Impact Factor 6.1

Journal of Cyber Security

ISSN:2096-1146

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Digital Technologies for Sustainable Crop Production: A Review

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Abstract

There will be 9.7 billion people in the world by 2050. Feeding them will require increasing current food production by up to 98 percent. This is not the only challenge. Climate change is an increasing threat to weather-dependent agriculture as we see more erratic rainfall patterns and more frequent floods and droughts. In addition, our current methods of food production contribute a quarter of global greenhouse gas emissions, further exacerbating climate change. Agriculture also has a significant impact on the environment as it consumes large amounts of precious natural resources like fresh water which are depleting rapidly. Moreover, we cannot expand the land under cultivation to increase food production without causing further deforestation. About 84 percent of the world's farmers are smallholders and produce 30–34 percent of the world's food. Yet, they contend with challenges such as low productivity, poor efficiency, and the effects of climate change mentioned. Increasing their productivity is essential for eliminating global poverty. To ensure food security for our future generations, agriculture needs become more sustainable—environmentally, economically, and socially—through applying technology, digital and innovation.

Key Words: Climate change, global greenhouse gas emissions, exacerbating climate change, precious natural resources, low productivity, global poverty.

1. Introduction:

China has the largest population of about 1.4 billion in the world, and it also ranks first in agricultural population of about 600 million. Agriculture is the most important industry in China. At present, China produces 25 percent of the world's food and feeds around 19 percent of the world's population with only 7 percent of the world's arable land. For a long time, farming in China has been a labor-intensive industry. In recent decades, the Chinese government has been paying close attention to agricultural science and technology, leading to a high growth rate in China's output of various agricultural products and enhancing the transformation from traditional to modern agriculture. Emerging digital technologies like artificial intelligence (AI), blockchain, cloud computing, and Internet of things (IoT) are already making an impact in several sectors and hold the potential to revolutionized food and agricultural systems globally. Precision agriculture technologies using AI that can improve resource efficiency and productivity of farming, blockchain systems integrated with IoT that can improve supply chain traceability, alternative proteins that can reduce the environmental impact of conventional meat production; these are among the many technologies that are changing the way we grow and consume food. The Global Centre is engaged in exploring the existing and emerging technologies that can help food systems become more sustainable and resilient, sharing knowledge and building capacity to help UNDP's field offices, policymakers and other stakeholders to understand these technologies and their applications – including the opportunities and challenges they present and building multi-stakeholder partnerships to support their large-scale adoption, especially in developing countries to benefit smallholder farmers.

Figure 1: Advanced technologies including satellite remote sensing and drone-powered data solutions help increase agricultural efficiency and productivity. ***Sources: Using satellite technology to transform agriculture in developing countries | UN Trade and Development (UNCTAD).***

Blockchain for Food Traceability

Blockchain for food traceability is gaining momentum in the agri-food sector globally. Yet, there is little understanding among ecosystem stakeholders and governments about what blockchain is, how it works and how it can be applied to the supply chain. Our aim is to make this information accessible and easy to understand for all. To achieve this, we are designing a case study and concept note that will explain how blockchain technologies work and its benefits to food traceability for different actors in the supply chain. This will include a guide explaining how blockchain can be applied to the food value chain, including examples and case studies where its application has been successful. We believe that blockchain technology will be transformational for a more efficient and transparent food system and can significantly contribute to international trade, improve food safety, and protect the rights of producers and consumers around the world.

2. Internet of Things (IoT) in Farming

A network of networked objects with sensors and software that enable data collection and exchange is referred to as the Internet of Things (IoT). IoT integration in farming entails the use of smart sensors, drones, and automated equipment to control and monitor agricultural operations. By enabling real-time data-driven decision-making, optimizing resource use, and boosting productivity, this technology transforms farming practices. The farms of today are increasingly becoming digitalized. Digital farms are often said to have improved profitability and sustainability, but how much these technologies can help assist smallholder farmers and whether they are economically viable are unanswered. Digital farming broadly encompasses technologies to assist producers in farming, most commonly known as precision agriculture technologies. We intend to design a report that will demonstrate the utility and viability of adopting digital farming technologies (focused on precision agriculture). This report will include detailed analyses of these technologies, their applications, outcomes and impact and feasibility of use.

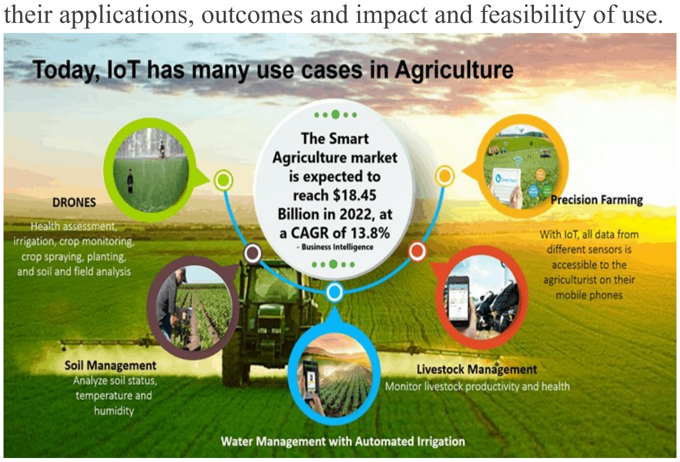

Figure 2:* Internet of Things (IoT) in Farming. *Sources: Smart Farming: Digital Transformation of Agriculture

Through this document, we hope to provide governments and policymakers with a detailed breakdown of quantifiable benefits of various digital farming technologies and inform them of the best methods through which these technologies should be transferred and applied. Digital Agriculture (DA) deals with the practice of advanced technological solutions such as sensors, robotics, and data analysis for improving the ecological and economic viability of agricultural operations, and simultaneously elevating crop output and quality. Conventional farming methods have faced significant challenges in the past three decades to respond to the increasing demand for food, rising labor costs, reducing carbon footprint, and climate change (Abbas et al., 2022a; Abbas et al., 2022b; Elahi et al., 2022; Elahi et al., 2024). On the other hand, improving long-term efficiency and maintaining the viability of crop production requires adaptations of digital technologies to reduce input costs and increase profit margins. Digitalization of agriculture benefits from a wide range of automation software and hardware platforms to contribute to replacing tedious manual operations with continuous automated processes with the ultimate objective of securing food production for the increasing world population. In modern farms, multiple ground-based sensors combined with maps and drone-generated images, as well as artificial intelligence (AI) and prediction models are delivering detailed agronomic data on crop conditions to support farmers with short-term and long-term decision-making. However, their impact on the entire agri-food value chain, as well as the relatively newer concepts such as the Internet-of-Things (IoT), mobile apps, robotics, Artificial Intelligence (AI), Unmanned Aerial Vehicles (UAV), big data analysis, digital twins, and Blockchain fall under the umbrella of digital agriculture (Fielke et al., 2020).Digital agriculture is being practiced in many regions, either on commercial scales or in pilot plants. The fundamentals for DA however began to shape after 2010, with the popularity of some of the core technologies such as low-power wide area network (LPWAN) for IoT applications (Klaina et al., 2022), open-source software for robotics (Mier et al., 2023), and machine learning tools for data processing (Sharma et al., 2020; Sharma et al., 2021), which redefined the existing concepts of precision agriculture and smart farming.

Digital technologies are revolutionizing crop production towards greater sustainability by optimizing resource use, enhancing yields, and improving efficiency. Key digital tools include sensors, drones, and AI, which enable precision agriculture and real-time monitoring. This shift from traditional farming methods to data-driven approaches is crucial for meeting the growing global demand for food while minimizing environmental impact.

Here's a more detailed look at how digital technologies are transforming crop production:

1. Precision Agriculture:

Sensors and IoT:

Wireless sensors collect data on soil conditions, moisture, temperature, and plant health, providing real-time insights for optimized irrigation, fertilization, and pest management.

Drones and Remote Sensing:

Drones equipped with cameras and sensors capture high-resolution images and data, enabling farmers to monitor crop health, identify issues early, and optimize resource allocation.

GPS and GIS:

Global Positioning Systems (GPS) and Geographic Information Systems (GIS) allow for precise mapping and management of fields, enabling targeted interventions and optimized input application.

2. Artificial Intelligence and Machine Learning:

Data Analysis:

AI and machine learning algorithms analyze vast amounts of data from sensors, drones, and other sources to identify patterns, predict yields, and optimize farming practices.

Robotics and Automation:

Robotic systems can automate tasks like planting, harvesting, and weeding, increasing efficiency and reducing reliance on manual labor.

Predictive Analytics:

AI can predict potential problems like disease outbreaks or nutrient deficiencies, allowing farmers to take proactive measures and prevent losses.

3. Farm Management Software and Blockchain:

Streamlined Operations:

Farm management software helps farmers organize data, track inventory, manage finances, and streamline operations, improving overall efficiency.

Traceability and Transparency:

Blockchain technology provides a secure and transparent way to track crops from farm to consumer, ensuring food safety and building trust in the supply chain.

4. Vertical Farming and Controlled Environment Agriculture:

Resource Efficiency:

Vertical farms and controlled environment agriculture (CEA) utilize hydroponics, aquaponics, and other techniques to maximize yields in a small footprint, minimizing land and water usage.

Reduced Pesticide Use:

CEA systems create a controlled environment that reduces the need for pesticides, promoting environmentally friendly crop production.

5. Digital Twins and Simulations:

Virtual Representation:

Digital twins create a virtual replica of the farm, allowing for simulations of different scenarios and optimizing crop management practices.

Agro-ecosystem Modeling:

Simulations can help understand how different factors affect the agro-ecosystem and make informed decisions about crop selection, planting density, and other management practices.

Benefits of Digital Technologies:

Increased Crop Yields:

By optimizing resource use and identifying potential problems early, digital technologies can significantly boost crop yields.

Reduced Environmental Impact:

Precision agriculture and CEA practices minimize water usage, fertilizer application, and pesticide use, leading to more sustainable farming practices.

Improved Efficiency and Profitability:

Automation, data-driven decision making, and streamlined operations can improve overall efficiency and increase profitability for farmers.

Enhanced Food Security:

By increasing yields and optimizing resource use, digital technologies can play a vital role in ensuring food security for a growing population.

Challenges:

Cost of Adoption: The initial investment in digital technologies can be a barrier for some farmers.

Digital Divide: *Access to technology and digital literacy can be unevenly distributed, creating a digital divide between different regions and farmers.*

Data Security and Privacy: *Protecting sensitive farm data from unauthorized access is crucial.*

Future Outlook:

Digital technologies are poised to play an increasingly important role in sustainable crop production, with ongoing research and development focused on further enhancing their capabilities and addressing the challenges of adoption. The integration of AI, robotics, and other emerging technologies promises to transform agriculture, making it more efficient, resilient, and environmentally friendly

2.1. Applications

IoT provides a wide range of applications for in-the-moment monitoring, data gathering, and decision-making in several industries. Drones can provide aerial images for crop health evaluation, while IoT sensors can monitor soil moisture, temperature, and nutrient levels in agriculture. Devices for tracking livestock allow for remote animal health monitoring. By integrating these data streams into analytics platforms, farmers are given the tools necessary to make educated decisions about irrigation, fertilization, disease prevention, and general farm management, ultimately enhancing productivity and sustainability.

2.2. Benefits

By maximizing resource consumption, increasing output, and lowering prices, IoT has a big positive impact on agriculture. Smart sensors keep an eye on crop health, weather patterns, and soil conditions to provide accurate watering and fertilization as well as effective resource management. Timely disease and pest management measures are made possible by real-time data. Automated equipment boosts operational effectiveness while labor costs are reduced by remote monitoring. All of these elements work together to improve farmer profitability by boosting yields, reducing waste, and reducing costs.

3. Automation and Robotics in Agriculture

Smart farming transforms agricultural practices by relying heavily on automation and robotics. Planting, harvesting, and irrigation operations are handled by automated machinery, which lowers labor requirements and boosts productivity. Robotics allows for selective harvesting and precise input application, reducing resource waste. Autonomous trucks improve logistics, while drones provide aerial data for agricultural monitoring. These technologies work together to improve modern agriculture's productivity, sustainability, and economic viability.

Figure 3: Agricultural Robots – How robotics is changing agriculture. ***Sources: Agricultural Robots – How robotics is changing agriculture***

The integration of automation and control systems alongside data processing software, web-based applications, and mobile tools has significantly influenced farming practices over the past three decades, largely aiming to enhance efficiency in land and resource utilization. Prior to 2010, farmers relied on technologies such as the Global Positioning System (GPS) (Shamshiri et al., 2013; Shamshiri and Ismail, 2013), ground-based sensing platforms, satellite maps, and local sensing devices like data loggers to monitor fields and identify deficiencies. However, the introduction of more compact technological solutions, such as autonomous drones, LiDAR sensors, high-resolution cameras, small-scale robots, and long-range wireless transmitters, has led to a shift in precision agriculture and smart farming methods towards digitization. These advancements have played a crucial role in fostering economic growth and promoting sustainability in food production. In its workflow, precision agriculture utilizes data from different resources, such as satellite images, in-situ sensors, and mobile sensing platforms, to identify deficiencies and enhance crop yield through improved resource management, including the application of variable rate technology (Shamshiri et al., 2018a

3.1. Examples

Self-driving tractors for planting and tillage as well as robotic milking systems in dairy farms are examples of automated farming equipment. Crop monitoring, disease detection, and pesticide application are all done by drones. Robotic harvesting technologies help with the selective gathering of produce like lettuce and strawberries. Additionally, autonomous cars optimize logistics by moving items within farms. By streamlining farming operations, these technologies lower labor costs, increase accuracy, and eventually boost yields and profitability.

3.2. Benefits

There are numerous advantages to automation in agriculture. It improves overall efficiency by handling monotonous activities, freeing farmers to concentrate on making strategic decisions. Cost reductions result from reduced labor demands. Automation also reduces the possibility of workplace accidents, improving farmworkers' safety. Automated systems increase production, decrease errors, and improve farm management through precise and consistent operations, making agriculture more economically and sustainably viable.

4. Data Analytics and Farm Management Systems

Smart farming depends on data analytics and farm management systems because they convert the enormous amounts of data gathered from sensors, drones, and other sources into insightful knowledge. With the use of this information, decision-makers may make well-informed choices that maximize resource use, forecast crop health, and improve overall productivity, resulting in more effective and environmentally friendly agricultural methods.

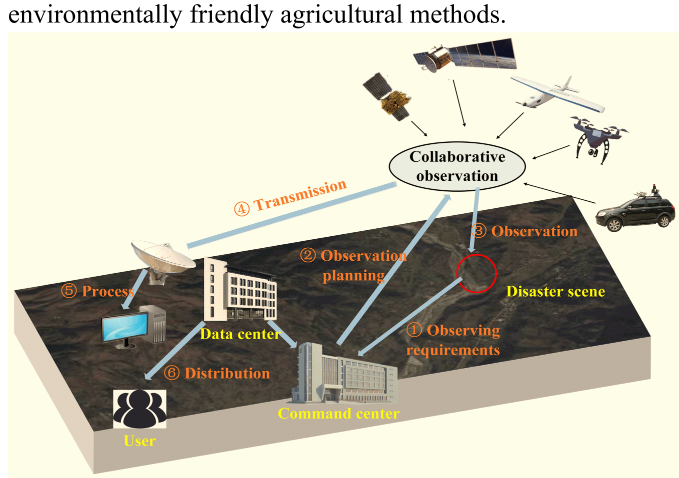

Figure 4: Collaborative remote sensing observation service system for geohazard emergency response. ***Sources: Liu, Y.***

and Zhang, J.,2022. Nat. Hazards Earth Syst. Sci., 22, 227–244, https://doi.org/10.5194/nhess-22-227-2022, 2022.

5. Sensor technology resource emergency service system

Current remote sensors can be divided into satellite, aerial and terrestrial types according to the platforms on which they are mounted (Grün, 2008). Satellite remote sensing is divided into land satellites, meteorological satellites and ocean satellites according to their fields of operation. Land satellites are mainly used to detect the resources and environment on Earth's surface and contain a variety of sensor types such as panchromatic, multispectral, hyperspectral, infrared, synthetic-aperture radar, video and luminescence (Belward and Skoien, 2015). Meteorological satellites observe Earth and its atmosphere, and their operations can be divided into Sun-synchronous polar orbit and geosynchronous orbit (NSMC, 2020; Wang et al., 2018). Oceanic satellites are dedicated satellites that detect oceanic elements and the marine environment with optical payloads generally including watercolor water thermometers and coastal zone imagers and microwave payloads including scatterometers, radiometers, altimeters and SAR (Fu et al., 2019). The countries and regions in the world that currently have autonomous remote sensing satellites include the United States, France, ESA members, Germany, Israel, Canada, Russia, China, Japan, South Korea and India. The main satellite launches are shown in Table A1. Aerial remote sensing is a technology that uses aircraft, airships and UAVs as sensor carriers for detection (Colomina and Molina, 2014).

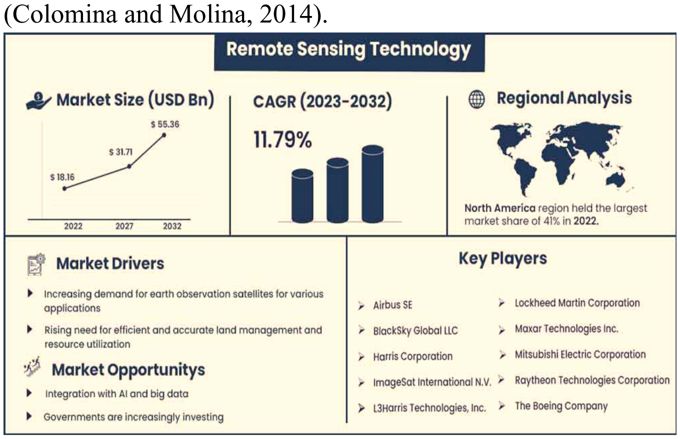

Figure 5: The global remote sensing technology market size was evaluated at USD 18.16 billion in 2022 and is expected to touch around USD 55.36 billion by 2032, growing at a noteworthy CAGR of 11.79% from 2022 to 2032. ***Sources:*** *Remote Sensing Technology Market Poised to Exceed CAGR 11.79% By 2032*

Remote sensing technology is a non-invasive way to gather information about the physical characteristics of the earth's surface using reflected and emitted light from satellites and aircraft. The market growth is primarily due to an increase in earth observation projects by different space agencies. For example, the Indian Space Research Organisation (ISRO) has thirteen earth observation satellites and plans to launch ten more during 2020-2021. During the COVID-19 pandemic, remote sensing technology gained more adoption as countries used it to monitor the virus's spread and study environmental changes.

New earth's observation dashboard was created by NASA, JAXA, and ESA in June 2020, which integrated various satellites to records to monitor changes in agriculture, climate and economic activity. The adoption of remote sensing technology in the smart city projects for zoning, urban planning, and security is paving ways for the market growth. Many countries are to investing heavily in smart city projects, which are expected to drive market growth during the forecast period.

Different airborne remote sensing devices have been developed to face various remote sensing tasks. These devices include digital aerial cameras, lidar, digital cameras, imaging spectrometers, infrared sensors and miniSAR (unmanned airborne microminiature synthetic-aperture radar). Ground remote sensing systems have two states: mobile and static. A mobile measurement system executes rapid movement measurement by means of vehicles (e.g., cars and boats) and consists of sensors such as charge-coupled device (CCD) cameras, cameras, laser scanners, GPS and inertial navigation systems (INSs) (Li et al., 2015). These can acquire the geospatial position of the target while collecting realistic images of the features. Static state measurement refers to the installation of sensors in a fixed place and includes laser scanners, cameras, ground-based SAR and surveying robots. These can form a ground sensor web through computer network communication and geographic information service technology.

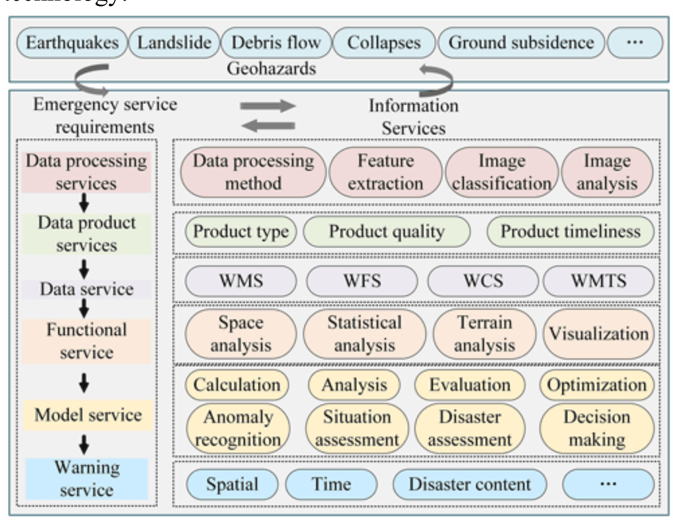

Figure 6: Emergency geographic information service. ***Sources: Liu, Y. and Zhang, J.,2022. Nat. Hazards Earth Syst. Sci., 22, 227–244, https://doi.org/10.5194/nhess-22-227-2022, 2022.***

In the face of geohazard emergency responses, space–air–ground remote sensors establish associations through collaborative planning to form a collaborative observation service system based on the process of "observation–transmission–processing–distribution", as shown in Fig. 1. In the event of a geological disaster, the emergency command center responds quickly, planning observation missions according to observation needs and the current technical environment (1, 2). After remote sensing systems carry out observation missions (3), the data are received, processed and distributed through the data center, providing emergency services mainly based on geographic information (4, 5, 6).

The geographic information services provided by the remote sensing emergency service system are shown in Fig. 2. These services include data processing, data products, data services, model services, functional services and warning services. Data processing refers to the process and method of obtaining effective emergency information from the collected data and includes the data processing method, feature extraction, image classification and image analysis. Data products refer to the quality and current potential of various types of remote sensing products. Data services provide disaster-related basic data, thematic data and analysis data through the web map service (WMS), web feature service (WFS), web coverage service (WCS) and web map tile service (WMTS). Functional services provide quantitative, qualitative, characterization and visualization of geospatial phenomena through spatial analysis services, terrain analysis services and visualization services. Model services provide various models for calculation, analysis, anomaly identification, damage assessment, situational assessment, evaluation, decision-making and optimization. Warning services provide early warnings of disasters with regard to space, time and situation.

6. Digitalization technology in Agriculture

6.1 Remote Sensing Technology:

Utilizing UAV imagery to estimate the height and density of plant canopies offers valuable insights into the growth status of field plants. This method can be outlined in three main steps as (i) generating a digital surface model (DSM), (ii) creating a digital terrain model (DTM), and (iii) determining plant height by subtracting the DTM from the DSM. This approach holds particular significance in crop management decisions reliant on site-specific canopy characterization. The information generated through this method find applications across various domains of DA and PA, including leaf area index evaluation (Comba et al., 2020), precision crop protection (Garcerá et al., 2021), site-specific irrigation (Jiménez-Brenes et al., 2017), nutrient management (Tee et al., 2023), yield prediction (Gené-Mola et al., 2020), autonomous navigation (Pathak et al., 2019; Fielke et al., 2020), and early disease detection (Jurado et al., 2020). UAV-based remote sensing platforms are mainly used to monitor soil properties and crop stress, creating valuable information for developing decision support systems in pest control applications, smart fertilization, and irrigation management (Lajoie-OMalley et al., 2020). Although satellite images can also provide information about the existing of such variability in the fields in a shorter period of time, however the quality of their images depends on a cloud-free view, which limits their applications at any time and location. In addition, they do not offer a flexible and affordable platform for experimenting with multiple sensors. On the other hand, UAVs offer higher spatial and temporal resolution data which makes them a versatile remote sensing platform in different season and growth stages for supporting a wide variety of applications such as plant phenotyping (Shamshiri et al., 2018c; Comba et al., 2020), Leaf Area Density (LAD) estimation (Garcerá et al., 2021; Bates et al., 2021), determination of Leaf Chlorophyll Content (LCC) (Vergara-Díaz et al., 2016), and plant breeding (Guo W. et al., 2021).

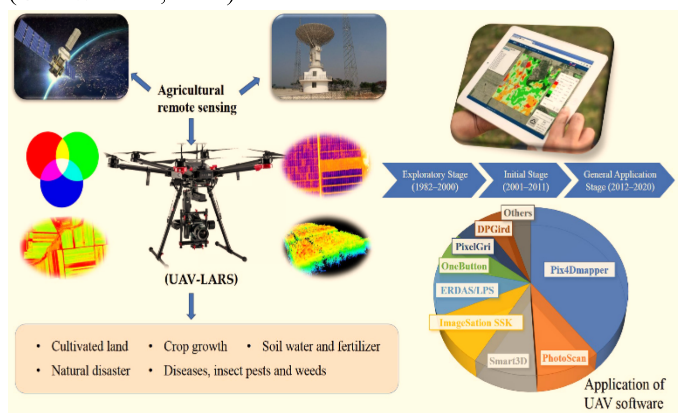

Figure 7: An emerging method of agricultural monitoring is unmanned aerial vehicle low-altitude remote sensing (UAV-LARS). ***Sources: Remote Sens.*** **2021, *13* (6), 1221; https://doi.org/10.3390/rs13061221**

Several studies have demonstrated the effectiveness of UAV-based LAI estimation methods across different crop types and environmental conditions. For instance, Córcoles et al. (Córcoles et al., 2013) employed a UAV-based automated infrared imaging system to estimate LAI for onion crops, showing a linear correlation between canopy cover and LAI. Lendzioch et al. (Lendzioch et al., 2019) successfully estimated winter LAI and snow depth in a spruce forest using UAV-based imagery, while Sha et al. (Sha et al., 2018) compared UAV-based LAI estimation with field measurements for grassland pastures in China, revealing inconsistencies in near-infrared spectrum measurements. Additionally, Roosjen et al. (Roosjen et al., 2018) estimated LAI and leaf chlorophyll content of potatoes using UAV imagery, noting the impact of multi-angular angles and zenith angle on LAI estimation accuracyMoreover, detailed and reliable canopy information aids farmers in making timely and site-specific management decisions, underscoring the potential of 3D point cloud datasets for economic and environmental conservation strategies. Leaf area index estimation is crucial for enhancing crop growth models and addressing field uncertainties such as terrain erosion (Rodrigo-Comino, 2018), soil organic carbon problems (Chen et al., 2021), and climate change impacts (Balasundram et al., 2023). Collecting LAI data traditionally involves manual measurements using in-field portable instruments (Mourad et al., 2020) such as LI-3000C (LI-COR Biosciences GmbH, Homburg, Germany) or AccuPAR LP-80 (Metergroup, Pullman, WA, United States). However, UAVs equipped with high-resolution imaging sensors, LiDAR, multi-spectral, and hyperspectral cameras (Zhang et al., 2009; Hardin and Jensen, 2011; Wallace et al., 2012; Knoth et al., 2013; Shahbazi et al., 2014; Whitehead et al., 2014; Linchant et al., 2015) have proven successful in estimating LAI for various crops, including maize (Han et al., 2018), berries (Herrero-Huerta et al., 2015), almonds (Torres-Sánchez et al., 2018), olives (Jiménez-Brenes et al., 2017), grapes (Mathews and Jensen, 2013), apples (Hobart et al., 2020), and pears (Guo Y. et al., 2021). UAV remote sensing also shows promise in estimating LAI and canopy coverage ratio at the plant and canopy levels (Lei et al., 2019), essential components for estimating evapotranspiration, surface energy, and water balance (Mourad et al., 2020).

6.2 Plant diseases using RGB images or visual inspection.

Identifying plant diseases using RGB images or visual inspection is often only feasible once visible symptoms manifest, often too late for effective intervention by farmers. For instance, Ganoderma disease, a significant threat to oil palm plantations, typically presents noticeable symptoms like foliar chlorosis, frond breakage, decayed tissues at the palm base, and fruiting body production at an advanced stage. This disease, causing both basal and upper stem rot, remains a severe issue in Southeast Asia, leading to stand loss, reduced yields, and the need for premature replanting. Young palms exhibiting symptoms may perish within 6–24 months, while mature palms can survive up to 3 years, although basal stem rot can destroy up to 80% of the total standing palms. Studies suggest a strong correlation between oil palm yields and nutrient levels. Hyperspectral analysis of images in agriculture offers promising opportunities for early Ganoderma disease detection in oil palms, with preliminary data indicating distinct spectral characteristics of infected leaves. Developing a rapid and effective field-level detection and mapping method for Ganoderma would aid growers in disease management and potentially enhance financial outcomes.

The methodology outlined in Figure 4 proposes a customizable solution, adaptable and scalable with various multi-spectral and hyperspectral cameras for disease detection. The procedure involves systematic steps involving (i) analyzing disease spectral characteristics in controlled lab settings, (ii) developing a classification method to differentiate the disease from other stresses and similar diseases, (iii) exploring the use of low-cost spectral radiometers for rapid screening, (iv) creating an instrumented platform for hyperspectral image collection and georeferencing on farms, and (v) conducting field trials to assess hyperspectral imagery effectiveness in diverse conditions. Adapting a UAV remote sensing platform for early disease detection entails addressing key questions: (i) the disease's detectability at different infection stages, (ii) unique spectral characteristics of Ganoderma reflectance data, (iii) optimal statistical or mathematical methods for analyzing Ganoderma spectral data, and (iv) the effectiveness of low-cost multiband radiometers in aiding scouting crews to identify suspiciously infected trees.

6.3. Hyperspectral imaging and line scanning

Traditional methods of phenotyping, such as manual measurement and visual inspection, can be time-consuming and labor-intensive. With computer vision, data can be collected at a much faster rate, allowing for more frequent and detailed monitoring of plant growth and development. In addition, computer vision can provide more accurate and consistent data than traditional methods. Human error and subjectivity can affect the accuracy and consistency of manual measurements and visual inspections. Computer vision algorithms, on the other hand, are able to provide a more objective and consistent assessment of plant characteristics, providing a cutting-edge solution to analyze plant stress and disease identification. This is done by capturing images of the plant and then using image processing algorithms to analyze the images for signs of stress or infection. Various studies have highlighted the contributions of computer vision to improving yields and reducing costs. The technology has been also used to automate the process of seedling counting and selection, using image processing algorithms to accurately count and identify seedlings, which can help to improve the efficiency and accuracy of seedling selection. The following sub-sections provide summary reports on some of the projects in digital agriculture that incorporated computer vision.

Hyperspectral imaging and line scanning are two advanced non-destructive and non-invasive techniques that are being used in digital agriculture to collect data on the crop, even during the growing season and without affecting crop yields, with the objective of improving crop monitoring and management. Hyperspectral imaging captures images of crop plants and leaves using a wide range of wavelengths of light, from the visible to the infrared, and uses these images to identify different plant species, detect signs of stress or disease, or measure the amount of moisture, chlorophyll, and other important plant characteristics. This technology can provide farmers with detailed information about the health and growth of their crops, and provide knowledge-based decisions about irrigation, fertilization, and pest control. In recent years, hyperspectral imaging has gathered a large amount of interest in the field of non-destructive techniques. Originally developed for remote sensing applications, hyperspectral imaging is now being widely used in a multitude of fields including the food and agricultural sector. In the food industry, the commonly used standard methods are destructive and invasive in nature. Thus, they are not only time-consuming but also resource and energy intensive. With varying quality parameters across different products, the food industry continuously seeks in/on-line processing techniques that meet the quality demands as well as provide rapid, accurate, and reliable results. This approach combines the salient features of machine vision and near-infrared spectroscopy (Yu et al., 2020). Through the spectral and spatial information obtained from hyperspectral imaging, detailed information on the product has now become possible. Of the different acquisition techniques, line scanning is one of the most commonly used methods within the food industry (Ma et al., 2019. Moreover, line scanning allows for continuous scanning of the product line-by-line, thus acquiring extensive spectral information on the product. This technique is being applied to predict moisture content and the distribution within fruits and vegetables such as apples, and purple-speckled cocoyam (Crichton et al., 2018; Ndisya et al., 2021). In addition, moisture content hyperspectral imaging has also shown the ability to predict several quality parameters such as total phenols and antioxidants properties in cocoa beans (Caporaso et al., 2018), chromaticity in apples' slices (Crichton et al., 2017), and total carotenoids content in carrots (Md Saleh et al., 2022). Crichton et al., 2017 also implemented HSI to classify the freshness in beef. The results from this investigation present successful classification between the different storage conditions (i.e., fresh, matured, fresh-frozen thawed and matured-frozen thawed) through the varying color changes among the beef slices. With the view of moving towards in-line monitoring using hyperspectral imaging, Sturm et al., 2020 (Sturm et al., 2020) integrated a Vis-NIR camera within a pilot-scale hop dryer to investigate the dynamic changes within the hop cones. The study shows a proof of concept of integration of method within semi-industrial scale drying systems to the dynamic changes occurring within the product. In conjunction with this study (Sturm et al., 2020; von Gersdorff et al., 2021; Shrestha et al., 2020), also compared hyperspectral imaging and standard laboratory methods to assess its applicability for continuous monitoring.

6.4 Wireless sensors Technology and IoT monitoring

Implementation of digital agriculture requires wireless communication between sensors and controllers for remote monitoring and sending warning messages in open-field and closed-field farming via a flexible and modular automation solution that is compact in size, cost-effective, and easy to install and maintain. Studies show that smart irrigation and fertilization management systems (Giannoccaro et al., 2020; Lin et al., 2020) are capable of maintaining optimum level of pH and nutrient contents for plants with minimum inputs. The success of such an optimization relies on the integration and adaptation of the sensors and controllers with wireless communication and the IoT concepts for incorporating real-time data transfer and live monitoring. Wireless sensor network (WSN) was adopted in agriculture in the early 2000s, and has served as the backbone of IoT-driven automation systems, comprising various sensor nodes, repeaters, and receivers interconnected and meshed across fields to sustain DA. In recent years, LoRa technology has emerged as a solution, enabling long-range communication between sensor nodes and receivers for field parameter monitoring. LoRaWAN, its networking protocol layer, is a leading LPWAN technology renowned for ultra-long-range wireless data transmission with minimal power consumption, ideal for digital agriculture applications (Shamshiri and Weltzien, 2021). LoRa bridges the gap between power efficiency and transmission range in remote areas lacking mobile coverage, utilizing reserved ISM radio bands like 433 MHz (Asia), 868 MHz (Europe), and 915 MHz (Australia and North America). Depending on network architecture and repeater node density, LoRa can cover distances of 2–10 km in rural areas, extendable to 100 km with repeaters.

6.5 Wireless monitoring of field machine index

By tracking of agricultural machinery using LoRa GPS tracker it is possible to determine their timeliness in large scale operations. This is of interest for growers from a management perspective, providing them with an overview of the efficient time that the machine has spent on the field, and the number of hours that has been spent on stops and row-end turning. For this purpose, information such as time, latitude, and longitude from standard NMEA GPS strings are stored and transmitted using one or multiple LoRaWAN GPS tracker modules.

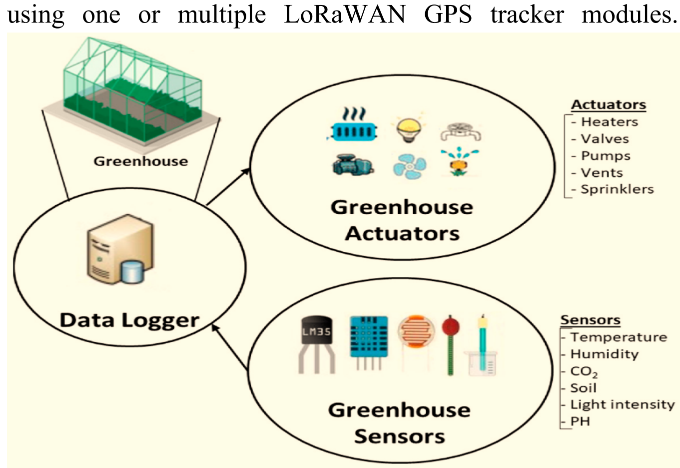

Figure 8: Smart greenhouse architecture diagram. *Sensors 2024, 24(8),2647; https://doi.org/10.3390/s24082647*

The messages are received by one or more LoRaWAN gateways that can be located up to 10 km or more from the machine. The gateways might benefit from preprocessing software before uploading the data to a cloud-based mobile management app, for live monitoring of the total operation time, total stops and row-end turning time (ineffective operation time), total covered area, and average travel speed. An overview of the steps involved in data collection and processing of this approach together with sample results are shown in Figure 8. The outputs of the software is directly used to calculate field efficiency and machine index (Shamshiri et al., 2013). One of the main difficulties in processing raw GPS data is that they usually contain empty lines or broken strings. The application software that was used to produce results demonstrated in Figure 8 has built-in features that can detect different interruptions and outliers before processing the data via a simple user interface. For offline data processing, the entire calculation is carried out via three simple steps: "Open data", "extract data", and "process data". As a result, the software generates an output table in Excel containing detailed information about the operation time and location of the machine in the field.

6.6 IoT-based monitoring of microclimate parameters

These sensors include the BME280 (for air temperature, humidity, and atmospheric pressure), DS18B20 (for soil temperature), LDR Photoresistor (for light sensing), SX239 (for soil moisture), and NEO-7 GNSS modules. To ensure robust and efficient processing, the sensor node utilizes powerful ESP32 and Atmega328P microcontrollers integrated with customized codes for high efficiency and ultra-low power consumption. Conventional data loggers that have been integrated with wireless modules and IoT patches have demonstrated to be a promising solution for improving the reliability of data collection for digital agriculture applications. These redundant devices minimize the disruptive effect of outdoor environment on field monitoring.

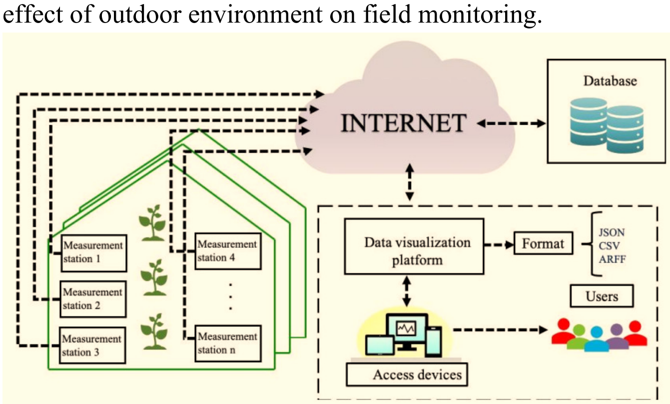

Figure 9: Design and implementation of a low-cost IoT-based agroclimatic monitoring system for greenhouses. ***Sources: AIMS Electronics and Electrical Engineering,2021, Volume 5, Issue 4: 251-283. doi: 10.3934/electreng.2021014***

A multi-channel hybrid data logger, illustrated in Figure 9A, features an IP66 enclosure, WiFi and LoRa antennas, an external power supply, and aviation plug connectors specifically designed for seamless integration with various sensor probes in both closed-field and open-field crop production systems. Each node is equipped with two separate circuit boards: one for transmitting sensor and GPS data via LoRa 868 MHz (Figure 9B) and another for LoRa/WiFi communication and data storage on an SD card (Figure 9C). This design facilitates the addition of new sensing capabilities to existing wireless networks and allows for easy replacement of defective sensor probes, minimizing network maintenance costs. The three connectivity boards demonstrated in Figure 9 include all necessary electronics and sockets for connecting typical sensors used in wireless monitoring of the indoor environment. For example, the logger board shown in Figure 9C supports Bluetooth and WiFi communication and can save data on an onboard SD card via SPI data transfer. This board can also be interfaced with other microcontrollers using the onboard CANBUS modules. All sensor boards have been optimized for low-power consumption (deep sleep mode) and utilize MOSFET transistors in switch mode for sensor probes and memory cards in a way that when the board wakes up from a deep sleep mode, its controller triggers the MOSFET transistor to activate all power lines.

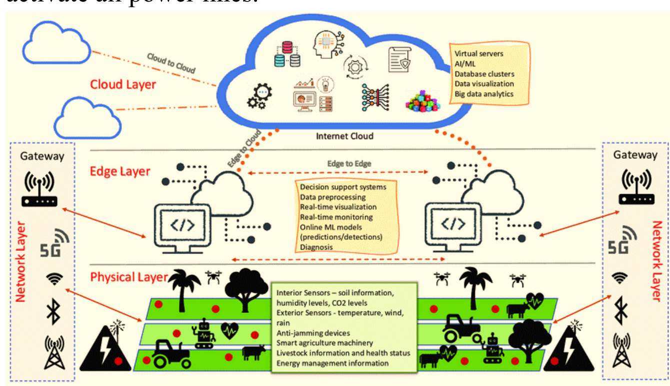

Figure 10: Multi-Layer Smart Farming Architecture. ***Sources: February 2020, IEEE Access PP(99):1-1. DOI:10.1109/ACCESS.2020.2975142***

The sensor node has a DS1337 IC for real-time logging clock and can access dates and times from an available world clock server in the presence of a WiFi network. The final log file is saved on a cloud server or the onboard SD card with GPS and time stamps and may include hundreds or thousands of data lines, depending on the data collection frequency and growing season. Several sensor nodes have been deployed and tested successfully in multiple farming applications and has measured, recorded, and transferred data without interruptions. The hybrid data logger system presented in Figure 9C is used for dynamic assessment of controlled environments, particularly regarding microclimate parameters and soil temperature (ST) set-points prior to cultivation. Understanding the reference values for air temperature, relative humidity

(RH), vapor pressure deficit (VPD), and ST across various growth stages of fodder production (Ahamed et al., 2023), allows for real-time visualization of collected data on a mobile app, offering insights into deviations from ideal conditions. This approach is vital for decision-making in large-scale productions, where a controlled environment model is initially constructed and tested. To facilitate the monitoring and download of data from multiple sensors and cloud storage, the two desktop software applications shown in Figures 9D, E were developed. These applications can interface with sensor controllers via multiple serial COM ports, allowing users to execute commands and configure custom settings. Additionally, the software enables users to download log files containing sensor performance data (e.g., battery status, clock status, and historical parameters) and upload stored data to a cloud server. The workflow of an IoT-based monitoring system that has been realized by means of distributed nodes and modular hardware in a digital agriculture project for berry orchards (Shamshiri and Weltzien, 2021) is shown in Figure 10. In this scheme, each platform is custom-designed for specific applications in open-field cultivations based on a powerful microcontroller (32-bit, dual-core, 240 MHz) with LoRa modulation at 868 MHz. The nodes' controllers were installed on long wood supports at an average height of 2 m from ground to overcome the issues with signal connectivity near high-density bushes and plants. For large-scale farms, the number of the sensor nodes, locations of the repeaters, power consumption, operating frequencies, and the distance between transmitters and receivers should be considered for continuous data collection.

6.7. Identification of plants and weeds on the basis of AI-based Technology:

An expert that assesses crop diseases in the field can easily distinguish yellow rust from other crop diseases and score its severity at that location. This is possible because the visual symptoms of most diseases have unique features that are quite different from each other. This is true for many weed plants and other pests as well. A monitoring system for crop protection that can exploit this information in a timely, site-specific and selective manner would help to improve control strategies for crop protection and reduce pesticides by applying measures more precisely and sustainably in the field. However, those systems would be in dire need of very high-resolution data about the crop canopy. Traditional methods of plant disease identification, such as visual inspections and manual measurements, are time-consuming and labor-intensive. Plant disease symptoms, weed plants, or pest insects are normally tiny constituents in a plant canopy and are usually hard to detect with conventional remote sensing applications specially in the early stages of the outbreak or growth of the pest. The plant disease yellow rust (Puccinia striiformis West. F. sp. tritici), for example, develops small but distinctive features as symptoms that resemble long and narrow yellow to orange stripes. They usually occur on the plant leaves between the veins and consist of Urediniospores pustules with a dimension of 0.4–0.7 mm accompanied by chlorosis and necrosis (Chen et al., 2015). The unique and decisive features cannot be found at the canopy or field scale but rather at the plant or leaf scale. Thus, even drones operating at altitudes 20–100 m typically used for photogrammetric orthophoto production cannot resolve the features accurately enough to detect and distinguish pests in the field successfully.

6.8 Detection of yellow rust with evaluation by CNNs

CNNs much more versatile and adaptable for automatic image evaluation. In Schirrmann et al. (2021) (Schirrmann et al., 2021), a deep learning model was trained to detect yellow rust from very high-resolution RGB images at different stages of the disease outbreak. A deep residual neural network (ResNet-18) was used as deep learning architecture. Res Nets are CNNs that include shortcut connections in the network architecture based on residual functions that enable skipping specific layers in the network, which increases the training performance of the deeper layers (He et al., 2016). Input for training and for testing included thousands of images taken at 2 m in nadir perspective from an RGB camera. The trained ResNet model showed high accuracy for estimating the yellow rust symptoms after the disease has spread into the canopy to about 2%–4%, which was after 40 days of inoculation (DAI).

6.9 Infrared, and LiDAR, to detect weeds

Some companies have developed sensor-based weed detection systems, which use a combination of sensors, such as cameras, infrared, and LiDAR, to detect weeds. Weed detection is one of the most important aspects of digital agriculture that has received significant attention in recent years, with the goal of applying computer vision and machine learning algorithms to analyze images of crops in real time for rapid identification and removal of weeds. These systems can be mounted on UAVs, field robots, tractors, or other ground vehicles to scan a field while the vehicle is in motion. In addition, some studies have reported on the development of weed detection systems that can scan a large area in a short time and are trained to recognize specific weeds by analyzing large amounts of image data in order to improve the accuracy and efficiency of weed classification based on their characteristics. An example includes the work of de Camargo et al. (2021) (de Camargo et al., 2021), in which the optimization of a ResNet-18 model for the classification of weed and crop plants in UAV imagery was considered. This study is part of a larger project that aims to develop an intelligent real-time monitoring and mapping system for the detection of weed distribution in cereal crops. The optimized model was implemented on an NVIDIA Jetson AGX Xavier embedded system with TensorRT (NVIDIA CORPORATE, Santa Clara, CA, United States). In 16-bit mode, a full-image evaluation with the optimized model was about 2.2 frames per second. No memory issues occurred during training and testing. Using images from a test field, the image classifier had an overall accuracy of 94%. Even in more challenging parts of the images where plants overlapped, the model quite accurately identified the weed species. Both exemplary research studies show that combining low-cost imaging technologies, e.g., RGB imaging, with artificial intelligence enables the extraction of more specific field information for crop protection.

7. Digitalization in automation and remote operation

7.1 Internet of robotic things (IoRT) for robot teleoperation

An effective IoRT-based solution should incorporate the use of long-range wireless communication, simulation environment, and web-based applications to constantly monitor the robot in the field, and transmit human-in-the-loop control commands for robot teleoperation. The integration of robotics and wireless connectivity that are integrated with virtual reality, digital twin concepts, and IoT platforms, is often denoted as the Internet of Robotic Things (IoRT) (Vermesan et al., 2020) and has emerged in the last few years for collaborative control and teleoperation (Su, 2020) to optimize the use of autonomous agricultural machinery in unstructured farms. The main justifications for the deployment of IoRT infrastructure in agriculture can be summarized as (i) to provide real-time monitoring and control of the robot's states and functionality (i.e., location, orientation, speed, distance to obstacles, and battery status), (ii) to feed these data to simulation models, digital shadows, and cloud-based decision support systems, and (iii) to send instant responses to the robot for assisting the autonomous navigation. A conceptual illustration of the proposed IoRT solution using a local LoRa network for exchanging messages between the actual mobile robot in the field and the digital shadow of that robot inside a virtual environment is shown in Figure 15. This approach assists the navigation of the robot in complex situations without the need for high-end network infrastructure.

7.2 Digital automation in variable rate applications

In precision agriculture, variable rate applications such as spraying or fertilizing were either realized by means of georeferenced prescription maps that were usually generated based on satellite remote sensing techniques, or by using on-the-go sensors. To this aim, tractors and other large machinery were required, and the availability of accurate GPS signals was crucial for the success of the operation. In digital agriculture however, drones (Shamshiri et al., 2018c) and swarms of small-scale robots that benefit from sensor fusion can operate in GPS denial environments and can deliver more precise VR applications by targeting individual plants (Shamshiri et al., 2018a). This is possible due to the availability of low-cost sensors, high-performance microcontrollers, and onboard computers that can process big data, support complex models, and simulate parallel decision-making scenarios for converting precise data into actions, which in return provides farmers with local-specific information on-the-go. In traditional agriculture, the same amount of agricultural input is applied across the field regardless of within-field variability, such as topography, variation in soil type, texture, or organic matter content, etc. This "one size fits all" approach to applying inputs may lead to either under- or over-applications of inputs, and consequently, variations in yield across the field, but it further impacts environmental sustainability and farm economics.Figure showcases a novel design of a variable rate liquid fertilizer applicator, featuring a distinctive flow control and spray system capable of administering NPK (Nitrogen, Phosphorus, and Potassium) simultaneously at variable rates around oil palm trees in a single pass. This system, developed following the spot application method, is capable of evaluating the NPK status of a 25 m2 soil area and applying N, P, and K nutrients at different variable rates using aqueous solutions of straight fertilizers (Yamin et al., 2020a; Yamin et al., 2020b).

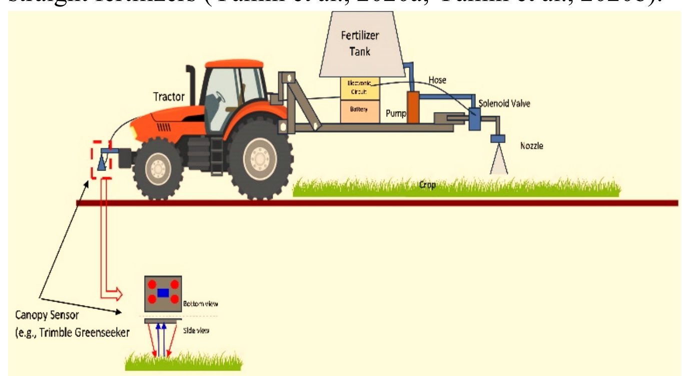

Figure 10: Conceptual schematic of a sensor-based variable rate fertilizer applicator. ***Sources:AE607/AE607: Variable Rate Technology and Its Application in Precision Agriculture***

Based on simulation analysis, six 8006 flat fan nozzles were meticulously chosen to ensure optimal swath coverage of fertilizer spray. Nozzles 1–3 were affixed vertically on the horizontal boom to apply spray on the machine side of oil palm trees, while nozzles 4–6 were positioned at −22°, −21°, and −20° angles to the horizontal plane on a 45° inclined boom to administer spray across the tree, employing the trajectory approach as depicted.

7.3 Agro-food robotics

Comprehensive research and development in agricultural robotics have been documented in a wide range of review papers (Shamshiri et al., 2018a; Bergerman et al., 2016; Duong et al., 2020; Kootstra et al., 2020; Oliveira et al., 2021a) covering specific tasks such as phenotyping (Atefi et al., 2021; Yao et al., 2021; Xu and Li, 2022), arable farming

(Emmi and Gonzalez-de-Santos, 2017), livestock farming (Ren et al., 2020), greenhouse horticulture (Barth et al., 2016), orchard management (Zhang et al., 2019), forestry (Oliveira et al., 2021b), and food processing (Duong et al., 2020).

Figure 11: Automated harvesters use a combination of machine vision with a grasping tool to pick fruit and vegetables with precision. For some crops, this is relatively straightforward; for example, a robot harvesting wheat only needs to recognised the shape of rows planted in a field, which can be done by emitting lasers at the crop and measuring the reflection. *Sources: Agro Robots | Which Robots Actually Work on Farms? | FoodUnfolded*

Agro-food robotics represents a fast advancing domain that is transforming farm production capacities, leveraging the advantages of robots over human labor, including heightened accuracy and efficiency, enhanced consistency and reliability, and reduced in digital agriculture, farmers are eager to identify deficiencies and variations in large-scale cultivations, employing precise technology and accurate management solutions to address them effectively. Furthermore, optimizing input utilization is a promising approach to boost farm profitability. Review papers also cover specific technologies used in agricultural robotics, such as computer vision (Lu and Young, 2020; Tian et al., 2020; Fountas et al., 2022; Wang et al., 2022), active perception (Magalhães et al., 2022), path planning (Santos et al., 2020), and grasping and soft grasping (Elfferich et al., 2022; Navas et al., 2024). operational costs. Robots that are equipped with several data acquisition devices such as multi-spectral (Karpyshev et al., 2021), hyperspectral (Zhang et al., 2012), NDVI (Tiozzo Fasiolo et al., 2022), thermal (da Silva et al., 2021), or NIR cameras (Milella et al., 2019) provide a great opportunity for field scouting (Yamasaki et al., 2022), early disease detection (Mishra et al., 2020), and yield estimation (Kurtser et al., 2020; Massah et al., 2021).

***The Agri Stack** is a collection of technologies and digital databases proposed by the Central Government focusing on India's farmers and the agricultural sector.*

- *The central government has claimed that these new databases are being built to primarily tackle issues such as poor access to credit and wastage in the agricultural supply chain.*
- *Under Agri Stack', the government aims to provide 'required data sets' of farmers' personal information to Microsoft to develop a farmer interface for 'smart and well-organized agriculture'.*
- *The digital repository will aid precise targeting of subsidies, services and policies, the officials added.*
- *Under the Programme, each farmer of the country will get what is being called an FID, or a farmers' ID, linked to land records to uniquely identify them. India has 140 million operational farm-land holdings.*
- *Alongside, the government is also developing a unified farmer service platform that will help digitize agricultural services delivery by the public and private sectors.*

7.4. ROS-based multi-channel infrared sensors

Data fusion and multiple perception solutions are usually employed to assist the existing GPS-based navigation and to improve the reliability of the operation. The data shows the hardware layer of a control system that benefits from a set of ROS-based multi-channel infrared sensors for providing feedback, and a Jetson Nano onboard computer for performing the computation. The system is expected to maintain an agricultural tractor between the plants' rows with an accuracy of 5–10 cm from the side with an ideal speed of 5–8 km/h (Weltzien and Shamshiri, 2019). In the software layer, different controllers including PID, machine learning, and fuzzy knowledge-based algorithms (Shamshiri et al., 2024) can be implemented and compared. However successful development of such systems requires a proof-of-concept via extensive validation tests with the digital representation of the sensors, a dynamic model of the robot platform, and a virtual replica of the orchard. The effectiveness and throughput of agricultural mobile robots are propelled by the utilization of machine learning (ML) and deep learning (DL) techniques, which empower robots to learn from and analyze data autonomously, without explicit programming. These data served as the foundation for creating a virtual orchard within Coppelius Sim (Shamshiri et al., 2018b), which was interfaced with the ROS (Quigley et al., 2009). This setup facilitated the testing of different sensors, hardware in the loop, and control algorithms on a full-scale simulated tractor and orchard model, as depicted in Figure. The simulation methodology involved translating raw data streams from various sensor inputs (such as GNSS, LiDAR, laser, radar, and RGB camera) into actionable information within the command and control system. This allowed for experimentation with autonomous navigation, enabling the tractor to avoid both moving and stationary obstacles within the orchard environment. Through this simulation-based approach, the proposed collision avoidance system could be thoroughly evaluated and refined before implementation in real-world settings.

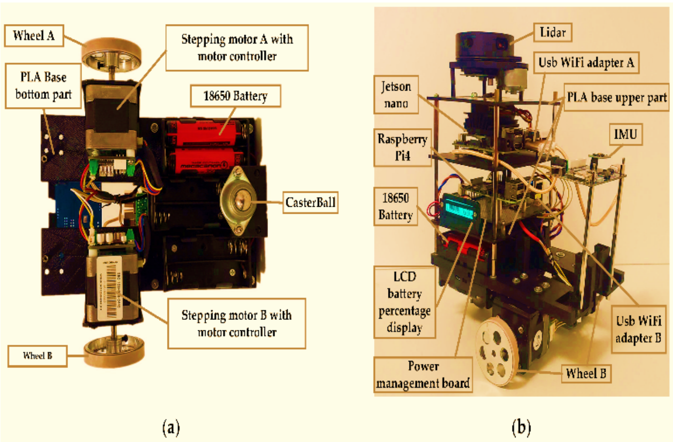

Figure 12: Owlbot robot and its components. (a) Bottom view; (b) Side view. Sources: Sensors ***2023***, 23*(7), 3648;* ***https://doi.org/10.3390/s23073648***

The result provided a safe, fast, and low-cost experiment platform for the development, testing, and validating of the sensing and control strategies with different algorithms. The simulation scene shown in Figure 18A enabled human-aware navigation by finding the best positions for each sensor on different tractors and provided a flexible solution for attaching other implements and determining the optimum row-end turning patterns in presence of random obstacles. It also accelerated complicated analysis with the weight distribution of the attached implements and to understand the behavior of the tractor on uneven terrains. The main elements of the simulation scenes in this project were (i) mesh files representing plants, tractors, and obstacles, (ii) API and codes that created interfaces between different software environments, and (iii) algorithms and dynamic models including image processing for human detection, inverse kinematics for the hydraulic arms, minimum distance calculation, steering system, path following, and obstacle avoidance algorithms.

7.5. Separate custom-designed IoT-based controller

Maintaining precise control of environmental variables within both open-field and closed-field production systems has significant potential for enhancing operational sustainability. By minimizing water, chemical, and energy demands while simultaneously mitigating disease spread, and increasing yield, such control measures can result higher profits. In controlled environments like aeroponic or hydroponic indoor farming, automation systems encounter various uncertainties and disturbances that elude complete modeling or implementation via conventional control algorithms. Since control of some actuators require separate driver boards that can only receive specific type of messages, a separate custom-designed IoT-based controller was designed that communicates with wireless sensor nodes, end-users, and actuators drivers, and can send and receive command signals via CANBUS as shown in Figure 20. This controller board benefits from a STM32 32-bit ARM processor, and an ESP8266 microcontroller, an onboard RTC clock, two CANBUS ports for industrial communication, and an SD card for data logging. The board can also be interfaced simultaneously with multiple controller driver boards such as relay modules via wired communication ports such as I2C, USART, and SPI, or by means of WiFi wireless signals. The control commands can be generated by the crop growth models that have been implemented in the processor as codes or Simulink blocks. Furthermore, the controller is capable of receiving command signals from cloud-based applications. Concurrently, environmental sensors are attached to collect measurements, storing data on an SD card, and transmitting data either directly to a web server or through wireless communication to a gateway utilizing LoRa modulation. An in-depth elucidation of this framework pertaining to greenhouse tomatoes is provided in (Shamshiri et al., 2020; Rezvani et al., 2020).

7.6 IoT-based monitoring in remote locations

These sensors are employed for IoT monitoring of various agricultural parameters, including air and soil temperature, relative humidity, soil moisture, leaf wetness, light conditions, and dew-point temperature. Using solar power, these sensors offer a sustainable solution for remote monitoring, ensuring battery charging for continuous data collection and transmission without relying on frequently battery replacement. In small-scale fields, the costs associated with maintenance and ownership may not be justifiable for farmers, particularly when concerns arise regarding the potential sharing of sensitive field information and the associated risks to their production reputation due to inadequate IoT security protocols. The differences between hardware and software from different manufacturers imply heterogeneity in wireless communication protocols and connectivity standards, making it difficult to integrate and standardize the IoT automation process. Additionally, there is currently a lack of standardization and regulation in the IoT industry, which can lead to confusion and complexity when implementing IoT devices in agriculture. Therefore, implementation and maintenance of IoT in commercial farms can be expensive and require significant investment in hardware, software, and network infrastructure. Moreover, the reliability of IoT-based automation systems in agriculture is significantly influenced by the harsh environmental conditions and varying climatic characteristics, such as high temperatures, wind speeds, heavy rain, and dusty environments, which can damage sensors or disrupt their performance. Consequently, selecting robust hardware setups capable of withstanding these conditions is paramount.

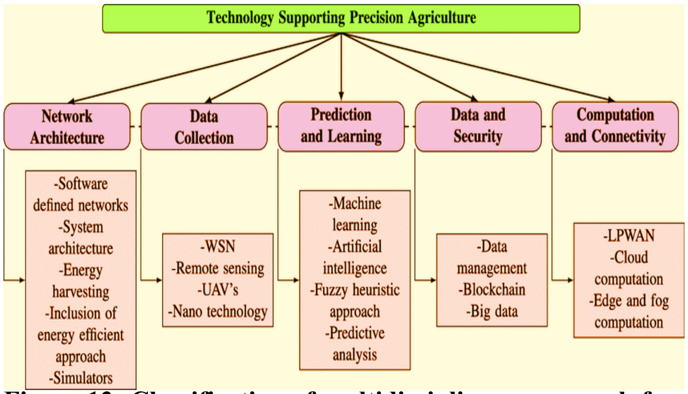

Figure 13: Classification of multidisciplinary approach for precision agriculture. (Precision Agriculture (PA) is a management strategy that utilizes communication and information technology for farm management. It is a key to improve productivity by using the best agricultural practices and optimal usage of resources. Agriculture faces diverse challenges due to soil degradation, climate variation, and increasing costs). ***Sources: Classification of multidisciplinary approach for precision agriculture. | Download Scientific Diagram***

8. Agriculture digitalization

8.1 5 G network

The 5G network will provide a reliable and secure communication infrastructure with low latency capabilities for the realization of automated farms (Ma et al., 2017; Khanna and Kaur, 2019; Valecce et al., 2019; Tang et al., 2021) with AI-robotics. Compared with 4G networks, 5G has a faster information transmission rate with higher quality of dissemination, which can effectively be used in developing smart systems with high-speed data transfer, up to 20 Gbps, and can connect more devices per square kilometer (Li and Li, 2020; Said Mohamed et al., 2021). This is crucial to enable robotization and digital agriculture processes. Simultaneous use of local mesh and cellular networks can effectively address the problems with poor communications, allowing growers to have uninterrupted stream of data (Franchi et al., 2021), including crop yield, soil, fertilization, smart monitoring, irrigation management, pesticide applications, disease management, autonomous navigation, fruits harvesting (Navas et al., 2024), and supply chain management (Khujamatov et al., 2021; Friha et al., 2021). An example lies in the work of Xue et al. (2021) (Xue et al., 2022), in which a frame structure for a drip irrigation remote control system (DIRCS) utilizing 5G-IoT technology alongside a mobile application was introduced. Additionally, Tang et al. (2021) (Tang et al., 2021) demonstrated significant benefits achieved through the implementation of IoT, including a 20% reduction in labor force, a corresponding 20% decrease in pesticide usage, and optimized utilization of water resources and fertilizers (Yu et al., 2021). Figure 22 visually depicts various applications of the 5G network in digital agriculture, illustrating the connectivity links between different sections. The deployment of the 5G mobile network is currently underway in some developed countries, including the United States, the United Kingdom, Germany, South Korea, Japan, and China. However, the initiation of 5G network deployment in many least developed countries is anticipated to require a significantly longer timeframe (Rahman et al., 2021). While the 5G network offers advantages in wireless communication, ensuring uninterrupted connectivity, there remain substantial challenges such as reducing interference, minimizing latency, optimizing power consumption, and enhancing data rates (Sah et al., 2022).

8.2. Digital twin (DT)

Digital Twins are typically accessed through a virtual interface, which displays information about the status on the 'thing' Interaction with a Digital Twin would usually be through a visual interface on a phone, tablet or computer. This would let you see information about the status of the thing, its history (e.g. an ewe's health history) or its predicted future (e.g. a crop growth forecast). You are also likely to be able to interact with the real-world system through the Digital Twin, such as switching on an irrigation system. Digital Twins have been used successfully in agriculture for developing autonomous farming robots (Foldager et al., 2020), identification of plant pests and diseases in crop production (Pylianidis et al., 2021), stock monitoring of feed silos of livestock farms (Raba et al., 2021), and energy management in commercial greenhouses (Ashraf et al., 2021; Chaux et al., 2021; Howard et al., 2021).Digital twin (DT) is one of the trending solutions toward real-time evaluation, optimization, and predictive control of complex systemic process, which has been successfully implemented in various industrial fields including manufacturing (Kritzinger et al., 2018), construction (Korenhof et al., 2021), automotive (Vachálek et al., 2017), energy (Howard et al., 2020). Originated back in 2003 by Michael Grieves (Jones et al., 2020), digital twin is commonly described as consisting of real-world entity (i.e., a physical product, a process, or a machine component) that is interfaced with a virtual replication of that entity (i.e., a simulation model) via bi-directional data connections for feeding data and exchanging information between the two (Grieves and Vickers, 2017).

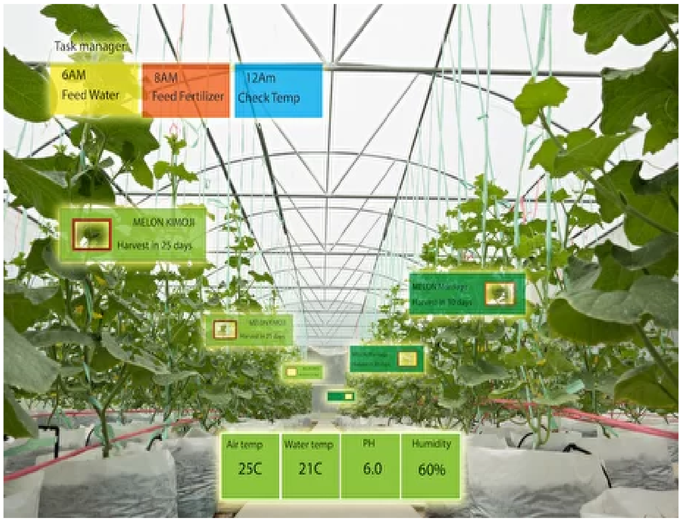

Figure 14: **How do you interact with a Digital Twin?**
Sources: **10 things about Digital Twins in agriculture**

In this concept, the physical system interacts with the digital counterpart within a centralized or cloud-based architecture in order to optimize the process, update control parameters, and generate predictive solutions for what-if scenarios. It should be noted that a system without a connection from the virtual object to the physical object is different from digital twin, and is called digital shadow (Elahi et al., 2022). Compared to the industrial application, the agricultural use of DT is still limited, but has a high potential to be expanded in the near future. The main use cases of digital twin in agriculture are focused on predictive analytics, remote monitoring, resource optimization, and risk mitigation (Purcell et al., 2023). Examples includes studies on predictive models that simulate crop growths and soil conditions in order to improve fertilizing and irrigation (Skobelev et al., 2021), or IoT monitoring of plants health and environmental conditions and simulate difference scenarios such as disease outbreaks to mitigate potential losses (Tekinerdogan and Verdouw, 2020).

8.3 Blockchain Technology

Blockchain can be used to create a digital ledger that records all of the data generated by sensors and controllers. Blockchain is an emerging digital technology that has the potential to revolutionize the way farming and food production is conducted by creating a decentralized and secure network, contributing to better transparency, traceability, and efficiency in the agricultural supply chain. This data can then be used to make more informed decisions about planting, fertilizing, and harvesting crops. For example, growers can use blockchain-based smart contracts to automatically adjust the amount of fertilizer used in their fields by considering the soil's nutrient content in order to reduce the amount needed and minimize environmental impact. A key application of this technology in digital agriculture is supply chain traceability, which means creating a digital ledger that records the entire history of a product, from farm to consumer. This can help to improve food safety, reduce the risk of fraud by tracking the origin of products, and ensure that they meet certain quality standards. Such information is required to improve the efficiency of supply chains, as it allows for better tracking of inventory and logistics. Another potential application of blockchain technology in agricultural robotics is the use of autonomous drones and other robots. Blockchain can be used to create a secure and decentralized network that allows drones and robots to communicate and share data in real-time. This can help to improve efficiency, reduce costs, and minimize human error in the agricultural supply chain. For example, drones can be used to survey crops and identify areas that require attention, while robots can be used to perform tasks such as planting, harvesting, and maintaining equipment. In addition to these applications, blockchain technology can be used to improve the way that agricultural land is managed. Additionally, blockchain can be used to create a digital record of land use, making it easier for farmers to access government subsidies and other benefits. In addition, it can help to reduce environmental impact, optimize crop yields, and increase revenue potential for farmers. This is particularly important in countries where land ownership records are often poorly maintained or subject to corruption.

Figure 15: Blockchain Technology, everything you need to know. ***Sources: Blockchain Technology, everything you need to know. Sources: Blockchain Technology, everything you need to know - Crypto Economy***

9. Economic, social, and technical considerations

While the highlighted technological solutions play a significant role in the digitalization of agriculture, there exists several limitations and barriers such as high costs that farmers, especially those operating on tighter budgets, must address to ensure broad acceptance, adoption, and utilization. For example, farmers should consider the return on investment (ROI) (Griffin et al., 2018) associated with deploying expensive 5G infrastructure (van Hilten and Wolfert, 2022), autonomous electric tractors and robots (Rose et al., 2021), and IoT devices (Liu and Wu, 2021), alongside exploring potential subsidies or financial support mechanisms. For ROI calculations, factors such as reduced labor costs, optimized resource utilization (such as water and fertilizers) (Sandor et al., 2022), minimized waste, and enhanced decision-making should be taken into account. Robotics, wireless automation, and live monitoring systems can provide excellent insights into crop health to prevent losses, as well as targeted application of inputs for cost savings and yield improvements. Therefore, calculating the ROI should involve evaluating not only the initial investment but also the long-term savings and increased productivity they offer. In addition, challenges related to the reliability and scalability of current technologies pose significant concerns to their widespread adoption. Looking to the future, potential breakthroughs in digital agriculture involve advancements in AI and machine learning algorithms for predictive modeling and decision support (Aworka et al., 2022), the integration of Blockchain technology for transparent and traceable supply chains (Kamilaris et al., 2019), and the development of biotechnology solutions for crop improvement and pest management (Steinwand and Ronald, 2020). Additionally, the continued expansion of rural connectivity and the adoption of 5G technology is expected to further accelerate the digital transformation, enabling real-time data exchange even in remote areas. This can divide and widen socioeconomic inequalities within rural communities, reinforcing disparities between large commercial farms and small-scale or subsistence farmers. Preserving and honoring these cultural legacies while simultaneously embracing innovation pose a delicate balancing act for rural communities undergoing digital transformation. To this aim, developing robots, sensors, mobile apps, and software that are compatible with low-resource settings and support multiple languages, or organizing community-based hands-on workshops, peer-to-peer learning networks, and collaboration between research institutions for enhancing digital literacy will accelerate the accessibility of technology to a broader range of farmers irrespective of their geographic location or socioeconomic status.

10. Conclusion and Summary

The digitalization of agriculture is revolutionizing the way crops are produced and food is secured. The use of cutting-edge technologies such as robotics, computer vision, IoT, 5G, digital twin, and blockchain has allowed farmers to make more informed decisions, optimize crop yields, and reduce costs. This has led to more sustainable and efficient agriculture, which is crucial for ensuring food security in an increasingly populated world. The use of robotics in agriculture has increased efficiency and reduced labor costs, while computer vision and IoT have allowed for real-time monitoring and data collection. Whether it is through the use of drones for crop scouting, autonomous tractors for tilling and planting, or robot manipulators for harvesting, agricultural robots are changing the way farming activities have been conducted for decades. The integration of 5G networks has improved connectivity and data transfer speeds, making it easier for farmers to access information and make decisions. Future trends in this field shows that new concepts such as digital twin allows for virtual testing and simulations, providing a cost-effective way for farmers to make informed decisions. In addition, blockchain technology has the potential to improve traceability and food safety by providing a secure and transparent way to track the movement of crops from the farm to the consumer. However, the widespread adoption of these technologies in agriculture is not without its challenges and limitations. Network coverage and connectivity, data management and storage, security and privacy, cost, interoperability and integration, and regulation and standards are just some of the challenges that were highlighted in this paper that need to be overcome. To address these challenges and promote the acceptance of digital technologies in agriculture, it is important for all stakeholders, including governments, industry, and the research community, to collaborate and work together. Governments can play a key role by providing funding and support for the development and implementation of these technologies. Industry can help by investing in research and development and providing solutions to the challenges faced by farmers. The research community can contribute by conducting studies to better understand the limitations and challenges of these technologies and exploring new and innovative solutions. In conclusion, with the right support and investments, digital agriculture has the potential to make a significant contribution to transform crop production into a more sustainable and efficient system that can ensure food security for generations to come. Future studies may involve analyzing of the socio-economic impacts of digital technologies in agriculture, such as the impacts of digitalization on farmers and rural communities, the accessibility and affordability of the existing solutions, and the policies and regulations that support or hinder the adoption of future developments.

11. Author Contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

12. Funding

This project was funded by Abu Dhabi Education and Knowledge (Grant No. 21S105) to KE-T and Khalifa Center for Genetic Engineering and Biotechnology-UAEU (Grant No. 31R286) to SA.

13. Acknowledgments

The authors would like to thank their respective institutions for their support. KE-T would also like to thank the library at Murdoch University, Australia, for providing the valuable online resources and comprehensive databases.

14.Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

15. Publisher's Note

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16. Author Disclaimer

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during writing or editing of this manuscript.

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