agriculture is a prerequisite for tangible global impact on crop yields, pest and disease management, and optimization of agricultural resources [168].

Despite the overwhelming evidence in support of AI, particularly robotics in harvesting, critics argue that AI cannot entirely "replace/replicate humans. Machines do not have the multi-perspective skills of humans, as they are typically programmed to perform specific tasks in constrained conditions” [69] (p. 9). The issues raised by [69] do not consider recent milestones with bio-inspired algorithms that improved the precision and reliability of AI and ML infrastructure in agriculture [169]. The use of bio-inspired hybrid algorithms for weed optimization was a case in point [14,105,135]. The role of AI algorithms highlighted by [14,105,135] was corroborated by Beloev et al. [131], who used image processing algorithms to improve the ground-based accuracy of a robotic system.

The selection of advanced algorithms, including Hierarchy/Hybrid Particle Swarm Optimization (HPSO), Grey Wolf Optimizer (GWO), Evolutionary Algorithm (EA), Direct Artificial Bee Colony (DABC), and Hybrid Genetic Algorithm with Particle Swarm Optimization (GA-PSO) among others involves a tradeoff between computational speed, path planning, fitness, root means squared, and mean absolute errors [85]. For example, the ANN algorithm had lower MAE and RSME values compared to the GEP testing and training evolutionary algorithm (see Table 4). However, the ANN required higher computational resources [14,170]. On a positive note, the technical constraints were short-term and should not be considered a critical impediment to the adoption of AI systems.

Table 4. Gene expression programming (GEP), ANN RSME, and MAE [85].

	ANN Testing	ANN Training	ANN CV	GEP Testing	GEP Training	GEP CV	
RMSE	0.070	0.068	0.070	0.095	0.091	0.095	
r-RMSE	13.07%	12.67%	14.25%	17.87%	17.13%	19.42%	
MAE	0.052	0.051	0.052	0.070	0.066	0.068	
Stage 2	0.933	0.969	0.968	0.970	0.930	0.930	0.943
RMSE	0.050	0.053	0.049	0.077	0.078	0.069	
r-RMSE	3.33%	3.47%	3.26%	5.06%	5.10%	4.57%	
MAE	0.039	0.040	0.038	0.058	0.058	0.054	
Stage 3	0.840	0.910	0.912	0.922	0.848	0.853	0.857
RMSE	0.087	0.086	0.081	0.114	0.113	0.113	
r-RMSE	3.44%	3.43%	3.18%	4.51%	4.48%	4.41%	
MAE	0.067	0.067	0.063	0.088	0.086	0.089	
Stage 4	0.849	0.911	0.908	0.911	0.860	0.856	0.843
RMSE	0.086	0.091	0.083	0.109	0.113	0.110	
r-RMSE	2.44%	2.58%	2.38%	3.09%	3.23%	3.17%	
MAE	0.063	0.065	0.061	0.087	0.090	0.091	

Beyond the technically related barriers to the widespread adoption of AI systems in smart farming, there were emerging concerns about the impact of farmer demographics on the adoption of AI systems. For example, the aging of the farmers was a major issue in Europe [67,161]. In light of the observations made by critics and proponents of AI in smart greenhouses and precision agriculture, the following fundamental issues emerge. First, AI technology critics negate smart agriculture’s immense contribution to farming. Second, the proponents of AI technology disregard the enormous capital requirements and the barriers to technology transfer in developing countries. On a positive note, there were successful cases in the developing countries in the global south. For example, Ethiopian scientists had developed an ERNN system to monitor humidity and temperature variations in greenhouse structures; the system had additional capabilities for wind velocity and carbon dioxide concentration measurement [170]. Proper temperature regulation and monitoring were necessary, considering a majority of the greenhouse crops; tomatoes were particularly susceptible to temperature variations [171]; the effect of chilling stress on greenhouse tomatoes in China was a case in point [171]. In practice, incorporating artificial intelligence technology in smart greenhouses should be supported by prior data on actual farm applications and short and long-term benefits vis-à-vis the costs and potentially detrimental environmental impacts.

The dynamic natural and physical conditions (including atmospheric, weather, soil, and humidity) and biological interactions between plants, pests, and diseases in greenhouses and open-field agriculture increase the complexity of the decision-making processes [6,15,57]. The sophisticated relationship between these variables would predict the utility of AI in agriculture and agricultural sustainability. On a positive note, emerging research on bio-inspired algorithms and selected applications of AI systems in agriculture confirmed that the benefits outweighed the risks [14,108,121]. Moreover, the ongoing R&D projects would resolve most of the shortcomings.

4.3. Sensor Signal Failure and Communication Barriers

The growing advocacy for the integration of AI in precision agriculture negates the technology-related challenges to commercial adoption. Singh et al. established that interferences often compromised communication between sensor nodes. There were multiple sources of interferences for sensor signal transfer in greenhouses, including crop canopy, soil, and temperature [87,164]. Similarly to Singh et al. [87], Shamshiri et al. [78] observed that the accuracy of the soil moisture sensors was notably low in regions with high vegetative diversity. Sensor accuracy was impaired by different hydrological properties and geography, especially in real-world conditions dissimilar to the training datasets. On a positive note, most of the constraints identified by Singh et al. [87] and Shamshiri et al. [78] have been addressed using AI technologies. In particular, Vanegas-Ayala et al. demonstrated the importance of fuzzy clustering techniques in the humidity prediction modules. The fuzzy logic controllers enabled the AI systems to model and predict the behavior of key greenhouse parameters. The system was appealing to the farmers because it was inexpensive and easy to use. A major concern was that these issues were often disregarded in research in favor of the mass transition to an intelligent greenhouse system.

The risk of impaired transmission identified by Singh et al. [87] may be resolved using the hardware configuration proposed by Serale et al. [58]. The configuration featured Siap+Micros t055 pyranometers and Apogee SQ-515 Quantum sensors with a 1.2 mV sensitivity of 1.2mV. The configuration proposed by Serale et al. [58] bears semblance to Afzali et al., who deployed Apogee instruments to measure the photosynthetic photon flux density (PPFD) over the plant canopy in a greenhouse structure [14]. The observations made by Serale et al. [58] and Afzali et al. [11] do not take into account the variable accuracy of the Apogee solar radiation sensors. According to Zamora-Izquierdo et al., the Apogee sensors had a mean accuracy of ±5% [172]. The accuracy of the sensor systems could be enhanced using the Remote Sensing Assisted Control System (RSCS), which offered multidimensional benefits, including the measurement of CO_2 emissions, soil moisture, irrigation control, and agricultural production capacities.

New experimental data have confirmed that using plastic mulches with sustainable remote sensing and AI technology systems is practical. In particular, Jim et al. [173] reported the successful use of Landsat-5 thematic mapper and hyperspectral airborne sensors to map plastic mulched farmlands and plastic-covered greenhouses. The data were, in turn, employed to identify regions where plastic mulches can be gradually replaced with biodegradable alternatives. The claims made by Jim et al. [173] concerning the role of technology in mapping plastic mulches were in tandem with Hasituya et al., who deployed remote-sensing aperture radar systems to map plastic mulches [174].

5. Future Perspectives

The critical review of the current body of knowledge supporting the integration of AI systems in agriculture yielded new insights and perspectives on how best to enhance the efficiency of smart greenhouses. However, certain issues should be addressed in upcoming studies. For example, the current body of knowledge did not establish a consensus on whether automated agricultural machinery manufacturers and commercial farms should transition from satellite triangulation to light imaging, detection and ranging (LIDAR), optical and electro-optical cameras [131], or Satellite-Differential GPS (S-DGPS). The mixed observations by Beloev et al. [131], John Deere [130], and Rahmadian and Widyartono [132] warrant further research inquiry considering there were different technical requirements for open space and indoor (greenhouse) robotic systems. Future research on LIDAR and optical camera systems for open space and greenhouse robotic tractors would provide better insights into the cost-benefits of available technologies to guide commercial adoption. Empirical and farm-based data are important, considering John Deere and other companies were commercializing new autonomous tractor models fitted with optical cameras [130,132]. Moreover, there was a growing acceptance of soft robotic systems for fruit and vegetable harvesting and pesticide application.

Beyond systems for robotic structures, current data on the suitability of different variants of bio-inspired algorithms (swarm intelligence, genetic and evolutionary) for pesticide application, and robotic harvesting, automated regulation of irrigation, soil treatment, fertilizer application, and seeding are specific to the Global North [105,135]. Future research should explore the suitability of bio-inspired algorithms to support the automation of greenhouses in developing countries. Isolated case studies of milestones in developing countries support the recommendation. For example, ERNN systems augmented temperature and humidity measurements in Ethiopia's greenhouses [170]. However, there were gaps in the knowledge, which may impede decision-making among stakeholders in the future. Future research should investigate whether the LoRa, Wi-Fi, Bluetooth, ZigBee, mobile, or RFID communication technologies were best suited for specific bio-inspired algorithms and the influence of local conditions and variables on performance and accuracy. At present, researchers are focusing on different algorithms to refine algorithm performance. For example, most studies focused on solar radiation intensity, transpiration, and CO_2 concentration to predict crop yields, even though the approach yielded inaccurate results [18]. The standardization of input variables would improve accuracy and performance. Upcoming studies should help establish whether intelligent IPM was a sustainable alternative to traditional chemical pesticides and biopesticides, considering pesticide resistance and the need to adopt sustainable agricultural practices.

Additionally, there is a growing demand for technological solutions to address climate change and global food insecurity, which urges the integration of AI technologies like light imaging, detection and ranging 1128 (LIDAR), optical and electro-optical cameras [131] or satellite-differential GPS (S-DGPS). Apart from the technological aspect, there is also a need to develop agricultural production policies that favor the funding of these technologies and their integration to agricultural production. Such policies can include setting aside grant funds for institutions and companies involved in their development. Such policies should also include solving the cost barriers that have consistently been highlighted in previous research. Most studies have also demonstrated the potential application of AI in large scale agricultural production. Policy incentives to facilitate their integration in small-scale farming may also encourage younger populations to participate in agricultural production, because most farmers today in Europe and North America are older. If the problem is not addressed in a timely manner using potential technological solutions, the issues of food insecurity are likely to worsen in the future.

6. Conclusions

The findings drawn from this research had practical consequences for commercial agriculture, considering a large body of knowledge focused on applying AI and IoT in traditional applications, and the emphasis on the benefits of the technology negated critical concerns about energy demand, sensor failure, accuracy, and long-term use. The findings broadened current knowledge on the cost benefits of sensors, robotic systems, algorithms, renewable energy systems for greenhouses, and support infrastructure. For example, users of soil and humidity sensors paired with fuzzy clustering techniques in the humidity prediction modules should be conscious of the fact that the accuracy of the measurements may be impaired by corrosion or hardware malfunction. Additionally, the new generation of new agricultural robotic systems largely depends on replacing GPS systems with LIDAR and optical camera systems, given the former exhibited poor object recognition. The performance of LIDAR systems was enhanced with image processing algorithms.

The commercial readiness of AI technologies was demonstrated by John Deere company, Blue River Technology, Autonomous Tractor Corp, and other companies that had developed intelligence systems for monitoring crop and soil health, weed control, and self-driving agricultural tractors. Despite the commendable milestones achieved so far, there were multiple barriers to the use of the technology. The barriers included the cost of AI technology, variable performance of the algorithm in real-world conditions vis-à-vis training, the financial status of the farmers, lack of information resources, aging, and lack of prior experience with technology. Despite the shortcomings, adopting AI systems should be encouraged, given they improved crop yields, water use, and fertilizer use efficiency, and reduced the effects of pesticide resistance through intelligent IPM. Moreover, bio-inspired algorithms improved energy management by integrating photovoltaics and dynamic pricing and autonomous communication between the greenhouse system and EPG supply. The emerging climate change risks further reinforce the case for smart greenhouses powered by AI systems.

In summary, most AI applications in agricultural production are in the development phase because they have not fully matured for commercialization purposes. The few AI solutions that have so far reached maturity and have been rolled out for commercial use despite challenges (e.g., accuracy) include the use of drones, sensors, and robots for harvesting crop yields. Although these technologies have been applied commercially, the challenge of accuracy and sustainability persists. For example, underground sensor hardware can be damaged by moisture and other unpredictable environmental conditions, leading to inaccurate data, which can easily mislead decisions in commercial farms, leading to huge losses. Therefore, although they have reached the commercial maturity, they still need further development to optimize their effectiveness in solving the identified problems and challenges. Furthermore, considering that many studies are currently being undertaken on this topic, it is also imperative to perform a similar mapping of the literature every three years to determine the current state of the art from time to time, because technological advancements are fast and imminent. Finally, more research is needed on overcoming the challenges of integrating AI applications into farm input in the Global South, which must include solving the cost barriers and knowledge and skills gaps.

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Abbreviations

AI	Artificial intelligence
AIAGS	Artificial Intelligence Automated Greenhouse System
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
CEA	Controlled environment agriculture
CFD	Computational fluid dynamics
CNN	Convolutional Neural Network
DABACA	Dynamic Artificial Bee-Ant Colon Algorithm
DSS	Decision support systems
EA	Evolutionary Algorithm
ERNN	Elman Recurrent Neural Network
GA	Genetic Algorithm
GPS	Geographic positioning systems
GVA	Gross value added
IoT	Internet of things
IPM	Integrated pest management
ITU	International Telecommunication Union
LIDAR	Light imaging, detection, and ranging
LSTM	Long short-term memory (LSTM) networks
MAE	Mean of absolute value of errors

ML	Machine learning
MPC	Model predictive control
PBM	Prediction-based method
PID	Proportional-integral-derivative
PPFD	Photosynthetic photon flux density
PSO	Particle Swarm Optimization
RFID	Radiofrequency identification
RNN	Recurrent neural network
RSCS	Remote Sensing Assisted Control System
RSME	Relative standard mean error
S-DGPS	Satellite-differential geographic positioning systems
SVM	*Support-vector machines*
UAV	Unmanned aerial vehicle
VAR	Variable rate application
WSAN	Wireless sensors and actuators networks
WSN	Wireless sensor network

References

1. Ruan, J.; Hu, X.; Huo, X.; Shi, Y.; Chan, F.T.S.; Wang, X.; Manogaran, G.; Mastorakis, G.; Mavromoustakis, C.X.; Zhao, X. An IoT-based E-business model of intelligent vegetable greenhouses and its key operations management issues. *Neural Comput. Appl.* **2020**, *32*, 15341–15356. [CrossRef]
2. Ewees, A.A.; Sahlol, A.T. Bio-Inspired Optimization Algorithms for Improving Artificial Neural Networks: A Case Study on Handwritten Letter Recognition. In *Computational Linguistics, Speech and Image Processing for Arabic Language*; World Scientific: Singapore, 2017; Volume 4, pp. 249–266.
3. Jellason, N.P.; Robinson, E.J.Z.; Ogbaga, C.C. Agriculture 4.0: Is sub-Saharan Africa ready? *Appl. Sci.* **2021**, *11*, 5750. [CrossRef]
4. European Institute of Innovation and Technology (EIT). *Emerging AI and Data Driven Business Models in Europe*; European Institute of Innovation and Technology (EIT): Budapest, Hungary, 2021; pp. 1–65.
5. Munoz, J.M. AI in Agriculture: Is the Grass Greener? California Management Review. 2020. Available online: https://cmr.berkeley.edu/2020/03/ai-agriculture/ (accessed on 25 June 2022).
6. Karnawat, M.; Trivedi, S.K.; Nagar, R. Future of AI in Agriculture. *Biot. Res. Today* **2020**, *2*, 927–929.
7. Cuffaro, N.; Prota, L.; Bertini, R. Are Large-Scale Land Acquisitions in Africa Pro-development? A Network Analysis of FDI in Land and Agro-industry BT—The Palgrave Handbook of Africa's Economic Sectors. In *The Palgrave Handbook of Africa's Economic Sectors*; Wamboye, E.F., Fayissa, B., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 87–116.
8. Zha, J. Artificial Intelligence in Agriculture. *J. Phys. Conf. Ser.* **2020**, *22*, 1693. [CrossRef]
9. Cama-pinto, D.; Holgado-terriza, J.A.; Damas-hermoso, M.; Francisco, G.; Cama-pinto, A. Radio Wave Attenuation Measurement System Based on RSSI for Precision Agriculture: Application to Tomato Greenhouses. *Inventions* **2021**, *6*, 66. [CrossRef]
10. Iddio, E.; Wang, L.; Thomas, Y.; McMorrow, G.; Denzer, A. Energy efficient operation and modeling for greenhouses: A literature review. *Renew. Sustain. Energy Rev.* **2020**, *117*, 109480. [CrossRef]
11. Afzali, S.; Mosharafian, S.; van Iersel, M.W.; Velni, J.M. Development and implementation of an IoT-enabled optimal and predictive lighting control strategy in greenhouses. *Plants* **2021**, *10*, 2652. [CrossRef]
12. Haque, M.A.; Haque, S.; Sonal, D.; Kumar, K.; Shakeb, E. Security Enhancement for IoT Enabled Agriculture. *Mater. Today Proc.* **2021**. [CrossRef]
13. Senavirathne, B.; Gunerathne, C.; Lanka, S.; Lanka, S. Greenhouse Automation with Artificial Intelligence and Industry 4.0 Integration. In Proceedings of the 12th International Research Conference 2019, KDU, Ratmalana, Sri Lanka, 11–12 September 2020; pp. 487–494.
14. Karar, M.; Alsunaydi, F.; Albusaymi, S.; Alotaibi, S. A new mobile application of agricultural pests recognition using deep learning in cloud computing system. *Alexandria Eng. J.* **2021**, *60*, 4423–4432. [CrossRef]
15. Lakshmi, V.; Corbett, J. How Artificial Intelligence Improves Agricultural Productivity and Sustainability: A Global Thematic Analysis. *Int. Conf. Syst. Sci.* **2020**, *3*, 5202–5211.
16. Kollia, I.; Stevenson, J.; Kollias, S. AI-Enabled Efficient and Safe Food Supply Chain. *Electronics* **2021**, *10*, 1223. [CrossRef]
17. Zhang, S.; Guo, Y.; Zhao, H.; Wang, Y.; Chow, D. Methodologies of control strategies for improving energy ef fi ciency in agricultural greenhouses. *J. Clean. Prod.* **2020**, *274*, 122695. [CrossRef]
18. Cao, X.; Yao, Y.; Li, L.; Zhang, W.; An, Z.; Zhang, Z.; Xiao, L.; Guo, S.; Cao, X.; Wu, M.; et al. iGrow: A Smart Agriculture Solution to Autonomous Greenhouse Control. *Artif. Intell.* **2022**, *36*, 11837–11845. [CrossRef]
19. Panaligan, N.A.P.; Aringo, M.Q.; Ella, V.B. Assessment of potential for adoption of wireless sensor network technology for irrigation water management of high value crops in the Philippines. *IOP Conf. Ser. Earth Environ. Sci.* **2022**, *1038*, 012027. [CrossRef]

20. Rokade, A.; Singh, M. Analysis of Precise Green House Management System using Machine Learning based Internet of Things (IoT) for Smart Farming. In Proceedings of the 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 7–9 October 2021; pp. 21–28.
21. Bekiaris, I.; Leonidis, A.; Korozi, M.; Stratakis, C.; Zidianakis, E.; Doxastaki, M.; Stephanidis, C. GRETA: Pervasive and AR Interfaces for Controlling Intelligent Greenhouses. In Proceedings of the 2021 17th International Conference on Intelligent Environments (IE), Dubai, United Arab Emirates, 21–24 June 2021.
22. Zhang, W.; Cao, Y.; Yao, Y.; An, Z. Robust Model-based Reinforcement Learning for Autonomous Greenhouse Control. In Proceedings of the 13th Asian Conference on Machine Learning, Virtually, 17–19 November 2021; Volume 157, pp. 1–16.
23. Maraveas, C.; Piromalis, D.; Arvanitis, K.G.; Bartzanas, T.; Loukatos, D. Applications of IoT for optimized greenhouse environment and resources management. *Comput. Electron. Agric.* **2022**, *198*, 106993. [CrossRef]
24. Gołasa, P.; Wysokiński, M.; Bieńkowska-Gołasa, W.; Gradziuk, P.; Golonko, M.; Gradziuk, B.; Siedlecka, A.; Gromada, A. Sources of Greenhouse Gas Emissions in Agriculture, with Particular Emphasis on Emissions from Energy Used. *Energies* **2021**, *14*, 3784. [CrossRef]
25. UNFCC. Climate Change Is an Increasing Threat to Africa. 2020. Available online: https://unfccc.int/news/climate-change-is-an-increasing-threat-to-africa (accessed on 26 July 2022).
26. European Commission—Joint Research Centre. World Atlas of Desertification—Rethinking Land Degradation and Sustainable Management. 2020. Available online: https://reliefweb.int/report/world/world-atlas-desertification-rethinking-land-degradation-and-sustainable-management (accessed on 26 July 2022).
27. Burrell, A.L.; Evans, J.P.; de Kauwe, M.G. Anthropogenic climate change has driven over 5 million km^2 of drylands towards desertification. *Nat. Commun.* **2020**, *11*, 3853. [CrossRef]
28. European Commission. *Desertification and Agriculture*; European Commission: Brussels, Belgium, 2020; pp. 1–12.
29. Mikhailov, D.; Fedorov, V.; Mitrokhin, M.; Pronichkin, A.K.; Soytong, K. Using artificial intelligence systems for intensive safe cultivation of crops-short communication. *Int. J. Agric. Technol.* **2021**, *17*, 987–990.
30. World Economic Forum. *Artificial Intelligence for Agriculture Innovation*; World Economic Forum: Cologny, Switzerland, 2021; pp. 1–32.
31. Linaza, M.; Posada, J.; Bund, J.; Eisert, P.; Quartulli, M.; Döllner, J.; Pagani, A.; Olaizola, I.G.; Barriguinha, A.; Moysiadis, T.; et al. Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture. *Agronomy* **2021**, *11*, 1227. [CrossRef]
32. Amudha, T.; Thilagavathi, N.; Sangeetha, A. A systematic study on bio-inspired frameworks for fertilizer optimization. *Int. J. Agric. Technol.* **2021**, *17*, 1287–1304.
33. Rao, N.S.; Soam, S.K.; Rao, C.S. Applications of Artificial Intelligence in Precision Agriculture. *Gravida Rev. J.* **2021**, *7*, 174–177.
34. Rosenblatt, F. The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain. *Psychol. Rev.* **1958**, *65*, 386–408. [CrossRef]
35. Asteris, P.G.; Gavriilaki, E.; Touloumenidou, T.; Koravou, E.-E.; Koutra, M.; Papayanni, P.G.; Pouleres, A.; Karali, V.; Lemonis, M.E.; Mamou, A.; et al. Genetic prediction of ICU hospitalization and mortality in COVID-19 patients using artificial neural networks. *J. Cell. Mol. Med.* **2022**, *26*, 1445–1455. [CrossRef] [PubMed]
36. Rahimi, I.; Gandomi, A.H.; Asteris, P.G.; Chen, F. Analysis and Prediction of COVID-19 Using SIR, SEIQR, and Machine Learning Models: Australia, Italy, and UK Cases. *Information* **2021**, *12*, 109. [CrossRef]
37. Mahanty, C.; Kumar, R.; Asteris, P.G.; Gandomi, A.H. COVID-19 Patient Detection Based on Fusion of Transfer Learning and Fuzzy Ensemble Models Using CXR Images. *Appl. Sci.* **2021**, *11*, 11423. [CrossRef]
38. Gavriilaki, E.; Asteris, P.G.; Touloumenidou, T.; Koravou, E.-E.; Koutra, M.; Papayanni, P.G.; Karali, V.; Papalexandri, A.; Varelas, C.; Chatzopoulou, F.; et al. Genetic justification of severe COVID-19 using a rigorous algorithm. *Clin. Immunol.* **2021**, *226*, 108726. [CrossRef] [PubMed]
39. Asteris, P.G.; Douvika, M.G.; Karamani, C.A.; Skentou, A.D.; Chlichlia, K.; Cavaleri, L.; Daras, T.; Armaghani, D.J.; Zaoutis, T.E. A Novel Heuristic Algorithm for the Modeling and Risk Assessment of the COVID-19 Pandemic Phenomenon. *Comput. Model. Eng. Sci.* **2020**, *125*, 815–828. [CrossRef]
40. Litjens, G.; Sánchez, C.I.; Timofeeva, N.; Hermsen, M.; Nagtegaal, I.; Kovacs, I.; Hulsbergen-van de Kaa, C.; Bult, P.; Van Ginneken, B.; Van Der Laak, J. Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis. *Sci. Rep.* **2016**, *6*, 26286. [CrossRef]
41. Tu, J.V. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *J. Clin. Epidemiol.* **1996**, *49*, 1225–1231. [CrossRef]
42. Kononenko, I. Machine learning for medical diagnosis: History, state of the art and perspective. *Artif. Intell. Med.* **2001**, *23*, 89–109. [CrossRef]
43. Kalogirou, S.A. Applications of artificial neural-networks for energy systems. *Appl. Energy* **2000**, *67*, 17–35. [CrossRef]
44. Gandomi, A.H.; Yang, X.-S.; Alavi, A.H. Mixed variable structural optimization using Firefly Algorithm. *Comput. Struct.* **2011**, *89*, 2325–2336. [CrossRef]
45. Huang, J.; Asteris, P.G.; Pasha, S.M.K.; Mohammed, A.S.; Hasanipanah, M. A new auto-tuning model for predicting the rock fragmentation: A cat swarm optimization algorithm. *Eng. Comput.* **2022**, *38*, 2209–2220. [CrossRef]
46. Yang, X.; Gandomi, A.H. Bat algorithm: A novel approach for global engineering optimization. *Eng. Comput.* **2012**, *29*, 464–483. [CrossRef]

47. Mirjalili, S.; Mirjalili, S.M.; Lewis, A. Grey Wolf Optimizer. *Adv. Eng. Softw.* **2014**, *69*, 46–61. [CrossRef]
48. Mirjalili, S.; Gandomi, A.H.; Mirjalili, S.Z.; Saremi, S.; Faris, H.; Mirjalili, S.M. Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Adv. Eng. Softw.* **2017**, *114*, 163–191. [CrossRef]
49. Cavaleri, L.; Chatzarakis, G.E.; Di Trapani, F.; Douvika, M.G.; Roinos, K.; Vaxevanidis, N.M.; Asteris, P.G. Modeling of surface roughness in electro-discharge machining using artificial neural networks. *Adv. Mater. Res.* **2017**, *6*, 169–184.
50. Psyllaki, P.; Stamatiou, K.; Iliadis, I.; Mourlas, A. Surface treatment of tool steels against galling failure. *MATEC Web Conf.* **2018**, *188*, 1–8. [CrossRef]
51. Lu, S.; Koopialipoor, M.; Asteris, P.G.; Bahri, M.; Armaghani, D.J. A Novel Feature Selection Approach Based on Tree Models for Evaluating the Punching Shear Capacity of Steel Fiber-Reinforced Concrete Flat Slabs. *Materials* **2020**, *13*, 3902. [CrossRef]
52. Harandizadeh, H.; Armaghani, D.J.; Asteris, P.G.; Gandomi, A.H. TBM Performance Prediction Developing a Hybrid ANFIS-PNN Predictive Model Optimized by Imperialism Competitive Algorithm. *Neural Comput. Appl.* **2021**, *33*, 16149–16179. [CrossRef]
53. Abualigah, L.; Diabat, A.; Mirjalili, S.; Elaziz, M.A.; Gandomi, A.H. The Arithmetic Optimization Algorithm. *Comput. Methods Appl. Mech. Eng.* **2021**, *376*, 113609. [CrossRef]
54. Taghizadeh-Mehrjardi, R.; Emadi, M.; Cherati, A.; Heung, B.; Mosavi, A.; Scholten, T. Bio-inspired hybridization of artificial neural networks: An application for mapping the spatial distribution of soil texture fractions. *Remote Sens.* **2021**, *13*, 1025. [CrossRef]
55. Nguyen, T.H.; Nguyen, L.V.; Jung, J.J.; Agbehadji, I.E.; Frimpong, S.O.; Millham, R.C. Bio-inspired approaches for smart energy management: State of the art and challenges. *Sustainability* **2020**, *12*, 8495. [CrossRef]
56. Itano, M.K.; Omura, K.N.; Amazaki, T.Y.; Wao, T.I.; Aitou, M.S. Internet of Plants (IoP) Empowers Bottom-up Innovations. *Environ. Control Biol.* **2022**, *60*, 3–12.
57. Rustia, D.J.A.; Chiu, L.; Lu, C.; Wu, Y.; Chen, S.; Chung, J.; Hsu, J.; Lin, T. Towards intelligent and integrated pest management through an AIoT-based monitoring system. *Pest Manag. Sci.* **2022**, *78*, 4288–4302. [CrossRef] [PubMed]
58. Serale, G.; Gnoli, L.; Giraudo, E.; Fabrizio, E. A Supervisory Control Strategy for Improving Energy Efficiency of Artificial Lighting Systems in Greenhouses. *Energies* **2021**, *14*, 202. [CrossRef]
59. Egorov, A.; Bubnov, A.; Pavluchenkova, L.; Partolina, A. Applying chemical control to suppress liverwort (*Marchantia polymorpha* L.) and other mosses when growing containerized seedlings of pine and spruce. *Balt. For.* **2021**, *27*, 114–120. [CrossRef]
60. Raatz, L.; Walzl, K.P.; Müller, M.E.H.; Scherber, C.; Joshi, J. Who is the culprit: Is pest infestation responsible for crop yield losses close to semi–natural habitats? *Ecol. Evol.* **2021**, *11*, 13232–13246. [CrossRef]
61. Beatriz, D.; Colomer, I.; Medina, P.; Vi, E. Compatibility of early natural enemy introductions in commercial pepper and tomato greenhouses with repeated pesticide applications. *Insect Sci.* **2020**, *27*, 1111–1124.
62. Chlorpyrifos-Methyl. National Library of Medicine. 2022. Available online: https://pubchem.ncbi.nlm.nih.gov/compound/Chlorpyrifos-methyl (accessed on 1 August 2022).
63. Sharma, A.; Tripathi, P. Artificial Intelligence in Agriculture: A Literature Survey. *Int. J. All Res. Educ. Sci. Methods* **2021**, *9*, 510–513.
64. Tang, J.; Liu, G.; Pan, Q. A Review on Representative Swarm Intelligence Algorithms for Solving Optimization Problems: Applications and Trends. *IEEE/CAA J. Autom. Sin.* **2021**, *8*, 1627–1643. [CrossRef]
65. Maraveas, C.; Loukatos, D.; Bartzanas, T.; Arvanitis, K.G. Applications of artificial intelligence in fire safety of agricultural structures. *Appl. Sci.* **2021**, *11*, 7716. [CrossRef]
66. Solmaz, E.; Çevik, B.; Ay, R. Abamectin resistance and resistance mechanisms in Tetranychus urticae populations from cut flowers greenhouses in Turkey. *Int. J. Acarol.* **2020**, *46*, 94–99. [CrossRef]
67. European Social and Economic Committee. *Boosting the Use of Artificial Intelligence in Europe's Micro, Small and Medium-Sized Enterprises*; European Social and Economic Committee: Brussels, Belgium, 2021; pp. 1–137.
68. Aggarwal, N.; Singh, D. Technology assisted farming: Implications of IoT and AI. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1022*, 012080. [CrossRef]
69. Loudjani, P.; Devos, W.; Baruth, B.; Lemoine, G. Artificial Intelligence and EU Agriculture. *Eur. Comm. Jt. Res. Cent.* **2020**, 1–28. Available online: https://marswiki.jrc.ec.europa.eu/wikicap/images/c/c8/JRC-Report_AIA_120221a.pdf (accessed on 25 August 2022).
70. Kendall, H.; Clark, B.; Li, W.; Jin, S.; Jones, G.D.; Chen, J.; Taylor, J.; Li, Z.; Frewer, L.J. *Precision Agriculture Technology Adoption: A Qualitative Study of Small-Scale Commercial "Family Farms" Located in the North China Plain*; Springer: New York, NY, USA, 2022; Volume 23.
71. Maloku, D. Adoption of Precision Farming Technologies: Usa and Eu Situation. *SEA Pract. Appl. Sci.* **2020**, *VIII*, 7–14.
72. Cisco and the International Telecommunication Union (ITU). *Harnessing the Internet of Things for Global Development*; Cisco and the International Telecommunication Union (ITU): Geneva, Switzerland, 2015.
73. Chung, S. Survey of actuators for environment management in Korean smart greenhouses. *Precis. Agric. Sci. Technol.* **2020**, *2*, 1–7.
74. Otazua, N.I. AI-Powered DSS for Resource-Efficient Nutrient, Irrigation, and Microclimate Management in Greenhouses. *Chem. Proc.* **2022**, *10*, 63.
75. Cui, B.; Niu, W.; Du, Y.; Zhang, Q. Response of yield and nitrogen use e fficiency to aerated irrigation and N application rate in greenhouse cucumber. *Sci. Hortic.* **2020**, *265*, 109220. [CrossRef]

76. Lin, N.; Wang, X.; Zhang, Y.; Hu, X.; Ruan, J. Fertigation management for sustainable precision agriculture based on Internet of Things. *J. Clean. Prod.* **2020**, *277*, 124119. [CrossRef]
77. Briciu-Burghina, C.; Zhou, J.; Ali, M.I.; Regan, F. Demonstrating the Potential of a Low-Cost Soil Moisture Sensor Network. *Sensors* **2022**, *22*, 987. [CrossRef] [PubMed]
78. Shamshiri, R.R.; Balasundram, S.K.; Rad, A.K.; Sultan, M.; Hameed, I.A. An Overview of Soil Moisture and Salinity Sensors for Digital Agriculture Applications. In *Digital Agriculture, Methods and Applications*; IntechOpen: London, UK, 2022.
79. Sharma, S.; Kaur, G.; Singh, P.; Alamri, S.; Kumar, R.; Siddiqui, M.H. Nitrogen and potassium application effects on productivity, profitability and nutrient use efficiency of irrigated wheat (*Triticum aestivum* L.). *PLoS ONE* **2022**, *17*, e0264210. [CrossRef] [PubMed]
80. Facchinetti, D.; Santoro, S.; Galli, L.; Fontana, G.; Fedeli, L.; Parisi, S.; Bonacchi, L.; Šušnjar, S.; Salvai, F.; Coppola, G.; et al. Reduction of Pesticide Use in Fresh-Cut Salad Production through Artificial Intelligence. *Appl. Sci.* **2021**, *11*, 1992. [CrossRef]
81. Claver, H. AI Precision Spraying Technology to Cut Herbicide Use by 78%. Future Farming. 2020. Available online: https://www.futurefarming.com/crop-solutions/weed-pest-control/ai-precision-spraying-technology-to-cut-herbicide-use-by-78/ (accessed on 12 September 2022).
82. Shankar, P.; Werner, N.; Selinger, S.; Janssen, O. Artificial Intelligence Driven Crop Protection Optimization for Sustainable Agriculture. In Proceedings of the IEEE ITU International Conference on Artificial Intelligence for Good (AI4G), Geneva, Switzerland, 21–25 September 2020; pp. 1–8.
83. Araújo, M. *Infrastructure Deployment in Unprofitable Areas: A Techno-Economic Model for Multiple Criteria Decision Analysis under the European Union Telecommunications Regulatory Framework*; Stock University: Galloway, NJ, USA, 2020; p. 74.
84. Placidi, P.; Morbidelli, R.; Fortunati, D.; Papini, N.; Gobbi, F.; Scorzoni, A. Monitoring soil and ambient parameters in the iot precision agriculture scenario: An original modeling approach dedicated to low-cost soil water content sensors. *Sensors* **2021**, *21*, 5110. [CrossRef]
85. Liu, L.W.; Ma, X.; Wang, Y.M.; Lu, C.T.; Lin, W.S. Using artificial intelligence algorithms to predict rice (*Oryza sativa* L.) growth rate for precision agriculture. *Comput. Electron. Agric.* **2021**, *187*, 106286. [CrossRef]
86. Singh, K.U.; Kumar, A.; Raja, L.; Kumar, V.; Kushwaha, A.K.S.; Vashney, N.; Chhetri, M. An Artificial Neural Network-Based Pest Identification and Control in Smart Agriculture Using Wireless Sensor Networks. *J. Food Qual.* **2022**, *2022*, 5801206. [CrossRef]
87. Singh, R.K.; Berkvens, R.; Weyn, M. Energy efficient wireless communication for IoT enabled Greenhouses. In Proceedings of the 2020 International Conference on COMmunication Systems & NETworkS (COMSNETS), Bengaluru, India, 7–11 January 2020; pp. 885–887.
88. Sacaleanu, D.; Rosu, S.-G.; Matache, M.-G.; Manciu, I.-P.; Perisoara, L.-A. Wireless actuator node for greenhouse microclimate control. In Proceedings of the 2022 14th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Ploiesti, Romania, 30 June–1 July 2022; pp. 1–4.
89. Qiang, W. Research on data transmission model of agricultural wireless sensor network based on game theory. *Acta Agric. Scand. Sect. B Soil Plant Sci.* **2022**, *72*, 67–80. [CrossRef]
90. Grum, M. *Humans Still Crucial as AI Image Analysis for Crop Pest and Disease Management Has a Long Way to Go*; Scarab-Solutions, 2022; pp. 1–2. Available online: https://www.scarab-solutions.com/humans-still-crucial-as-ai-image-analysis-for-crop-pest-and-disease-management-has-a-long-way-to-go (accessed on 30 November 2022).
91. Kootstra, G.; Wang, X.; Blok, P.M.; Hemming, J.; van Henten, E. Selective Harvesting Robotics: Current Research, Trends, and Future Directions. *Curr. Robot. Rep.* **2021**, *2*, 95–104. [CrossRef]
92. Lee, J.; Nazki, H.; Baek, J.; Hong, Y.; Lee, M. Artificial Intelligence Approach for Tomato Detection and Mass Estimation in Precision Agriculture. *Sustainability* **2020**, *12*, 9138. [CrossRef]
93. Vidwath, S.M.G.; Rohith, P.; Dikshithaa, R.; Suraj, N.N.; Chittawadigi, R.G.; Sambandham, M. Soft Robotic Gripper for Agricultural Harvesting BT. In *Machines, Mechanism and Robotics*; Springer: Berlin, Germany, 2022; pp. 1347–1353.
94. Navas, E.; Fernández, R.; Sepúlveda, D.; Armada, M.; Gonzalez-De-santos, P. Soft grippers for automatic crop harvesting: A review. *Sensors* **2021**, *21*, 2689. [CrossRef]
95. Tianhua, L.; Ni, Z.; Shi, G.; Zhou, J. Design and Testing of an Inter-row Sprayer in a Chinese Solar Greenhouse. *J. Eng. Sci. Technol. Rev.* **2020**, *13*, 32–41.
96. Homayoonzadeh, M.; Ghamari, M.; Torabi, E.; Talebi, K.; Nozari, J. A Novel Biopesticide Formulation for Organic Management of Aphis gossypii. In Proceedings of the First International Online Conference on Agriculture—Advances in Agricultural Science and Technology, Basel, Switzerland, 10–15 February 2022; Volume 4, pp. 1–4.
97. Hou, J.; Zhang, J.; Wu, W.; Jin, T.; Zhou, K. Research on Agricultural Machinery Rental Optimization Based on the Dynamic Artificial Bee-Ant Colony Algorithm. *Algorithms* **2022**, *15*, 88. [CrossRef]
98. Cao, R.; Li, S.; Ji, Y.; Zhang, Z.; Xu, H.; Zhang, M.; Li, M.; Li, H. Task assignment of multiple agricultural machinery cooperation based on improved ant colony algorithm. *Comput. Electron. Agric.* **2021**, *182*, 105993. [CrossRef]
99. Huang, Y. Research status and applications of nature-inspired algorithms for agri-food production. *Int. J. Agric. Biol. Eng.* **2020**, *13*, 1–9. [CrossRef]
100. Roy, D.K.; Lal, A.; Sarker, K.K.; Saha, K.K.; Datta, B. Optimization algorithms as training approaches for prediction of reference evapotranspiration using adaptive neuro fuzzy inference system. *Agric. Water Manag.* **2021**, *255*, 107003. [CrossRef]

101. Proietti, M.; Bianchi, F.; Marini, A.; Menculini, L.; Termite, L.; Garinei, A.; Biondi, L.; Marconi, M. Edge Intelligence with Deep Learning in Greenhouse Management. In Proceedings of the 10th International Conference on Smart Cities and Green ICT Systems, Online, 28–30 April 2021; pp. 180–187.
102. Gao, L.; Gong, D.; Cui, N.; Lv, M. Evaluation of bio-inspired optimization algorithms hybrid with artificial neural network for reference crop evapotranspiration estimation. *Comput. Electron. Agric.* **2021**, *190*, 106466. [CrossRef]
103. Hu, P.; Sun, Y.; Zhang, Y.; Dong, J.; Zhang, X. Application of WDNN for Photosynthetic Rate Prediction in Greenhouse. In Proceedings of the 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Nanchang, China, 26–28 March 2021.
104. Tao, T.; Wei, X. A hybrid CNN-SVM classifier for weed recognition in winter rape field. *Plant Methods* **2022**, *18*, 29. [CrossRef]
105. Qasim, W.A.; Mitras, B.A. A Hybrid Algorithm Based on Invasive Weed Optimization Algorithm and Grey Wolf Optimization Algorithm. *Int. J. Artif. Intell. Appl.* **2020**, *11*, 30–44.
106. Emamgholizadeh, S.; Mohammadi, B. New hybrid nature-based algorithm to integration support vector machine for prediction of soil cation exchange capacity. *Soft Comput.* **2021**, *25*, 13451–13464. [CrossRef]
107. Codeluppi, G.; Davoli, L.; Ferrari, G. Forecasting Air Temperature on Edge Devices with. *Sensors* **2021**, *21*, 3973. [CrossRef]
108. Ibrahim, A.; Anayi, F.; Packianather, M.; Alomari, O.A. New Hybrid Invasive Weed Optimization and Machine Learning Approach for Fault Detection. *Energies* **2022**, *15*, 1488. [CrossRef]
109. Wu, L.; Zhou, H.; Ma, X.; Fan, J.; Zhang, F. Daily reference evapotranspiration prediction based on hybridized extreme learning machine model with bio-inspired optimization algorithms: Application in contrasting climates of China. *J. Hydrol.* **2019**, *577*, 123960. [CrossRef]
110. Chahidi, L.O.; Fossa, M.; Priarone, A.; Mechaqrane, A. Evaluation of Supervised Learning Models in Predicting Greenhouse Energy Demand and Production for Intelligent and Sustainable Operations. *Energies* **2021**, *14*, 6297. [CrossRef]
111. Liu, K.; Zhang, C.; Yang, X.; Diao, M.; Liu, H.; Li, M. Development of an Occurrence Prediction Model for Cucumber Downy Mildew in Solar Greenhouses Based on Long Short-Term Memory Neural Network. *Agronomy* **2022**, *12*, 442. [CrossRef]
112. Han, G.D.; Choi, J.M.; Choi, I.; Kim, Y.; Heo, S.; Chung, Y.S. From crop specific to variety specific in crop modeling for the smart farm: A case study with blueberry. *PLoS ONE* **2022**, *17*, e0273845. [CrossRef]
113. Abdulridha, J.; Ampatzidis, Y.; Roberts, P. Detecting powdery mildew disease in squash at different stages using UAV-based hyperspectral imaging and artificial intelligence. *Biosyst. Eng.* **2020**, *197*, 135–148. [CrossRef]
114. Pane, C.; Manganiello, G.; Nicastro, N.; Cardi, T. Powdery Mildew Caused by Erysiphe cruciferarum on Wild Rocket (*Diplotaxis tenuifolia*): Hyperspectral Imaging and Machine Learning Modeling for Non-Destructive Disease Detection. *Agriculture* **2021**, *11*, 337. [CrossRef]
115. Ni, L.; Punja, Z.K. Management of powdery mildew on greenhouse cucumber (*Cucumis sativus* L.) plants using biological and chemical approaches. *Can. J. Plant Pathol.* **2021**, *43*, 35–42. [CrossRef]
116. el Arnaouty, S.A.; Afifi, A.I.; Heikal, I.H.; Kortam, M.N. Comparative study between biological and chemical control programs of certain sweet pepper pests in greenhouses. *Egypt. J. Biol. Pest Control* **2020**, *30*, 28–34. [CrossRef]
117. Glinushkin, A.P.; Yakovleva, I.N.; Meshkov, Y.I. Toxicity Pesticides used in Greenhouses and Promising for Predatory Mite Neoseiulus Barkeri (Mesostigmata: Phytoseiidae). *J. Phys. Conf. Ser.* **2021**, *1942*, 012071. [CrossRef]
118. Kirisik, M.; Dagli, F. Resistance To Bifenazate And Abamectin In Tetranychus Urticae (Acari:Tetranycidae) Greenhouse Populations Collected From Coastal Regions of Turkey in 2016. *Fresenius Environ. Bull.* **2022**, *30*, 7672–7679.
119. Alpkent, Y.N.; Inak, E.; Ulusoy, S.; Ay, R. Acaricide resistance and mechanisms in Tetranychus urticae populations from greenhouses in Turkey. *Syst. Appl. Acarol.* **2020**, *25*, 155–168.
120. Eurostats. 346,000 Tonnes of Pesticides Sold in 2020 in the EU. 2022. Available online: https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20220502-1 (accessed on 21 October 2022).
121. Liu, Z.; Gao, Z.; Geng, X.; Wen, L.; Kiprop, E. Risk aversion, marketing outlets, and biological control practice adoption: Insight from pear farmers in China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 84798–84813. [CrossRef] [PubMed]
122. Helepciuc, F.-E.; Todor, A. Evaluating the effectiveness of the EU's approach to the sustainable use of pesticides. *PLoS ONE* **2021**, *16*, e0256719. [CrossRef] [PubMed]
123. Australian Government. Bugs for Bugs—Creating Biological Alternatives to Chemical Pesticides. 2022. Available online: https://business.gov.au/grants-and-programs/research-and-development-tax-incentive/how-the-rdti-has-helped-other-companies/bugs-for-bugs (accessed on 22 October 2022).
124. Jacquet, F.; Jeuffroy, M.-H.; Jouan, J.; Le Cadre, E.; Litrico, I.; Malausa, T.; Reboud, X.; Huyghe, C. Pesticide-free agriculture as a new paradigm for research. *Agron. Sustain. Dev.* **2022**, *42*, 8. [CrossRef]
125. Thomine, E.; Mumford, J.; Rusch, A.; Desneux, N. Using crop diversity to lower pesticide use: Socio-ecological approaches. *Sci. Total Environ.* **2022**, *804*, 150156. [CrossRef]
126. Neumeister, L. *Locked-in Pesticides. The European Union's Dependency on Harmful Pesticides and How to Overcome It*; Food Watch, 2022; pp. 1–116. Available online: https://www.foodwatch.org/en/reports/2022/locked-in-pesticides-europes-dependency-on-harmful-pesticides-and-how-to-overcome-it/?cookieLevel=not-set (accessed on 12 November 2022).
127. European Commission. Farm to Fork: New Rules to Reduce the Risk and Use of Pesticides in the EU. 2022. Available online: https://ec.europa.eu/commission/presscorner/detail/en/qanda_22_3694 (accessed on 12 November 2022).

128. Agarwal, M.; Verma, A. Modern Technologies for Pest Control: A Review. In *Heavy Metals—Their Environmental Impacts and Mitigation*; Intechopen: London, UK, 2021.
129. Ayanoğlu, F.B.; Elçin, A.E.; Elçin, Y.M. Bioethical issues in genome editing by CRISPR-Cas9 technology. *Turkish J. Biol. = Turk Biyol. Derg.* **2020**, *44*, 110–120. [CrossRef]
130. Deere, J. John Deere Reveals Fully Autonomous Tractor at CES 2022. 2022. Available online: https://www.deere.com/en/news/all-news/autonomous-tractor-reveal/ (accessed on 11 November 2022).
131. Beloev, I.; Kinaneva, D.; Georgiev, G.; Hristov, G.; Zahariev, P. Artificial intelligence-driven autonomous robot for precision agriculture. *Acta Technol. Agric.* **2021**, *24*, 48–54. [CrossRef]
132. Rahmadian, R.; Widyartono, M. Autonomous Robotic in Agriculture: A Review. In Proceedings of the 2020 Third International Conference on Vocational Education and Electrical Engineering, Surabaya, Indonesia, 3–4 October 2020; pp. 1–6.
133. Aghelpour, P.; Bahrami-Pichaghchi, H.; Kisi, O. Comparison of three different bio-inspired algorithms to improve ability of neuro fuzzy approach in prediction of agricultural drought, based on three different indexes. *Comput. Electron. Agric.* **2020**, *170*, 105279. [CrossRef]
134. Soheli, S.J.; Jahan, N.; Hossain, M.; Adhikary, A.; Khan, D.M.A.; Wahiduzzaman, M. Smart Greenhouse Monitoring System Using Internet of Things and Artificial Intelligence. *Wirel. Pers. Commun.* **2022**, *124*, 3603–3634. [CrossRef]
135. Salam, A.; Javaid, Q. Bio-inspired cluster-based optimal target identification using multiple unmanned aerial vehicles in smart precision agriculture. *Int. J. Distrib. Sens. Netw.* **2021**, *17*, 1–17. [CrossRef]
136. Howard, D.A.; Ma, Z.; Veje, C.; Clausen, A.; Aaslyng, J.M.; Jørgensen, B.N. Greenhouse industry 4.0—Digital twin technology for commercial greenhouses. *Energy Inform.* **2021**, *4*, 37. [CrossRef]
137. Jiang, X.; Liu, B.; Guan, X.; Wang, Z.; Wang, B.; Zhao, S.; Song, Y.; Zhao, Y.; Bi, J. Proper deficit irrigation applied at various stages of growth can maintain yield and improve the comprehensive fruit quality and economic return of table grapes grown in greenhouses*. *Irrig. Drain.* **2021**, *70*, 1056–1072. [CrossRef]
138. Bersani, C.; Ouammi, A.; Sacile, R.; Zero, E. Model Predictive Control of Smart Greenhouses as the Path towards Near Zero Energy Consumption. *Energies* **2020**, *13*, 3647. [CrossRef]
139. Ben, R.; Bouadila, S.; Mami, A. Experimental validation of the dynamic thermal behavior of two types of agricultural greenhouses in the Mediterranean context. *Renew. Energy* **2020**, *147*, 118–129. [CrossRef]
140. Achour, Y.; Ouammi, A.; Zejli, D. Technological progresses in modern sustainable greenhouses cultivation as the path towards precision agriculture. *Renew. Sustain. Energy Rev.* **2021**, *147*, 111251. [CrossRef]
141. Ullah, I.; Fayaz, M.; Aman, M.; Kim, D. An optimization scheme for IoT based smart greenhouse climate control with efficient energy consumption. *Computing* **2022**, *104*, 433–457. [CrossRef]
142. Zhang, K.; Yu, J.; Ren, Y. Demand side management of energy consumption in a photovoltaic integrated greenhouse. *Int. J. Electr. Power Energy Syst.* **2022**, *134*, 107433. [CrossRef]
143. Jia, W.; Liu, M.; Zhou, J. Adaptive Chaotic Ant Colony Optimization for Energy Optimization in Smart Sensor Networks. *J. Sens.* **2021**, *2021*, 5051863. [CrossRef]
144. Chen, J.; Cai, Y.; Xu, F.; Hu, H.; Ai, Q. Analysis and Optimization of the Fan-Pad Evaporative Cooling System for Greenhouse Based on CFD. *Adv. Mech. Eng.* **2014**, *2014*, 1–8. [CrossRef]
145. Rasakhodzhaev, B.S.; Akhmadjanov, U.Z.; Boboeva, M.O.; Mashrapova, I.R.; Tokonova, T.S. Investigation of solar greenhouses with transformable (adjustable) body depending on indoor and outdoor air temperature. *IOP Conf. Ser. Earth Environ. Sci.* **2022**, *1070*, 012030. [CrossRef]
146. Khalilpourazari, S.; Khalilpourazary, S.; Özyüksel, A.; Weber, G.; Weber, G. Designing Energy-Efficient High-Precision Multi-pass Turning Processes via Robust Optimization and Artificial Intelligence. *J. Intell. Manuf.* **2021**, *32*, 1621–1647. [CrossRef]
147. An, Z.; Cao, X.; Yao, Y.; Zhang, W.; Li, L.; Wang, Y.; Guo, S.; Luo, D. A Simulator-based Planning Framework for Optimizing Autonomous Greenhouse Control Strategy. In Proceedings of the Thirty-First International Conference on Automated Planning and Scheduling, Guangzhou, China, 2–13 August 2021.
148. Bersani, C.; Ruggiero, C.; Sacile, R.; Soussi, A.; Zero, E. Internet of Things Approaches for Monitoring and Control of Smart Greenhouses in Industry 4.0. *Energies* **2022**, *15*, 3834. [CrossRef]
149. Chen, C.; Huang, Y.; Li, Y.; Chang, C.; Huang, Y. An AIoT Based Smart Agricultural System for Pests Detection. *IEEE Access* **2020**, *8*, 180750–180761. [CrossRef]
150. Henningsson, A. *Survey of the Application of Machine Learning to Automated Greenhouses*; Uppsala University: Uppsala, Sweden, 2021; pp. 1–43.
151. Siskandar, R.; Santosa, S.H.; Wiyoto, W.; Kusumah, B.R.; Hidayat, A.P. Control and Automation: Insmoaf (Integrated Smart Modern Agriculture and Fisheries) on The Greenhouse Model. *J. Ilmu Pertan. Indones.* **2022**, *27*, 141–152. [CrossRef]
152. Mu, M.; Zhang, S.; Yang, S.; Wang, Y. Phase change materials applied in agricultural greenhouses. *J. Energy Storage* **2022**, *49*, 104100. [CrossRef]
153. Elsayed, M.; Ran, Y.; Ai, P.; Azab, M.; Mansour, A.; Jin, K.; Zhang, Y.; Abomohra, A.E.-F. Innovative integrated approach of biofuel production from agricultural wastes by anaerobic digestion and black soldier fly larvae. *J. Clean. Prod.* **2020**, *263*, 121495. [CrossRef]
154. Kong, Q.; Mu, H.; Han, Y.; Wu, W.; Tong, C.; Fang, X.; Liu, R.; Chen, H.; Gao, H. Biodegradable phase change materials with high latent heat: Preparation and application on Lentinus edodes storage. *Food Chem.* **2021**, *364*, 130391. [CrossRef]

155. Siti, G.; Abdul, A.; Shima, J.S.; Zainal, A.S. Waste materials as the potential phase change material substitute in thermal energy storage system: A review. *Chem. Eng. Commun.* **2020**, *208*, 687–707.
156. Aira, J.R.; Gallardo-Saavedra, S.; Eugenio-Gozalbo, M.; Alonso-Gómez, V.; Muñoz-García, M.Á.; Hernández-Callejo, L. Analysis of the viability of a photovoltaic greenhouse with semi-transparent amorphous silicon (A-si) glass. *Agronomy* **2021**, *11*, 1097. [CrossRef]
157. Varjovi, A.E.; Babaie, S. Green Internet of Things (GIoT): Vision, applications and research challenges. *Sustain. Comput. Inform. Syst.* **2020**, *28*, 100448. [CrossRef]
158. Al-helal, I.; Alsadon, A.; Marey, S.; Ibrahim, A.; Shady, M.; Abdel-ghany, A. Geothermal Energy Potential for Cooling / Heating Greenhouses in Hot Arid Regions. *Atmosphere* **2022**, *13*, 105. [CrossRef]
159. Mirzamohammadi, S.; Jabarzadeh, A.; Shahrabi, M.S. Long-term planning of supplying energy for greenhouses using renewable resources under uncertainty. *J. Clean. Prod.* **2020**, *264*, 121611. [CrossRef]
160. University of Georgia. 'Smart' Greenhouses Could Slash Electricity Costs. 2022. Available online: https://www.sciencedaily.com/releases/2022/02/220202165939.htm (accessed on 14 September 2022).
161. Mohr, S.; Kühl, R. Acceptance of artificial intelligence in German agriculture: An application of the technology acceptance model and the theory of planned behavior. *Precis. Agric.* **2021**, *22*, 1816–1844. [CrossRef]
162. Fernando, S.; Nethmi, R.; Silva, A.; Perera, A.; De Silva, R.; Abeygunawardhana, P.W.K. AI Based Greenhouse Farming Support System with Robotic Monitoring. In Proceedings of the 2020 IEEE Region 10 Conference (TENCON), Osaka, Japan, 16–19 November 2020; pp. 1368–1373.
163. Yaqot, M.; Meneze, B.C. Unmanned Aerial Vehicle (UAV) in Precision Agriculture: Business Information Technology Towards Farming as a Service. In Proceedings of the 2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA), Sana'a, Yemen, 10–12 August 2021; pp. 1–7.
164. Saddik, A.; Latif, R.; el Ouardi, A.; Elhoseny, M. Computer development based embedded systems in precision agriculture: Tools and application. *Acta Agric. Scand. Sect. B—Soil Plant Sci.* **2022**, *72*, 586–611. [CrossRef]
165. Yun, W.; Kumar, J.P.; Lee, S.; Kim, D.S.; Cho, B.K. Deep learning-based system development for black pine bast scale detection. *Sci. Rep.* **2022**, *12*, 606. [CrossRef]
166. Nanni, L.; Maguolo, G.; Pancino, F. Insect pest image detection and recognition based on bio-inspired methods. *Ecol. Inform.* **2020**, *57*, 101089. [CrossRef]
167. Xasanov, S. Analysis of Methods for Detecting Phytophthora, Mildew Diseases of Tomatoes and Cucumbers in Greenhouses. *EPRA Int. J. Clim. Resour. Econ. Rev.* **2021**, *9*, fnz199.
168. Ruzzante, S.; Labarta, R.; Bilton, A. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Dev.* **2021**, *146*, 105599. [CrossRef]
169. Kondoyanni, M.; Loukatos, D.; Maraveas, C.; Drosos, C.; Arvanitis, K.G. Bio-Inspired Robots and Structures toward Fostering the Modernization of Agriculture. *Biomimetics* **2022**, *7*, 69. [CrossRef]
170. Aytenfsu, S.A.; Beyene, A.M.; Getaneh, T.H. Controlling the interior of greenhouses using Elman recurrent neural network. In Proceedings of the 2020 Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), London, UK, 27–28 July 2020; pp. 32–39.
171. Cai, B.; Ning, Y.; Li, Q.; Li, Q.; Ai, X. Effects of the Chloroplast Fructose-1, 6-Bisphosphate Aldolase Gene on Growth and Low-Temperature Tolerance of Tomato. *Int. J. Mol. Sci.* **2022**, *23*, 728. [CrossRef] [PubMed]
172. Zamora-Izquierdo, M.A.; Martı, J.A.; Skarmeta, A.F. Intelligent Systems for Environmental Applications Smart farming IoT platform based on edge and cloud computing. *Biosyst. Eng.* **2018**, *177*, 4–17. [CrossRef]
173. Jim, R.; Aguilar, F.J.; Nemmaoui, A.; Aguilar, M.A. Remote Sensing of Agricultural Greenhouses and Plastic-Mulched Farmland: An Analysis of Worldwide Research. *Remote Sens.* **2020**, *12*, 2649.
174. Hasituya; Zhongxin, C.; Fei, L.; Yuncai, H. Mapping plastic-mulched farmland by coupling optical and synthetic aperture radar remote sensing. *Int. J. Remote Sens.* **2020**, *41*, 7757–7778. [CrossRef]