Artificial Intelligence: The Future of Sustainable Agriculture? A Research Agenda

Jonas Witte
Technical University of Darmstadt
jonas.witte@stud.tu-darmstadt.de

Kevin Gao
Technical University of Darmstadt
kevin.gao@stud.tu-darmstadt.de

Anne Zöll
Technical University of Darmstadt
anne.zoell@tu-darmstadt.de

Abstract

Global warming and the increasing food demand are problems of the current generation and require a change towards sustainable agriculture. In recent years, research in the field of artificial intelligence has made considerable progress. Thus, the use of artificial intelligence in agriculture can be a promising solution to ensure sufficient food supply on a global scale. To investigate the state-of-the-art in the use of artificial intelligence-based systems in agriculture, we provide a structured literature review. We show that research has been done in the field of irrigation and plant growth. In this regard, camera systems often provide images as training/input data for artificial intelligence-based systems. Finally, we provide a research agenda to pave the way for further research on the use of artificial intelligence in sustainable agriculture.

Keywords: Agriculture, Artificial Intelligence, Sustainability, Smart Farming

1. Introduction

The ever-increasing size of the world's population poses many challenges - especially for agriculture. The United Nations estimate that 9.7 billion people will live on this planet as early as 2050 (United Nations, 2019). Thus, industrial agriculture plays an essential and responsible role to produce food for the world's population. However, global agriculture also has a significant impact on global warming. In 2017, agriculture emitted 10.4 billion metric tons of carbon dioxide equivalent, through arable and livestock production, net forest conversion, and peatland degradation (FAO, 2020). Agriculture is both a driver of global warming and an industrial pathway that suffers significant damage from climate change. Over the course of time, climate change has contributed to an increase in droughts resulting in crop failures (Masson-Delmotte et al., 2021). At the same time, it has also caused some regions to experience heavy rainfall (Masson-Delmotte et al., 2021). Furthermore, pesticides are used to maximize agricultural yields, which are harmful to animals, plants, and humans.

Modern agriculture should pursue the goal of sustainability in order not to exacerbate climate change and to protect the environment and human health. Smart farming describes a system of data-driven decision-making tools used in agriculture (Jerhamre et al., 2022) to optimize land use, animals, and personnel, among other things (Eastwood et al., 2019). Artificial intelligence (AI) can be an essential solution to support smart farming by offering possibilities such as controlling and automating agricultural processes (e.g., Partel et al., 2021). Nevertheless, there are still potential application areas that can be further explored to make agriculture more sustainable (Subeesh & Mehta, 2021). For instance, Partel et al. (2021) developed a system that used image recognition of trees to reduce the number of pesticides needed by 28%. Although the use of AI-based systems in agriculture seems logical and inevitable as they become cheaper and more robust (Subeesh & Mehta, 2021), they have rarely been applied in practice.

Considering this research gap, we seek to undertake an extensive review and synthesis relevant publications, aiming to present the state-of-the-art of AI-based systems in agriculture. In particular, we give an overview on how these systems can contribute and leverage sustainable agriculture. Thus, we shed light on the following research question:

"How can artificial intelligence be used for future sustainable agriculture?"

By using a structured literature review in line with vom Brocke et al. (2009), we present an overview of the current research status. We contribute to research by providing a research agenda to push the utilization of AI-based systems in sustainable agriculture forward. The research agenda includes research directions on plant growth, cultivation areas, and used technologies in combination with AI algorithms. This paper is structured as follows: First, we introduce the theoretical background. We then explain the research method introduced by vom Brocke et al. (2009). Afterward, we

URI: https://hdl.handle.net/10125/102722
978-0-9981331-6-4

present the main contribution of our work, the research agenda. We conclude with a short summary, presenting the key findings, and critically discuss the limitations of our study.

2. Theoretical Background

2.1. Artificial Intelligence

There is no universally accepted definition for the term artificial intelligence (Wang, 2019). Kaplan & Haenlein (2019) distinguish between three levels of AI: Artificial Narrow Intelligence, Artificial General Intelligence, and Artificial Super Intelligence, each acting more independently from humans than the previous one. Whenever we use the term AI, we refer to Artificial Narrow Intelligence. An AI-based system is able to execute cognitive functions that are related to human reasoning, such as self-learning and decision-making (Berente et al., 2021; Rai et al., 2019). Moreover, AI perceive "its environment through sensors and acting upon that environment through actuators" (Russell & Norvig, 2021). In this regard, AI comprises machine learning, deep learning, robotic process automation, and rule-based expert systems (Benbya et al., 2021; Collins et al., 2021). Given the large spectrum of application scenarios in agriculture, AI is considered as a general-purpose technology (GPT) requiring purpose-specific considerations (Brynjolfsson et al., 2017).

2.2. Smart Farming

The term "Smart Farming" (also called Agriculture 4.0 or Agriculture Technology) is an umbrella term for smart technologies in agriculture and still emerging in the literature. In the context of agriculture, it refers to data-driven decision-making systems that can be used to optimize the management of land (Eastwood et al., 2019). In our context, it refers to the adoption of digital technologies, for example, smart sensors, machine learning algorithms, or robotics (Moysiadis et al., 2021). We would like to point out that technologies mostly appear in combination with other technologies. It is thus challenging to draw a clear line between AI-based systems as GPT and other smart technologies. These borders are rather fluid. Technologies will only unfold their full potential when merged with other technologies, e.g., a combination of sensors, robotics, and AI-based systems could transform collected data into knowledge (Araújo et al., 2021). However, the focus of this research paper is on AI-based systems in sustainable agriculture.

2.3. Sustainability in Agriculture

Sustainability is generally understood as considering future generations when using resources (UnitedNations, 1987) e.g., not consuming more than can be regrow. The focus is on a resource-saving use of available resources. With a growing population, it is also important to use these resources as efficiently as possible in order to produce enough food for everyone. Simultaneously, it is essential not to produce more than is needed since overproduction can also lead to resources being wasted, such as the precious resource of water (Darlington et al., 2009). When growing food, it is important to have as little impact on the environment as possible. On the one hand, generations are confronted with producing enough food for all people. On the other hand, production of food should be sustainable to preserve the environment for future generations. Above all, toxins such as pesticides must be reduced to damage the environment as little as possible (Gil & Sinfort, 2005).

2.4. Related Literature on Digitization and Sustainability

The following research papers provide valuable insights concerning digitization and sustainability. Mellaku et al. (2022) presented a mathematical model for decision-making, which has enormous potential to make agriculture more sustainable and efficient. Yet, they did not give a holistic overview of possible use cases for AI in sustainable agriculture and did not consolidate future research direction in this area. Kim et al. (2019) emphasized the potential of unmanned aerial vehicles (UAV) in agriculture while highlighting the barriers to their use. They pointed out that UAVs can be used in harvesting, spraying, mapping, and sensing, but also discussed problems of limited battery capacity and inadequate user interface. However, they did not consider the sustainability aspect. The Internet of Things (IoT) has become an integral part of everyday life and holds great potential in agriculture (Bulut & Wu, 2022). Navarro et al. (2020) studied the main devices, platforms, network protocols, data processing technologies, and the applicability of these technologies in agriculture. Debauche et al. (2021) examined different cloud architectures for eight different characteristics due to the large amounts of data required for AI-based systems in agriculture. Sharma et al. (2021) focused on the prediction of soil parameters, crop yields, disease, and weed detection. Islam et al. (2021) explored the main applications of IoT and UAV combined with AI to contribute to greater sustainability. Moysiadis et al. (2021) presented an overview of the status-quo in smart farming in Europe. However, none of this work has attempted to combine agriculture, sustainability and AI.

To the best of our knowledge, we identified no paper that provides a holistic overview of how AI can be used for sustainable agriculture in crop production. Therefore, we contribute to research by presenting how AI can be used for sustainable agriculture considering the different stages in plant growth. In addition, we contribute to research by presenting an agenda according to "Analyzing the Past to Prepare for the Future" (Webster & Watson, 2002).

3. Methodology

The aim of this paper is to provide a holistic overview of the current state of research of AI-based system to achieve sustainable agricultural arable farming. To investigate the research question, we conducted a structured literature review consisting of five phases, following vom Brocke et al. (2009).

In **phase 1**, we determined an appropriate scope for the literature review. Vom Brocke et al. (2009) recommend the taxonomy by Cooper (1988) to set up the goals of the structured literature review. The taxonomy consists of six characteristics that consider various categories. Different characteristics do not automatically exclude each other (perspective and coverage). We present the taxonomy for our structured literature review in Table 1; the grey highlighted boxes represent the selected categories.

Table 1: Taxonomy of Cooper (1988).

Characteristics:	Categories			
Focus:	Research outcomes	Research methods	Theories	Applications
Goal:	Integration	Criticism		Central issues
Perspective:	Neutral representation		Espousal of position	
Coverage:	Exhaustive	Exhaustive and selective	Representative	Central/pivotal
Organization:	Historical	Conceptual		Methodological
Audience:	Specialized scholars	General scholars	Practitioners and politicians	General public

When conducting a structured literature review, we are interested in providing a research agenda, hence the *focus* is on the research outcome. The *goal* of this paper is to summarize the existing literature in the field of arable farming for sustainable agriculture. Therefore, we strive to take a neutral *perspective*. Furthermore, we chose a representative *coverage, i.e.,* we provide individual examples from literature to represent larger groups of topics. This automatically results in the *organization*, which is conceptual. For this purpose, previous research with the same subject matter is considered together. Finally, this paper addresses specialized scholars, the *audience*.

After establishing the objectives of the structured literature review, we conceptualized the topic during **phase 2.** The aim was to create an overview of the existing state of knowledge on the subject and to identify knowledge gaps. During our unstructured research we identified relevant search terms for the search string. We have often encountered the following terms: “Smart Farming”, “Agriculture Technology”, “Agriculture 4.0”, and many more. Thus, the following search string tries to cover all relevant key words:

(*“artificial intelligence”) AND (“smart farming” OR “agriculture technology”) AND (“seeding” OR “planting” OR “irrigation” OR “weeding” OR “plant protection” OR “harvesting”).*

In the next step **phase 3**, we established the link to sustainability. We divided analysis phase 3 into four sub phases suggested by vom Brocke et al. (2009). They recommend starting the search process by applying the search string to different journals (sub phase 3.1). We have deliberately chosen to omit sub phase 3.1, as we did not want to stick to one or a few journals but wanted to provide a holistic overview on AI in sustainable agriculture. Vom Brocke et al. (2009) suggest searching scientific databases for the topic, which corresponds to sub phase 3.2. In this regard, we identified the following relevant databases: EBSCOhost, Web of Science, and ScienceDirect. We considered the time period from 2020 to 2021 since smart farming is a very fast developing topic that is continuously evolving (Ronaghi & Forouharfar, 2020). In order to filter obsolete knowledge and to include current literature in this paper, the time period was narrowed down. The relevant databases were then searched in sub phase 3.3 with the search string defined in phase 2. We evaluated all relevant articles by checking if the topic of AI and agriculture appears in titles and abstracts. We then examined selected papers, particularly regarding their relation to sustainability. In this vein, we eliminated duplicates, i.e., same articles found in different databases. We present the results of phase 3 in Table 2.

After the literature search in phase 3, we analyzed and synthesized the resulted papers in **phase 4**. Vom Brocke et al. (2009) recommend to create a concept matrix, as developed by Salipante et al. (1982), which was adapted for IS literature reviews by Webster and Watson (2002). It divides the different topics into different units. In this way, we were able to examine the papers in terms of their concepts. The analysis results are presented in **phase 5**. In this final step, the results are translated into a research agenda with possible further research questions.

Table 2: Results of the structured literature review.

Database	Hits	Round: First	Round: Second
EBSCOhost	13	5	4
ScienceDirect	250	36	19
Web of Science	14	4	2
Sum	277	45	25 -> 23 (without duplicates)

4. Analysis and Results

In general, agriculture can be divided into two areas: Arable farming and livestock farming (Lehman et al., 1993). However, our literature review focuses exclusively on the field of arable farming. We structured the results using the following four categories: Stages in plant growth, cultivated areas, technologies, and used AI algorithms. Two out of four categories reflect the agriculture aspect (stages in plant growth, cultivated areas) while the other two categories represent the AI aspect (technologies, used AI algorithms). In this way we investigated the combination of both.

Based on Mehta et al. (2019), we divided the plant growth into four stages: *Seeding, Irrigation, Growing, and Harvesting*. These four stages hold potentials to make agriculture more sustainable with the support of AI (Schoormann et al., 2021). Seeding deals with both the prediction of crop yields from planting and the actual seeding itself. By irrigation, we mean irrigation systems that autonomously decide when to water plants, considering weather forecasts, measured values, and plant data. The growing phase is divided into fertilizers, weed detection, and pest control in fields. We assign harvesting and forecasting of crop yields during plant growth to the harvesting phase (Mehta et al., 2019; Subeesh & Mehta, 2021).

Table 3: Concept matrix - AI use cases for sustainable agriculture.

Paper	Year	Concepts: Stages in plant growth: Seeding	Irrigation	Growing	Harvesting	Cultivated areas: Field	Greenhouse	Technologies: Camera System	Sensor	Satellite /GPS	UMV /UAV	Other	AI algorithms: NN	SVM	RF	Other
Albanese et al.	2021			X		X		X					X			
Barbosa et al.	2021				X	X		X		X	X		X	X	X	X
Castañeda-Miranda et al.	2020		X				X		X	X			X			
Esmail Karar et al.	2021			X		X			X			X	X			
Espejo-Garcia et al.	2021			X		X		X					X			
Gonzalez Perea et al.	2021		X			X		X	X	X			X			
Heiß et al.	2020			X		X			X							X
Hussain et al.	2021			X		X		X					X			
Ikeda et al.	2021			X		X		X				X	X			
Khan et al.	2020			X		X		X					X			
Lin et al.	2021			X			X	X	X	X						X
Liu et al.	2020		X			X		X	X				X			
Pallathadka et al.	2021			X		X		X					X	X		X
Partel et al.	2021			X		X		X	X	X			X			
Sabzi et al.	2020			X		X		X					X	X	X	
Saggi et al.	2020		X			X			X						X	
Saravi et al.	2021				X	X			X				X	X		
Shin et al.	2020			X		X		X					X	X		
Umamageswari et al.	2021			X		X		X					X			
Wan & Goudos	2020				X	X		X					X			
Yu et al.	2020		X			X			X				X			
Zhou et al.	2021				X	X		X			X					X
Zia et al.	2021		X			X			X	X		X				X
Total		0	6	13	4	21	2	16	11	6	2	3	18	5	3	6

4.1. Stages in Plant Growth

Our literature review revealed no paper related to the *seeding* phase with the applied search string (see Table 3). However, we identified several papers concerning the *irrigation* phase. These papers highlighted that freshwater has become an increasingly valuable resource and that increasing consumption is leading to water scarcity (Schestak et al., 2022). Water scarcity results from the increasing world population, rising prosperity, and the expansion of artificial in agriculture. Irrigation of crops uses about 70% of water consumed worldwide (Abdelkhalik et al., 2019). Water scarcity challenges academia and industry to explore innovative approaches to the sustainable use of water as a limited resource. For accurate crop irrigation, it is essential to predict the actual evapotranspiration of plants in order to save water (Liu et al., 2020). We mean with evapotranspiration the total evaporation of a vegetated soil surface. Apparently, evapotranspiration is determined using lysimeters, but they are expensive to use and time-consuming to maintain (Liu et al., 2020). For this reason, researchers investigated approaches to determine evapotranspiration using AI (Liu et al., 2020; Saggi & Jain, 2020). Both the approach using an Elman neural network (NN) model (Liu et al., 2020) and the one using regularization random forest (RF) (Saggi & Jain, 2020) are efficient and could represent alternatives to lysimeters. To develop appropriate irrigation schedules, it is relevant to know the soil water content (Yu et al., 2020). Zia et al. (2021) conducted a case study in Pakistan and concluded that the self-developed intelligent irrigation system outperformed the classically used irrigation system. They saved 46% of the used water, and also achieved 35% more crop yields (Zia et al., 2021). Their AI algorithm receives data from three sources. 1) IoT devices as they measure soil moisture, temperature, and humidity, 2) satellite data that provides wind speed and direction, and 3) predefined data such as crop type, soil type, location (longitude and latitude), and date of cultivation. Based on these results the researchers were able to determine if and how much water is needed. Afterward, farmers were informed and could irrigate the plants accordingly (Zia et al., 2021).

Table 3 also shows that the *growing* phase plays a central role in research with approximately half of the identified publications assigned to it. This phase deals with how the growth of plants can be made more sustainable through AI. The use of fertilizer (Heiß et al., 2020), pesticides (Albanese et al., 2021; Esmail Karar et al., 2021; Ikeda et al., 2021; Lin et al., 2021; Pallathadka et al., 2021; Partel et al., 2021; Shin et al., 2020; Umamageswari et al., 2021), and the detection of weeds (Espejo-Garcia et al., 2020; Hussain et al., 2021; Khan et al., 2020; Sabzi et al., 2020) are aspects that takes into account the growth phase of plants. Reducing the use of fertilizers and pesticides has a significant impact on sustainable agriculture (Kim et al., 2019). Pesticides harm animals, plant life, and humans. In addition, agents could reach neighboring areas and water bodies through run-off and contaminate groundwater (Gil & Sinfort, 2005). To enable pesticide reduction, Partel et al. (2021) developed an intelligent sensor system for tree plantations that, compared to conventional spraying systems, opens the nozzles for pesticides when the plants exhibit characteristics of plant diseases with four different sensors. The sensor system consists of a 2D LiDAR sensor to measure tree height and leaf density, two cameras to capture images for image classification by using a convolutional neural network (CNN) and fruit count, a Global Positioning System (GPS) sensor for location determination, and two flow meters to analyze the sprayed amount. Using a 50-layer NN, the input values were analyzed and the images classified. After the case study, Partel et al. (2021) concluded that the AI-based system was able to reduce the amount of pesticide by 28%, with an error rate of only 8%. They highlighted that the intelligent sensor system has great potential for optimizing spray systems to reduce chemical consumption (Partel et al., 2021). Sabzi et al. (2020) developed a prototype that can distinguish potato plants from the five most common weed species in potato fields. They used video processing and a hybrid neural network image classification algorithm. In general, the AI-based system consists of two processing steps. First, the background is removed from each captured frame in the segmentation phase, and then the frame's objects are identified. After that, the identified objects are converted into a binary image, and the noise is removed. Through a hybrid NN - genetic algorithm, they were able to select six features that are particularly accurate in classifying the objects. They were able to determine that the color features play an important role, since four of the six features refer to the color of the objects. Based on the six features, a hybrid NN - cultural algorithm classifies the detected objects. A test with 4784 objects, where 80% were training data and 20% validation data, showed that about 98% of the objects were classified correctly (Sabzi et al., 2020). In a final step, the approach could be combined with an unmanned vehicle (UMV), which has the function of pulling weeds or spraying herbicides only on weeds to reduce the amount used and not contaminate plants.

In the field of *harvesting*, we identified several publications using AI-based systems for both the actual harvesting and the prediction of crop yields. One of the goals of sustainable agriculture should be to feed all people on the planet, while producing as much food as necessary to minimize waste of food. By making accurate predictions, the area under cultivation can be reduced in future growing seasons if necessary, leading to a reduction in the need for water and pesticides. Using new robotics technology, productivity on plantations can be increased due to automation (Wan & Goudos, 2020). In addition, the use of UMV can increase fruit quality due to the possibility that fruits can be classified into different categories using image classification (Wan & Goudos, 2020). The images needed for classification can be taken from the air or the ground, but the experiment of Zhou et al. (2021) revealed that taking images from the ground provides more detailed information about the degree of maturity. However, the current non-AI-based crop prediction methods are very complex and require many input variables. For this reason, Saravi et al. (2021) propose an NN, for crop yield prediction. AI-based systems cannot consider all features of plants because it would lead to inefficiency due to slowed processing time, as well as possible errors in classification (Sabzi et al., 2020). In this regard, for the prediction of crop yields for coffee plants, the features "Leaf area index" and "Crown diameter" are dominant (Barbosa et al., 2021).

4.2. Cultivation Areas

We generally distinguish between two cultivation areas: classical fields and greenhouses. Both cultivation techniques are presented in today's agriculture. The majority of the identified literature addresses how AI can improve the sustainability of classical arable farming (see Table 3). Most of the paper regarding classical fields deal with the detection of weed/pest infestations and the differentiation of healthy plants. For instance, Partel et al. (2021) developed a sensor system to minimize pesticide use. Other papers covered evapotranspiration estimation (Liu et al., 2020; Saggi & Jain, 2020), water use prediction (Gonzalez Perea et al., 2021), optimize water usage (Yu et al., 2020; Zia et al., 2021), and yield prediction (Barbosa et al., 2021; Saravi et al., 2021). Wan & Goudos (2020) developed a fruit classification system, while Zhou et al. (2021) use a deep learning method to evaluate the maturity of fruits. Heiß et al. (2020) use sensors to determine the crop's supply status.

A few relevant publications address how AI-based systems can improve the sustainability of greenhouse agriculture (see Table 3). Greenhouses could become more relevant for food supply in the future, as they can be used more independently from extreme environmental conditions, which can play a crucial role in times of climate change (Lin et al., 2021). Overall, greenhouses can provide better control for plants to increase crop yields. In order to provide optimal conditions for each plant species, temperature, light conditions, irrigation, and fertilization need to be adjusted individually. Lin et al. (2021) propose classifying remote sensing images (from a Terra remote sensing satellite) using an AI algorithm to identify pests and diseases in greenhouses.

4.3. Technologies

The aim of various technologies is mainly to generate data and to collect data from a real-world environment using UMV to train AI-based systems. These technologies are equipped with sensors that convert a non-electrical input signal into an electrical output signal. In addition, camera systems and GPS are used to observe and track the real-world environment in the fields. All in all, the collected data help improving decisions-making and predictions or classifying images. In the following, we present a detailed overview of the technologies (see Table 3).

Camera systems, sensors, satellites/GPS are used to collect data for the AI-based systems and to improve the automation processes on fields (UMV, GPS). Many publications are based on the image classification approach (e.g., Sabzi et al., 2020). Therefore, images are collected using *camera systems*. For instance, the spatial distribution of water demand and agroclimatic data are determined on the basis of captured images (Gonzalez Perea et al., 2021). A more significant application for image analysis is detecting weeds and identifying plant diseases or undesirable organisms on plants. The individual plants in images can thus be identified using AI-based systems and then subsequently classified into "weed" and "wanted plant" groups (Hussain et al., 2021; Khan et al., 2020; Sabzi et al., 2020). For plant protection, the captured images are examined for pest infestation (Albanese et al., 2021; Esmail Karar et al., 2021; Ikeda et al., 2021), plant diseases (Ikeda et al., 2021; Lin et al., 2021; Pallathadka et al., 2021; Shin et al., 2020; Umamageswari et al., 2021), and to distinguish plant from non-plant (e.g., human, field constructions) (Partel et al., 2021). Based on the results of AI algorithms, the dosage of pesticides can be optimized, resulting in a lower environmental impact. In the field of harvesting, the images are needed to make statements about the degree of ripeness (Zhou et al., 2021), predicted crop yield (Barbosa et al., 2021; Partel et al., 2021; Wan & Goudos, 2020), and to increase fruit quality (Wan & Goudos, 2020). *Sensors* also play a crucial role related to camera systems. Sensors measure soil moisture (Albanese et al., 2021; Liu et al., 2020; Zia et al., 2021), humidity (Zia et al., 2021), field size (Heiß et al., 2020), tree height, and canopy leaf density (Partel et al., 2021), to monitor the general environment of plants (Lin et al., 2021), and determine the ambient temperature (Zia et al., 2021). Thus, there is a wide range of applications for sensors in smart farming. *GPS* is used for georeferencing the drone (Barbosa et al., 2021) and for determining the location where AI-based systems are used to obtain better data from external sources such as weather stations (Castañeda-Miranda & Castaño-Meneses, 2020). Lin et al. (2021) use satellites to take images of the area under investigation to examine area-wide changes. The images from satellites can also be used as input data for AI-based systems (Gonzalez Perea et al., 2021). In addition, wind speed and direction can be determined by using satellites (Zia et al., 2021). Barbosa et al. (2021) and Zhou et al. (2021) capture the images needed for the AI-based algorithm using drones. Furthermore, productivity on plantations can be increased through automation with the help of robots (Wan & Goudos, 2020). UMVs/UAVs are also used for data acquisition. Barbosa et al. (2021) use UAVs to estimate crop yields using a NN based on leaf area index, tree height, crown diameter, and the individual RGB band values. The UAV images can also be used for image classification, as shown by Zhou et al. (2021). Although Espejo-Garcia et al. (2020) and Wan & Goudos (2020) highlighted that AI-based systems could reach their full potential in combination with UMVs/UAVs.

4.4. AI Algorithms

In many scientific publications, AI algorithms such as NNs, RF, or support-vector machines (SVM) were used for AI-based systems (see Table 3). Barbosa et al. (2021) and Sabzi et al. (2020) compare AI algorithms such as NN, SVM, and RF in terms of accuracy. Both conclude NNs have the highest accuracy. Furthermore, research papers applying image processing used CNN to classify images (e.g., Hussain et al., 2021; Khan et al., 2020). However, Pallathadka et al. (2021) identified that SVM outperforms CNN algorithms for image classification. Sabzi et al. (2020) concluded that RF algorithms provide a high accuracy, which is however below the accuracy of the CNN. In addition, Saggi & Jain 2020 used a RF due to the efficient training possibility. We further noticed that AI algorithms such as "You Only Look Once" (Zhou et al., 2021) or gradient boosting regression (Barbosa et al., 2021) are used less frequently. Finally, we cannot make an all-encompassing statement about which algorithm is best suited for a particular use case, as there are different dimensions for the evaluation (e.g., accuracy).

5. Research Agenda

Agriculture impacts the environment due to its food supply activities and the ever-increasing population. The emission of carbon dioxide equivalents, excessive use of pesticides, or the large amounts of water used for artificial irrigation are just a few examples illustrating that agriculture raise potential regarding sustainability. New ways and approaches must be developed to ensure the goal of sustainable agriculture in the future. This paper explored how AI-based systems can be used for sustainable agriculture. Our structured literature review revealed that AI-based systems for sustainable agriculture have entered the IS community. In the following, we present the research agenda.

Stages in plant growth: We identified no paper related to the *seeding* phase based on our literature research (see Table 3). Thus, our literature review revealed that this stage is significantly under-researched compared to the other stages. To keep the soil fertile in the long term, farmers rotate crops in their fields. Crop rotation means that the same crop is not always planted in the same field (Bowles et al., 2022). Different plants need different amounts of nutrients from the soil. By rotating crops, the soil is given time to regenerate nutrients that have been used up. This allows higher yields in future periods (Chen et al., 2018). Therefore, we recommend investigating how AI can be used for soil samples in conjunction with weather data and crop information to determine which crop should be grown in each field to generate the highest possible crop yield. While this information would not reduce the use of water or pesticides, it would lead to a more efficient use of resources as the input to output ratio increases.

Cultivation areas: Even though greenhouses could play a more decisive role in agriculture, we identified only two papers on how AI could be used in this area. However, autonomous greenhouses could be developed with the help of AI-based systems. For instance, these systems could register, and catalogue cultivated plants. In addition, data about pests and diseases could enable recommendation systems that suggest how to deal with these pests and diseases. Finally, AI-based systems could be used to support manual work processes in the greenhouses.

Technologies and AI algorithms: Since many AI-based systems rely on image classification, camera systems are often needed to capture these images to train AI-based systems using data such as temperature or soil moisture. These data are collected using sensors. Therefore, several AI-based systems have been created using NNs that get data via cameras and/or sensors (e.g., Partel et al., 2021). What is important, NNs have the advantage of being accurate (e.g., Barbosa et al., 2021; Sabzi et al., 2020). However, to save costs as much as possible, we suggest that further research could investigate how NNs could be pre-trained to reuse the models and thus also save resources (Espejo-Garcia et al., 2020). In addition, more developments towards robustness, scalability, and generalization of AI algorithms will also be essential for sustainable agriculture. For the development of new AI algorithms, a large and complete set of training data with a wide range of variations is needed.

UMV could work in the field all day, inspecting each plant for specific characteristics, including the degree of ripeness. UMV could inspect the fruit individually and harvest only when it is ripe. Thus, UMV could increase productivity (Jha et al., 2019). We recommend investigating the research question of how UMV can be used for harvesting processes. For the development of UMV, we recommend conducting a design science study to understand which functions and design factors are important and how they can be applied technically.

Further research areas: Besides, researching and providing systems that could lead to more sustainability, new technologies must be deployed and accepted by farmers. Thus, we suggest conducting qualitative studies related to the acceptance of these innovative technologies by applying the Technology Acceptance Model (Davis et al., 1989; Venkatesh, 2000) or Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003).

Restructuring processes for sustainable agriculture requires a lot of materials and energy rendering the "sustainability balance" negative. Future work could address how and when agricultural enterprises should be restructured to best protect the environment, and how and when restructuring should be done to both protect the environment but also consider the economic interests of farmers. This work focused exclusively on how AI can lead to greater sustainability in crop growth. Further research could expand on the aspect of animal husbandry/breeding.

Moreover, an emergent research effort could explore biases, concerns, and potential barriers in adopting AI for sustainable agriculture. This is especially important since future agriculture relying on these technologies could potentially yield erroneous results causing severe economic consequences for the companies and jeopardizing the world food supply. Incorrect decisions of an AI-based irrigation system could contribute to water waste, reducing yields or complete crop failure.

6. Conclusion

In this paper, we have answered the question of how AI can be used for future sustainable agriculture using a structured literature review. With the help of three databases, we identified 23 relevant publications and presented them in a concept matrix (see Table 3), which consists of the topics stages of plant growth, cultivation areas, technologies, and AI algorithms. Based on this literature review, we contribute to research by presenting a research agenda and highlighting the potential of AI for more sustainable agriculture in the future.

This research paper comes with some limitations. First, a different composition of the search string could lead to other matches in the databases. Therefore, for further literature reviews in the context of AI for sustainable agriculture, we recommend considering further synonyms. While the search terms were still determined with utmost care, a different selection of search terms could lead to different results. Second, the search was limited to the three databases ScienceDirect, EBSCOhost, and Web of Science. While these databases cover many publications, we suggest applying the search string on additional databases. Third, we did not perform a forward and backward search (Webster & Watson, 2002). Therefore, we suggest performing these searches to identify further literature. Since we recognized the topic of sustainable agriculture be highly relevant (Bulut & Wu, 2022), further research could consider a larger time period and extend the review on further agriculture-related topic such as livestock farming.

Acknowledgements

This research work was funded by the German Federal Ministry of Education and Research and the Hessen State Ministry for Higher Education, Research and the Arts through their joint support of the National Research Center for Applied Cybersecurity, ATHENE.

References

Abdelkhalik, A., Pascual-Seva, N., Nájera, I., Giner, A., Baixauli, C., & Pascual, B. (2019). Yield response of seedless watermelon to different drip irrigation strategies under Mediterranean conditions. *Agricultural Water Management*, *212*, 99–110.

Albanese, A., Nardello, M., & Brunelli, D. (2021). Automated Pest Detection with DNN on the Edge for Precision Agriculture. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, *11*(3), 458–467.

Araújo, S. O., Peres, R. S., Barata, J., Lidon, F., & Ramalho, J. C. (2021). Characterising the agriculture 4.0 landscape—emerging trends, challenges and opportunities. *Agronomy*, *11*(4), 1–37.

Barbosa, B. D. S., Ferraz, G. A. e S., Costa, L., Ampatzidis, Y., Vijayakumar, V., & dos Santos, L. M. (2021). UAV-based coffee yield prediction utilizing feature selection and deep learning. *Smart Agricultural Technology*, *1*, 100010.

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Artificial Intelligence in Organizations : Implications for Information Systems Research. *Journal of the Association for Information Systems*, *22*(2), 281–303.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artifical Intelligence. *MIS Quarterly*, *45*(3), 1433–1450.

Bowles, T. M., Jilling, A., Morán-Rivera, K., Schnecker, J., & Grandy, A. S. (2022). Crop rotational complexity affects plant-soil nitrogen cycling during water deficit. *Soil Biology and Biochemistry*, *166*.

Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial Intelligence and the modern productivity paradox: A Clash of Expectations and Statistic. *NBER Working Paper No. 24001*.

Bulut, C., & Wu, P. (2022). *AIS Electronic Library (AISeL) IoT adoption in agriculture : a systematic review IoT adoption in agriculture : a systematic review*. 0–10.

Castañeda-Miranda, A., & Castaño-Meneses, V. M. (2020). Internet of things for smart farming and frost intelligent control in greenhouses. *Computers and Electronics in Agriculture*, *176*.

Chen, S., Liu, S., Zheng, X., Yin, M., Chu, G., Xu, C., Yan, J., Chen, L., Wang, D., & Zhang, X. (2018). Effect of various crop rotations on rice yield and nitrogen use efficiency in paddy–upland systems in southeastern China. *Crop Journal*, *6*(6), 576–588.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial Intelligence in Information Systems Research: A Systematic Literature Review and Research Agenda. *International Journal of Information Management*, *60*.

Cooper, H. M. (1988). Organizing Knowledge Syntheses: A Taxonomy of Literature Reviews. *Knowledge in Society*, *1*(104).

Darlington, R., Staikos, T., & Rahimifard, S. (2009). Analytical methods for waste minimisation in the convenience food industry. *Waste Management*, *29*(4), 1274–1281.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003.

Debauche, O., Mahmoudi, S., Manneback, P., & Lebeau, F. (2021). Cloud and distributed architectures for data management in agriculture 4.0: Reiew and future trends. *Journal of King Saud University - Computer and Information Sciences*.

Eastwood, C., Klerkx, L., Ayre, M., & Dela Rue, B. (2019). Managing Socio-Ethical Challenges in the Development of Smart Farming: From a Fragmented to a Comprehensive Approach for Responsible Research and Innovation. *Journal of Agricultural and Environmental Ethics*, *32*(5–6), 741–768.

Esmail Karar, M., Abdel-Aty, A. H., Algarni, F., Fadzil Hassan, M., Abdou, M. A., & Reyad, O. (2021). Smart IoT-based system for detecting RPW larvae in date palms using mixed depthwise convolutional networks. *Alexandria Engineering Journal*.

Espejo-Garcia, B., Mylonas, N., Athanasakos, L., & Fountas, S. (2020). Improving weeds identification with a repository of agricultural pre-trained deep neural networks. *Computers and Electronics in Agriculture*, *175*.

FAO. (2020). World Food and Agriculture - Statistical Yearbook 2020. In *World Food and Agriculture - Statistical Yearbook 2020*. FAO.

Gil, Y., & Sinfort, C. (2005). Emission of pesticides to the air during sprayer application: A bibliographic review. *Atmospheric Environment*, *39*(28), 5183–5193.

Gonzalez Perea, R., Ballesteros, R., Ortega, J. F., & Moreno, M. Á. (2021). Water and energy demand forecasting in large-scale water distribution networks for irrigation using open data and machine learning algorithms. *Computers and Electronics in Agriculture*, *188*.

Heiß, A., Paraforos, D. S., Sharipov, G. M., & Griepentrog, H. W. (2020). Modelling and simulation of a fuzzy system for site-specific nitrogen fertilization. *IFAC-PapersOnLine*, *53*(2), 15790–15795.

Hussain, N., Farooque, A. A., Schumann, A. W., Abbas, F., Acharya, B., McKenzie-Gopsill, A., Barrett, R., Afzaal, H., Zaman, Q. U., & Cheema, M. J. M. (2021). Application of deep learning to detect Lamb's quarters (Chenopodium album L.) in potato fields of Atlantic Canada. *Computers and Electronics in Agriculture*, *182*.

Ikeda, M., Ruedeeniraman, N., & Barolli, L. (2021). An intelligent VegeCareAI tool for next generation plant growth management. *Internet of Things (Netherlands)*, *14*.

Islam, N., Rashid, M. M., Pasandideh, F., Ray, B., Moore, S., & Kadel, R. (2021). A review of applications and communication technologies for internet of things (Iot) and unmanned aerial vehicle (uav) based sustainable smart farming. *Sustainability*, *13*(4), 1–20.

Jerhamre, E., Carlberg, C. J. C., & van Zoest, V. (2022). Exploring the susceptibility of smart farming: Identified opportunities and challenges. *Smart Agricultural Technology*, *2*(August 2021), 100026.

Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. In *Artificial Intelligence in Agriculture* (Vol. 2, pp. 1–12).

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 1–11.

Khan, A., Ilyas, T., Umraiz, M., Mannan, Z. I., & Kim, H. (2020). Ced-net: Crops and weeds segmentation for smart farming using a small cascaded encoder-decoder architecture. *Electronics (Switzerland)*, *9*(10), 1–16.

Kim, J., Kim, S., Ju, C., & Son, H. Il. (2019). Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. *IEEE Access*, *7*.

Lehman, H., Clark, E. A., & Weise, S. F. (1993). Clarifying the definition of Sustainable agriculture. *Journal of Agricultural and Environmental Ethics*, *6*(2), 127–143.

Lin, F., Weng, Y., Chen, H., & Zhuang, P. (2021). Intelligent greenhouse system based on remote sensing images and machine learning promotes the efficiency of agricultural economic growth. *Environmental Technology & Innovation*, *24*, 101758.

Liu, J., Meng, X., Ma, Y., & Liu, X. (2020). Introduce canopy temperature to evaluate actual evapotranspiration of green peppers using optimized ENN models. *Journal of Hydrology*, *590*.

Masson-Delmotte, V., Zhai, P., Chen, Y., Goldfarb, L., Gomis, M. I., Matthews, J. B. R., Berger, S., Huang, M., Yelekçi, O., Yu, R., Zhou, B., Lonnoy, E., Maycock, T. K., Waterfield, T., Leitzell, K., & Caud, N. (2021). *Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change Edited by* (I. P. on C. Change (ed.)).

Mehta, C. R., Jena, P. C., Chandel, N. S., & Jha, A. (2019). Indian agriculture counting on farm mechanization. *Agricultural Mechanization in Asia, Africa and Latin America*, *50*(1), 84–89.

Mellaku, M. T., & Sebsibe, A. S. (2022). Potential of mathematical model-based decision making to promote sustainable performance of agriculture in developing countries: A review article. *Heliyon*, *8*(2).

Moysiadis, V., Sarigiannidis, P., Vitsas, V., & Khelifi, A. (2021). Smart Farming in Europe. *Computer Science Review*, *39*, 100345.

Navarro, E., Costa, N., & Pereira, A. (2020). A Systematic Review of IoT Solutions for Smart Farming. *Sensors*,

20(15), 1–29.
Pallathadka, H., Ravipati, P., Sekhar Sajja, G., Phasinam, K., Kassanuk, T., Sanchez, D. T., & Prabhu, P. (2021, December). Application of machine learning techniques in rice leaf disease detection. *Materials Today: Proceedings*.
Partel, V., Costa, L., & Ampatzidis, Y. (2021). Smart tree crop sprayer utilizing sensor fusion and artificial intelligence. *Computers and Electronics in Agriculture*, *191*.
Rai, A., Constantinides, P., & Sarker, S. (2019). Next-Generation Digital Platform : Toward Human-AI Hybrids. *MIS Quarterly*, *43*(February), 1–9.
Ronaghi, M. H., & Forouharfar, A. (2020). A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT). *Technology in Society*, *63*.
Russell, S. J., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach (4th ed.)*. Pearson Education.
Sabzi, S., Abbaspour-Gilandeh, Y., & Arribas, J. I. (2020). An automatic visible-range video weed detection, segmentation and classification prototype in potato field. *Heliyon*, *6*(5).
Saggi, M. K., & Jain, S. (2020). Application of fuzzy-genetic and regularization random forest (FG-RRF): Estimation of crop evapotranspiration (ETc) for maize and wheat crops. *Agricultural Water Management*, *229*.
Salipante, P., Notz, W., & Bigelow, J. (1982). A Matrix Approach to Literature Reviews. *Research in Organizational Behavior*, *4*, 321–348.
Saravi, B., Nejadhashemi, A. P., Jha, P., & Tang, B. (2021). Reducing deep learning network structure through variable reduction methods in crop modeling. *Artificial Intelligence in Agriculture*, *5*, 196–207.
Schestak, I., Styles, D., Black, K., & Williams, A. P. (2022). Circular use of feed by-products from alcohol production mitigates water scarcity. *Sustainable Production and Consumption*, *30*, 158–170.
Schoormann, T., Möller, F., Petrik, D., Schoormann, T., & Möller, F. (2021). Achieving Sustainability with Artificial Intelligence — A Survey of Information Systems Research. *Proceedings of the International Conference on Information Systems*.
Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2021). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*, *9*, 4843–4873.
Shin, J., Chang, Y. K., Heung, B., Nguyen-Quang, T., Price, G. W., & Al-Mallahi, A. (2020). Effect of directional augmentation using supervised machine learning technologies: A case study of strawberry powdery mildew detection. *Biosystems Engineering*, *194*, 49–60.
Subeesh, A., & Mehta, C. R. (2021). Automation and digitization of agriculture using artificial intelligence and internet of things. *Artificial Intelligence in Agriculture*, *5*, 278–291.
Umamageswari, A., Bharathiraja, N., & Irene, D. S. (2021). A Novel Fuzzy C-Means based Chameleon Swarm Algorithm for Segmentation and Progressive Neural Architecture Search for Plant Disease Classification. *ICT Express*.
United Nations. (2019). *World Population Prospects 2019 Highlights*.
UnitedNations. (1987). *Report of the World Commission on Environment and Development - Our Common Future*.
Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research*, *11*(4), 342–365.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478.
Vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. *Proceedings on the European Conference on Information Systems*.
Wan, S., & Goudos, S. (2020). Faster R-CNN for multi-class fruit detection using a robotic vision system. *Computer Networks*, *168*.
Wang, P. (2019). On Defining Artificial Intelligence. *Journal of Artificial General Intelligence*, *10*(2), 1–37. https://doi.org/10.2478/jagi-2019-0002
Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *26*(2), xiii–xxiii.
Yu, J., Tang, S., Zhangzhong, L., Zheng, W., Wang, L., Wong, A., & Xu, L. (2020). A deep learning approach for multi-depth soil water content prediction in summer maize growth period. *IEEE Access*, *8*, 199097–199110.
Zhou, X., Lee, W. S., Ampatzidis, Y., Chen, Y., Peres, N., & Fraisse, C. (2021). Strawberry Maturity Classification from UAV and Near-Ground Imaging Using Deep Learning. *Smart Agricultural Technology*, *1*, 100001.
Zia, H., Rehman, A., Harris, N. R., Fatima, S., & Khurram, M. (2021). An experimental comparison of iot-based and traditional irrigation scheduling on a flood-irrigated subtropical lemon farm. *Sensors*, *21*(12).