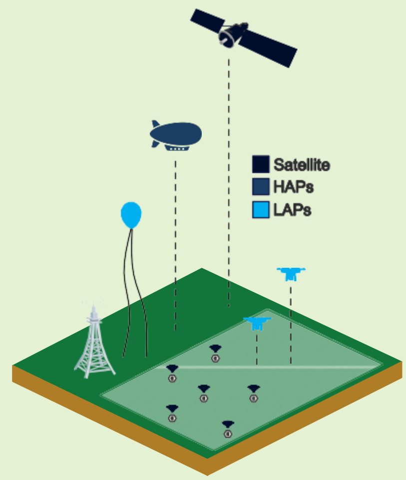
Potential of Satellite-Airborne Sensing Technologies for Agriculture 4.0 and Climate-Resilient: A Review

Asa Ibnu Hazmy, Ammar Hawbani, Xingfu Wang, Ahmed Al-Dubai, Aiman Ghannami, Ali Abdullah Yahya, Liang Zhao, Saeed Hamood Alsamhi

***Abstract*—Agriculture 4.0 offers the potential to revolutionize the agriculture sector through improved productivity and efficiency. However, adopting Agriculture 4.0 requires a period of transition and effort. Satellite-Airborne sensing technologies may become an opening enabler technology of this new paradigm due to its fast deployment process and flexible infrastructure. This paper provides an overview of the technology, trends, challenges, and opportunities in agriculture and climate-resilient sensing technologies. The research covers critical enabling technologies such as Low Altitude Platforms (LAPs) (i.e., Drones, Tethered Ballon), High Altitude Platforms (HAPs) (i.e., Airships, HAPs Balloons, and Aircraft), and satellites, as well as recent advancements in data processing,and digital twins, with some examples from agricultural research projects. Furthermore, this paper explores some challenges in agriculture and the technological deployment of satellite-airborne sensing technologies. Finally, this paper provides some potential opportunities for satellite-airborne sensing technologies for agricultural purposes. This paper may become a guide for adopting Industry 4.0 by leveraging satellite-airborne network technologies.**

***Index Terms*— Agriculture 4.0, Airborne network, HAPs, Satellite, Smart farming, UAVs**



I. Introduction

AGRICULTURE is a vital industry that has undergone significant technological advancement in recent years, leading to the emergence of Agriculture 4.0. Adopting Agriculture 4.0 can provide numerous benefits, including increased efficiency and productivity through precision farming techniques and autonomous vehicles, improved sustainability through reduced use of water, fertilizers, and fossil fuels, enhanced data analysis and decision-making through real-time data generated by IoT sensors, and increased food safety through the ability to detect and address potential issues that could affect food safety. However, this transformation is not without its challenges, as the adoption of these advanced technologies requires a period of transition and effort. One enabler of Agriculture 4.0 is the advancement of sensing technology [1]. The availability of powerful and efficient data sensing technology and the numerous advancements in edge devices have greatly expanded the deployment of Agriculture 4.0.

IoT sensors also become cheaper every year, as shown in Fig. 1. These conditions make IoT more and more acces-sible, which will drive more than 70 billion devices to be connected by the end of 2025 [2, 3]. However, implementinga massive static sensing network can trigger problems such as integrating data from the distributed sensors to generalize inference. Increasing interest in the Airborne communication

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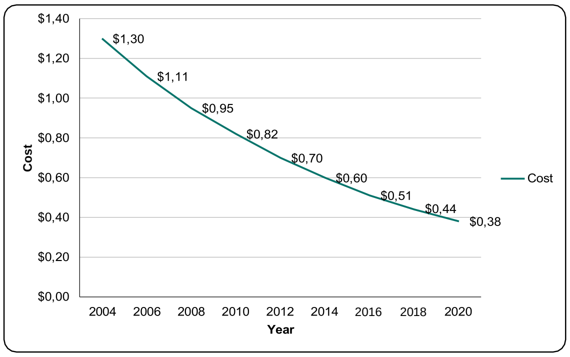

Fig. 1: The declining cost of IoT sensors [5].

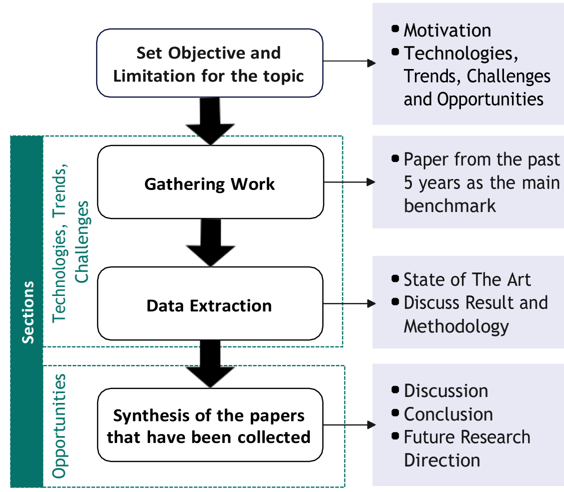

Fig. 2: Survey methodology.

network (ACN) may become a potential way to address this problem. ACN can be deployed in a large coverage area but still provides a flexible infrastructure by leveraging various technologies such as Low-altitude platforms (LAPs), High-altitude platforms (HAPs), and Satellite. ACN infrastructure is usually considered as an enabling technology for 5G and beyond-5G systems [4]. Based on this idea, this survey will explore the technology of Satellite-Airborne Networks in the context of Agriculture 4.0. The promise of scalability in Airborne Networks may also become the enabler to initiate the adoption of this new paradigm.

Looking back at history, agriculture has developed through several phases, from Agriculture 1.0 until the recent Agriculture 4.0 driven by the industrial revolution 4.0 [6]. In Agriculture 1.0, the process still required much manual labor, limiting productivity. The industrial revolution 1.0, driven by the rise of steam engines and water power technology, paved the way for Agriculture 2.0, enabling new applications such as agricultural machinery to make work more efficient. Then in the 20th century, the industrial revolution 2.0 and 3.0 drove Agriculture 3.0, enabling useful techniques such as precision agriculture, partially automated systems, and green energy. The ongoing Agriculture 4.0 is enabled based on several key technologies such as the Internet of Things (IoT), Robotics, Big Data, Artificial Intelligence (AI), and blockchain. This survey's objective is to contribute to navigating the enabling technologies, trends, challenges, and opportunities, in the context of the agricultural domain, covering the sensing and data processing aspects.

Within Agriculture 4.0, certain technologies potentially play important roles of the overall technological adoption. A prime example of this is the use of satellite and air- borne sensing technologies. Satellite and airborne sensing technologies provide valuable tools for collecting data on various agricultural parameters at different scales. Satellites offer a global perspective, capturing large-scale information on climate patterns, vegetation indices, and land use [7]. The observations aid in understanding climate dynamics and identifying regions vulnerable to climate change impacts. On the other hand, airborne sensing technologies, such as drones and aircraft, offer a finer-scale perspective, enabling detailed monitoring of crop health, soil moisture, and pest infestations [8]. The combination of satellite and airborne data provides a comprehensive understanding of agricultural systems, facilitating evidence-based decision-making. Integrating satellite and airborne sensing technologies enables a holistic approach to addressing climate resilience in agriculture. By leveraging the strengths of both platforms, a more accurate and timely assessment of climate-related risks and vulnerabilities can be achieved. For instance, satellite imagery can provide early indications of drought-prone areas, while drones with advanced sensors can accurately assess crop stress levels. The integrated approach enhances the capacity to develop targeted adaptation strategies, optimize resource management, and mitigate the negative impacts of climate change on agricultural productivity [9].

The novelty of this proposed survey lies in its exclusive focus on satellite-airborne sensing technologies in Agricul- ture 4.0 and climate resilience, exploring the applications, trends, challenges, and opportunities. Furthermore, the survey goes beyond individual technologies by examining integration, identifying potential synergies with emerging technologies,and addressing scalable solutions for less developed areas. Additionally, the survey provides comprehensive coverage of application domains, showcasing the diverse uses of airborne sensing technologies in agriculture. The unique approach contributes to advancing knowledge and understanding in the field, offering valuable insights for academia, industry, policymakers, and stakeholders to harness the full potential of satellite and airborne sensing technologies in driving sustainable and climate-resilient agriculture.

A. Motivations

This survey is driven by several compelling motivations centred around the transformative potential of Agriculture 4.0 technologies, specifically satellite and airborne sensing technologies. Understanding the capabilities, limitations, and emerging trends of these technologies can provide fertile ground for innovation in academia and industry and lead to

TABLE I: Surveys in Agriculture 4.0.

Reference (Year)	Sensing Technology	Research Objective	Use cases in Agriculture
[6] (2020)	SAGUIN: Remote Sensing, drones, WSNs, mobile crowd sensing	Examine the enabler of agriculture 4.0 based on emerging industry 4.0 technologies	Precision farming, livestock monitoring, smart greenhouse, fishery management, and weather tracking
[10] (2021)	Sensors, satellite remote sensing instrument, crowd sensing devices, plant phenotype measuring instrument, edge node	Technology of smart farming and its application, security, and privacy concern	Field agriculture, aquaculture, poultry and livestock breeding, greenhouse, plant factory, photovoltaic agricultural, solar insecticidal
[11] (2021)	Sensor nodes, agricultural robots, driverless tractors, radio frequency identification (RFID), unmanned aerial vehicles (UAVs)	Emerging technology for sustainable agriculture to meet global food demand	Smart monitoring, smart water management, agrochemicals applications, disease management, smart harvesting, supply chain management, smart agricultural practices
[12] (2021)	IoT and UAVs	Application and communication technology for IoT and UAVs in smart farming	Field Monitoring, livestock monitoring and tracking, application in greenhouses, compost management, offspring care
[13] (2021)	UAVs, Bluetooth low energy, agricultural sensors.	Enabling technology, opportunity and requirement for UAVs in smart farming	Sky-farmers, precision agriculture, irrigation monitoring, aerial mustering, artificial pollination
This survey	IoT, LAPs, HAPs, and Satellite	Satellite-Airborne technologies for Agriculture 4.0 and climate-resilient	Technological adoption for remote field agriculture and climate resilient

significant societal benefits. Critical motivations for this survey include:

- Agriculture 4.0 promises to vastly improve the efficiency and productivity of the agricultural sector. However, comprehensive adoption of these technologies often requires significant initial investment, which can be a barrier for many farmers. Airborne technologies present an interesting solution to this challenge, potentially enabling incremental adoption of Agriculture 4.0 technologies. By investigating the applications and potential of these technologies, we aim to identify opportunities for such gradual integration.
- This survey offers a focused exploration of satellite and airborne sensing technologies, identifying their diverse applications and untapped potential in driving innovation and progress in agriculture. These technologies provide opportunities to enhance productivity, optimize resource management, and mitigate climate change impacts. This survey will offer critical insights by identifying gaps in existing knowledge and implementation.
- While many surveys on Agriculture 4.0 review all key enabling technologies, this review seeks to find a scalable solution for adopting these technologies that could contribute to less developed areas.
- Lastly, our motivation stems from the urgent need for a comprehensive analysis of the integration of satellite and airborne sensing technologies, especially regarding climate resilience in agriculture. Climate change poses significant challenges to agricultural systems, and this survey addresses the critical gap in understanding how these sensing technologies can contribute to climate-resilient agricultural practices.

The survey aims to bridge the knowledge divide by addressing this gap and informing researchers, practitioners, and policymakers about the opportunities and strategies for harnessing these technologies to build resilient agricultural systems in a changing climate.

B. Related Surveys

In the past five years, significant research has been dedicated to smart agriculture, resulting in numerous comprehensive surveys. The selection presented in Table I is intentionally curated to focus on works that directly address the confluence of satellite-airborne sensing technologies and their application in intelligent farming systems. These surveys were chosen based on stringent criteria: their relevance to the integration of IoT with LAPs, HAPs, and satellite technologies; the depth of their analysis on the limitations and opportunities within the field; and the insights they offer into emerging trends and challenges specific to Agriculture 4.0. This focused approach allows us to delve deeply into the most pertinent studies that align with our paper's objectives — to critically evalu-ate satellite-airborne sensing technology's role in advancing climate-resilient agricultural practices. By concentrating on a select number of high-quality surveys, we ensure a detailed and targeted analysis that underscores the transformative po- tential of these technologies in the context of smart agriculture and climate change adaptation.

C. Contributions

Specifically, addressing satellite-airborne sensing technology is the main differentiation of this survey compared to previous works in smart agriculture. Moreover, this study explores the integration between some specific technologies and tries to find potential opportunities for the whole integrated sensing system. Generally, this survey's contributions are as follows:

TABLE II: Works on agriculture using satellite data.

Reference (Year)	Satellite	Data Processing Techniques	Agriculture Application
[14] (2020)	Sentinel-2	Multi-layer perceptron Neural Network	Crop field identification and information extraction
[15] (2020)	Sentinel-1	Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (NN)	Automated crop classification workflow
[16] (2022)	Sentinel-2A	Neural ordinary differential equations (NODEs) + recurrent neural networks (RNNs)	Crop Classification Under Varying Cloud Cover
[17] (2021)	Gaofen-1	NIR and red spectral domain (NRSD)/Priestley–Taylor Coefficient	Estimate evapotranspiration
[18] (2017)	Landsat-7	PROSAIL model and Modified Verhulst logistic equation	Crop Growth Model
[19] (2022)	Sentinel 2B and Landsat-8	Normalized Difference Vegetation Index (NDVI) and Normalized Difference Wetness Index (NDWI)	Agri-insurance claim settlement process

- We explore the application of satellite-airborne technologies (such as LAPs, HAPs, and Satellite) and related technologies, including Terrestrial sensors, in agricultural use cases. Technical features of the technologies are also provided.
- We present trends related to satellite-airborne sensing technologies and research projects in smart agriculture sponsored by the EU, US, and China.
- We address challenges confronting the agricultural sector, such as those posed by climate change, and explore potential solutions facilitated by satellite and airborne technologies. We also highlight potential challenges associated with deploying these technologies.
- We explore potential opportunities for integrating terrestrial and non-terrestrial sensing networks with emerging technologies such as machine learning and digital twins. We then proposed synergy strategies between sensing technologies while exploring the potential use of multi-modalities in ubiquitous sensing and optimization.

D. Research Methodology and Outlines

This survey is conducted based on the methodology outlined in Figure 2, which classifies various sensing technologies in both terrestrial and non-terrestrial networks. This paper is outlined as follows. Section II of the survey will provide an introduction to each key enabling technology related to satellite-airborne sensing. Section III will examine current trends that can be integrated into these technologies as well as related projects that can serve as benchmarks for implementing these critical technologies. Section IV will explore the main challenges the agricultural sector faces and potential solutions to address these problems. Section V will discuss opportunities presented by currently available technologies and trends. In Section VI, the research challenges and insights gained while conducting the survey will be discussed, and finally, Section VII will explore potential future research directions in this field.

II. Technologies

This section explores the technological capability and limitation of the airborne network, Agricultural sensors, and Edge Computing as the key enabling technology and the connection between each technology to improve agricultural performance.

Airborne Networks (AN) can be classified based on their deployment layer, which is: satellites, high-altitude platforms (HAPs), and low-altitude platforms (LAPs) [4].

A. Satellites

In the agricultural context, satellites are commonly used to provide surface imagery for vast agricultural fields. This imagery data will then be processed using machine learning techniques (i.e., Random Forest, Deep Learning) to gain insight, classification, or prediction of the field performance. According to [21], the satellite is the most used capture platform for research in remote sensing for the agricultural sector. Some problems satellite imagery monitors are land use/land cover, soil health, plant physiology, crop damage, and yield [20]. Although much research uses this satellite imagery data, another type of satellite provides other data points valid for agricultural purposes, such as soil moisture data. Some examples of this satellite are Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP). Some work using satellite data and its application in agriculture is summarized in Table II. Furthermore, this section will provide some details on the satellite technology used in agriculture.

Satellites used in agriculture: Examples of satellite application in smart farming are summarized in Figure 3.

1) Terra and Aqua: Terra satellite was launched on December 18, 1999, and the Aqua satellite was launchedon May 4, 2002, orbiting at 705 km above the earth. These two satellites provide one crucial instrument called MODIS (Moderate Resolution Imaging Spectroradiometer). Terra MODIS and Aqua MODIS view the entire earth's surface and acquire data in 36 spectral bandwidths every 1to 2 days. MODIS can capture different kinds of use cases based on its 36 bands. Bands 1 and 2 are used to capture land/cloud/aerosols Boundaries. Band 3-7 are used to capture land/cloud/aerosols Properties. Band 8-16 are used to capture ocean color/phytoplankton/biogeochemistry. Band 17-19 are used to capture Atmospheric water vapor. Band 20-23 are used to capture surface/cloud temperature. Band 24 and 25 are usedto capture atmospheric temperature. Band 26-28 are used to capture cirrus clouds' water vapor. Band 29 is used to capture cloud properties. Band 30 is used to capture ozone. Band 31 and 32 are used to capture surface/cloud temperature. Band 33-36 are used to capture cloud top altitude.

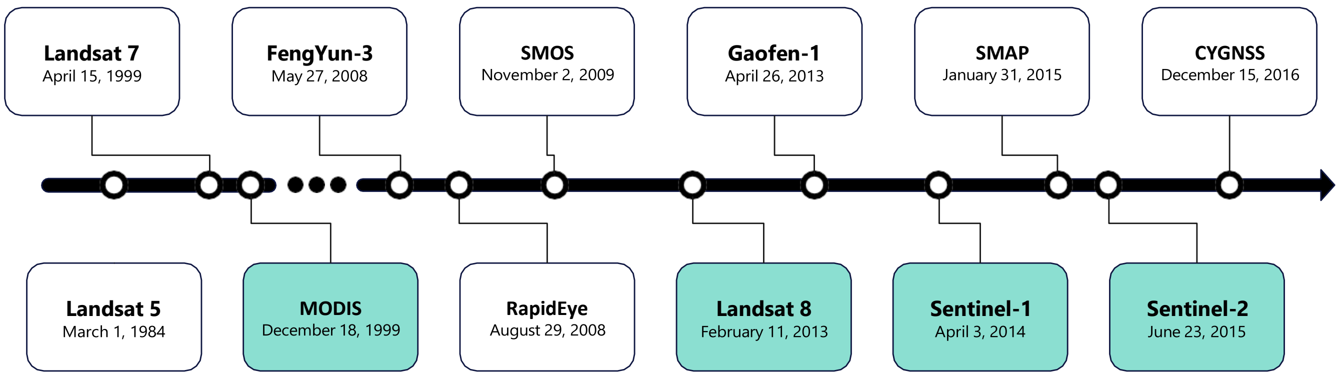

Fig. 3: Launching timeline of satellite. The colored ones are the most commonly used satellites for agricultural research [20].

2) Landsat: Landsat 1 was launched on July 23, 1972. the first Landsat satellite is also the earth-observing satellite launched to study and monitor the Earth. The most recent Landsat satellite is Landsat 9 [22], which launched on September 27, 2021. Landsat 9 replaces Landsat 7, which pairs with Landsat 8 to provide eight days gap revisit times. Landsat 8 and 9 have a higher image capacity than the past Landsat satellite, which can capture up to 1400 scenes daily. Landsat 8 and 9 have nine spectral bands on Operational Land Imager (OLI) and two bands on Thermal Infrared Sensor (TIRS),which is more compared to Landsat 7, that only has 8 Bands.

3) Sentinel: There are seven series of Sentinel satellite missions. The series are Sentinel 1, 2, 3, 4, 5, 5P, and 6. Each mission has a different earth observation objective. Sentinel-1 was launched in April 2014 to monitor land and the ocean. Sentinel-2 was launched in June 2015 to monitor land and provide high-resolution imagery. The sentinel-3 mission objective is marine observation, including sea-surface topography, sea and land surface temperature, and ocean and land color. Sentinel-4, 5, and 5P generally focus on monitoring earth air quality. Moreover, The last Sentinel-6 is used to continuously monitor the mean sea level and the ocean sea state, which has been monitored since 1992.

4) Soil Moisture and Ocean Salinity (SMOS): SMOS Satellite was launched on November 2, 2009. SMOS is the first satellite to provide microwave L-band measurement, which enabled the global measurement of soil moisture and sea surface salinity. SMOS satellite orbiting on 761.3 ~~788.4~~above the earth's surface. Initially, the SMOS mission was designed as a five years mission. However, due to its excellenttechnical and scientific performance, it extended until 2021 and beyond.

5) Soil Moisture Active Passive (SMAP): SMAP satellite was launched on January 2015 and then operated in April 2015. SMAP is designed to measure soil moisture everywhere on Earth that is not covered with water or frozen. This satellite will take the data at a spatial resolution of 36 kmevery 2-3 days. Similar to SMOS, SMAP uses L-band as its measurement instrument to measure soil moisture.

In agricultural monitoring, the capability to capture color imagery is vital for assessing vegetation health, land use, and water bodies. However, the majority of current satellites used in this domain are passive systems satellites, which inherently face several limitations. A significant challenge for these passive system satellites is their susceptibility toatmospheric conditions, particularly cloud cover, which can obstruct their sensors and impede the acquisition of clear,consistent imagery. This limitation highlights the need forinnovative solutions or alternative technologies that can cir- cumvent such obstacles, ensuring reliable and continuous monitoring of agricultural landscapes.

B. High-altitude Platforms (HAPs)

Under the satellite layer, some HAPs operate in stratospheric altitudes [23, 24, 25, 26]. HAPs provides both vast area coverage, and flexibility compare to satellite. HAPs can be manned or unmanned; due to their long-term operation, itis often unsuitable for a human pilot to operate it. Therefore, unmanned HAPs are more attractive to many stakeholders. Based on the design, HAPs are commonly classified into two types which are aerostatic and aerodynamic platforms [27]. Aerostatic HAPs such as airships (Fig. 4a) and balloons (Fig. 4b) employ buoyancy as their flying mechanism. High-altitude balloons may need to be tethered to stay in one spot. On the other hand, airships employ gasoline engines or solar power to stay in one spot to maintain a good Quality of Service (QoS). Aerodynamic HAPs, high-altitude aircraft (Fig. 4c), cannot stay in the air unless they move. Therefore, high- altitude aircraft typically fly on a circular path to provide goodQoS to maintain a quasi-stationary position. Regarding the energy source for airships, balloons, and aircraft, they can use the solar cell as their energy source [28].

HAPs can provide connectivity for a large area with a diameter of up to 200 km [33]. With these capabilities, HAPs open up an opportunity to provide sensing and communi-cation coverage for hard-to-reach areas, which is suitable for agricultural cases usually located in an area with little terrestrial network infrastructure development. Several HAP projects have been conducted, such as project Loon (2013) by Loon LLC, which is a subsidiary of Alphabet Inc. Loon project

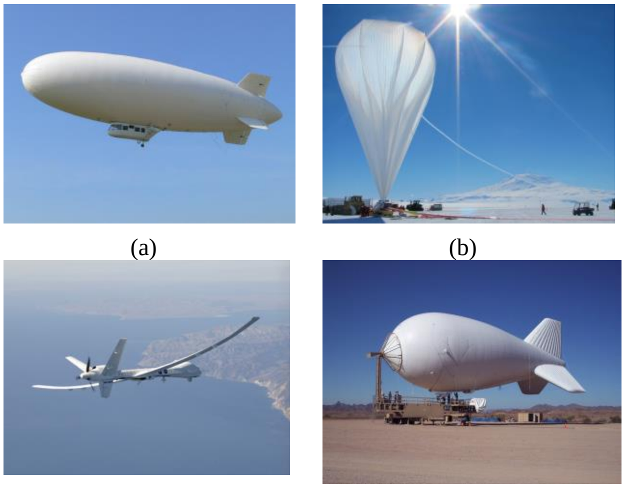

Fig. 4: (a) Airship [29], (b) High-altitude Balloon [30], (c) High-altitude Aircraft [31], (d) Aerostat [32].

Fig. 5: Drone example for agriculture [61, 62].

was conducted in New Zealand using 30 balloons deployed in the stratosphere that covers 5000 for over 100 days with only using solar panels as it energy source [34, 24]. Another HAP project by Facebook called Aquila (2014) planned to provide high-speed wireless communication to remote areas [24, 35]. In January 2018, AeroVironment and Softbank developed a HAP project called Hapsmobile, which intends to provide commercial wireless communication services [36].

C. Low-altitude Platforms (LAPs)

Under the HAPs layer, there is the Low-altitude platforms (LAPs) layer. This section will explore two kinds of LAPs technologies: tethered balloons and drones.

1) Tethered Balloon: is filled with helium or hot air and can be designed in an aerodynamic shape called Aerostat (Fig. 4d). Concerning the HAPs technologies, work in [37] proposes a collaboration between HAPs drones and tethered balloons as a relay to maximize the sum rate between HAPs and the ground station. Furthermore, another work in [38] explores the tethered balloon as a healthier and environment-friendly replacement for the conventional ground base station (GBS). The tethered balloon provides several advantages due to its cost-efficient deployment and operation, more coverage area, low propagation delay, easy reconfiguration, and better LoS than GBS [39, 40]. In the context of sensing technologies, work in [41] used a tethered aerostat as a platform to acquire aerial imagery data to perform an object detection algorithm. Furthermore, Tethered balloon technology is used to support many applications such as disaster management [42, 43], smart environments [44]

2) Drones: Another airborne technology in LAPs is drones. Various types of drones are available in the market, which can be classified based on size, flight range, rotors, landing style, and aerodynamics [45]. Based on the size, UAVs can be classified into four categories: micro UAVs, Mini UAVs, Medium UAVs, and Large UAVs. Based on the flight range of UAVs, there are three categories: medium range, short range, and close range. Based on the type of rotors, UAVs can be classified into four categories which are tricopter, quadcopter, Hexacopter, and octocopter. Based on the landing style, UAVs can be classified into two categories: vertical take-off and landing (VTOL) and horizontal take-off and landing (HTOL). Then based on aerodynamics, UAVs can be classified into four categories: fixed wing, flapping wing, ducted wing, and multi-motor. UAVs can also onboard several sensors and cameras, such as RGB cameras, UAV LiDars, hyperspectral sensors, lightweight cameras, and lightweight thermal infrared sensors.

Drones implementations have increasingly become standard in agriculture due to competition on the commercial side that can reduce the cost of it. According to [46, 47, 48], UAVs can improve the productivity of farming activities and do some tasks that the farmers usually do [49, 50]. The type of drones will differ based on the task they need to complete (Fig. 5). Drones may have several objectives to improve productivity in the agriculture sector. These objectives include optimizing the spraying process, crop monitoring, crop maturity monitoring, detecting and predicting various crop diseases, irrigation management, artificial pollination, greenhouse temperature and humidity monitoring, and water assessment.

Drones Routing Problem: Deploying drones in agricultural use cases needs to consider solving some optimization problems. The first problem that needs to consider is drone path planning. In the agricultural context, the path planning problem is to cover all the fields, which can be said as Coverage Path Planning (CPP) [51, 52, 53]. One common example of a CPP technique used in agriculture is boustrophedon. Some recent work has been applying this technique for agricultural uses case. In [54], the authors improved this technique by considering wind conditions. Another work in [55] used boustrophedon to cover large-scale are in hard-to-reach areas (i.e., mountains). However, implementing boustrophedon for a large area of coverage can be inefficient. Which can only cover less than half a hectare in one flight [56]. This inefficiency happens due to energy limitations in UAVs. Although most prior works assume that the UAV has enough available energy, some consider energy usage and limitation when implementing CPP [57, 58, 59]. Another method, like the Voronoi-based path generation (VPG) algorithm, considers the energy constraint while planning the coverage path planning [60]. This algorithm proposed a good balance between run-time and optimality. However, VPG only provides a near-optimal path, meaning the drones will not hover at every point in the area. However, considering the energy limitation, partial coverage may give enough QoS to the system.

TABLE III: Sensors and its application for agriculture .

Type of Sensors	Application
Location sensors	Location sensors such as GPS can be used to provide the precise position of some agricultural activities (e.g. when implementing CPP using drones) to measure actual effectiveness
Optical sensors	Optical sensors can be use to measure the vegetation health of the farm
Mechanical sensors	One conventional example of mechanical sensors is Tensiometer that can be used to monitor soil moisture conditions to schedule irrigation
Electro-chemical sensors	By detecting specific ions in the soil, this sensor can measure Nitrogen Phosphorus Potassium (NPK) in the soil that is important for the plant
Dielectric soil moisture	Measuring the soil water sensors using Frequency domain reflectometry (FDR) or Time Domain Reflectometry (TDR)
Air flow sensors	Measuring air moisture level that can impact the plant vegetation

Drones Scheduling Problem: The scheduling problem is an important consideration when deploying UAVs for agricultural purposes. One of the main challenges is the limited flight time of most UAVs. Most drones can only fly for a few hours, so we must be carefully scheduled to ensure they can complete their tasks within the available flight time. Work by [63] tries to tackle this problem using Lyapunov optimization for scheduling problems on renewable charging station use cases. Another potential problem when deploying UAVs as data collection tools in the field is when an unexpected condition changes the initial knowledge of the scheduled plan (i.e., when the UAVs and the ground sensors do not have a good enough data collection velocity). To address this problem, Work in [64] proposed a Multi-UAV Deep reinforcement learning-based scheduling algorithm (MADRL-SA) that reduces the data loss even with the outdated knowledge of the current network condition. The scheduling problem can be particularly challenging when multiple tasks need to be completed, which has been proved as an NP-hard combinatorial optimization problem[65]. To solve this multi-UAV task scheduling problem, some approaches such as Genetic algorithm (GA), tabu search (TS), ant colony optimization (ACO), simulated annealing (SA),and particle swarm optimization (PSO) are considered, which potentially provides a globally optimal solution.

D. Sensing in Agriculture 4.0

Airborne sensing technologies can be important in Agriculture 4.0, especially for outdoor farmland. Sensing technology will provide the data to make decisions or interventions in the field to reach the desired outcome to perform various kinds of applications in smart farming (Table I).

Agriculture typically has more land usage compared to other industries. This condition makes agriculture have a unique technological deployment problem. The sensing technologies in agriculture should be scalable enough to reach the Quality of Service (QoS) for a vast coverage area. To reach enough QoS for the system, solving a scalability problem may come with a trade-off to maintain the reliability of the sensing network. Furthermore, the sensing technologies should be deployed in many sensing dimensions to gain more complete farm conditions. Liu et al. introduced Space-Air-Ground-Undersurface Integrated Network (SAGUIN) that provides ubiquitous agriculture sensing and networking [6].

1) IoT Sensors: Data collection in agriculture cannot forget the role of sensors as a data collection method in the field. Innovation in sensor technology provides us with smaller and cost-efficient sensors that are increasingly suitable to be deployed in agricultural cases. In some cases, these sensors are equipped with electronic components such as processing units, modems, and antennas enabled to access the internet as a stand-alone object called the Internet of Things (IoT) [66, 67]. This advancement in ground-level data capture is intrinsi-cally linked to the broader scope of satellite-airborne sensing, signifying a shift towards a more integrated and intelligent data collection framework. Furthermore, this integration has given rise to a new paradigm in monitoring and surveillance, where 'smart' observational chains form between terrestrial and non-terrestrial sensing. [68].

In the agricultural context, several kinds of sensors are usually used in the field. These sensors are location, optical, mechanical, electrochemical, dielectric soil moisture, and airflow sensors [69]. They can be implemented in several applications, as listed in Table III. Each type of sensor exhibits unique properties in terms of metrological characteristics.

Location sensors typically prioritize high accuracy and precision to ensure reliable positional data. The most common example of this sensor is the global positioning system (GPS). Optical sensors are designed with high sensitivity to discern subtle changes in various light properties, such as intensity, polarization, spectrum, and phase. Their detection capabilities range from basic light detection, useful in applications such as ambient light sensing, to more complex image detection used in digital cameras, barcode readers, and machine vision systems.

Mechanical sensors, particularly those used for stress or strain measurements such as in tensiometers, necessitate high-resolution capabilities that enable them to detect subtle variations in mechanical forces. Furthermore, producing consistent measurements under unchanged conditions (i.e., repeatability) is also crucial. This ensures the reliability and accuracy of these sensors in various applications.

Electrochemical sensors, utilized to monitor chemical changes, depend critically on their sensitivity and specificity. Sensitivity is crucial as it determines the sensor's ability to detect changes in the concentration of specific chemical elements. On the other hand, specificity ensures the sensor can distinguish between different chemical elements, preventing cross-reactivity and false readings.

Dielectric soil moisture sensors measure the dielectric constant of soil, thereby detecting variations in moisture content. Maintaining the accuracy and precision of these sensors is essential to obtain reliable data.

Lastly, airflow sensors, such as hot-wire anemometers, are

TABLE IV: Classification of Algorithms for 1D and 2D Data in Agriculture 4.0

Algorithm Category	Examples of Algorithms	Data Dimension
Regression	Linear Regression, Polynomial Regression, Support Vector Regression (SVR), Random Forest Regression, Artificial Neural Networks (ANN)	1D
Classification	Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naive Bayes, Artificial Neural Networks (ANN)	2D
Clustering	K-Means, Hierarchical Clustering, DBSCAN, Gaussian Mixture Models (GMM), Self-Organizing Maps (SOM), Agglomerative Clustering	2D
Time Series Analysis	ARIMA (AutoRegressive Integrated Moving Average), Exponential Smoothing, Seasonal Decomposition of Time Series (STL), Recurrent Neural Networks (RNN)	1D
Image Processing	Convolutional Neural Networks (CNN), Histogram-based Thresholding, Edge Detection, Image Segmentation, Object Detection	2D
Data Mining	Association Rule Mining, Decision Tree Mining, Clustering, Sequential Pattern Mining	2D

utilized to detect changes in the rate of airflow or measure air moisture levels. Maintaining swift response times is essential in many instances to facilitate real-time monitoring. While some of these sensors are in-situ ground-based sensors (i.e., Mechanical, Electrochemical, Dielectric soil moisture), and some can be employed in UAVs as airborne sensors. However, these two types of measurement can complement each other, enabling us to acquire a more complete and detailed understanding of the overall environmental and agricultural conditions.

2) Data Crowd-sensing: Deploying many sensors in an agricultural field needs to consider how to collect the data from a vast area of deployment. One approach to address this issue is using the mobile crowd-sensing technique to do data sensing on a vast data source [70]. However, unlike the typical crowd-sensing method that uses a mobile device such as a smartphone, tablet, or wearable device, it is rarely available for agricultural use cases, usually in rural areas. Therefore [71] proposed a UAV-Assisted crowd-sensing that can be used in rural, remote, and inaccessible areas.

Increasing the number of outputs (i.e., yields) or reducing the input (i.e., water, fertilizer) required to get the same output will directly impact our food welfare. One factor that provides us the opportunity to improve our current agricultural condition is the innovation of some technology that makes things that seem impossible possible.

E. Mobile Edge Computing (MEC)

Combining terrestrial and non-terrestrial networks such as LAPs, HAPs, and satellite opens up a new opportunity to develop a more flexible system in a vast coverage area. There is another paradigm that can complete the combination of terrestrial and non-terrestrial networks, which is Mobile Edge Computing. By definition, mobile edge computing refers to a set of techniques designed to move the storage and computing power of a cloud server closer to its data source [72]. With this new approach, the system will have a low latency capability that enables a faster result based on the data input from the sensing device. This approach also has a better privacy-preserving design due to its data handling methods that are computed locally.

Combining UAV capabilities in a MEC system can in-crease the system flexibility compared to conventional IoT architecture. UAV can be deployed as Airborne Base Stations (ABS) [73], data collectors, relay nodes [74], Jammers [75], Monitors [76], edge and cloud computing servers [77], and power suppliers [78] to support the IoT system. In general, UAV- Enabled MEC can give several benefits, such as flexible and efficient communication due to its line-of-sight (LoS) link, which can provide a broader range of applications. UAV-Enabled MEC provides a low latency computation offloading, which can improve the energy efficiency of the overall system.

Intuitively UAVs can have many contributions to MEC servers due to their versatility and ease of deployment. In a MEC system, UAV can act as an Edge Computing node that offloads its computing result to the MEC Server, a MEC server itself that is responsible for monitoring a group of end nodes, or become a gateway between end nodes and the MEC server (Fig 6). When deploying a UAV-MEC system, some aspects need to be considered, such as Communications security issues, computational and task offloading, Latency, Energy efficiency, consumption, UAV Trajectory Planning, quality of Service (QoS), Resources Allocation, Computation overhead and cost reduction.

III. Agriculture 4.0 Trends

In recent years, several emerging technologies can complement the sensing technologies discussed in this survey. This section will discuss emerging technologies, such as Machine Learning (ML) and Digital Twins (DT). Furthermore, this section will discuss the research projects in Agriculture 4.0 from several countries (i.e., EU, US, and China).

A. The Rise of Powerful Data Processing

Obtaining large amounts of data is only the first step to extracting value from it. Processing large amounts of data needs a robust algorithm and resources. Thanks to emerging techniques such as machine learning that enable extracting value from massive volumes of data. Many kinds of machine learning models are used in many different use cases. Some of the traditional machine learning methods are the K-means algorithm [79], Support Vector Machine (SVM) [80], andthe expectation–maximization (EM) algorithm [81]. No one method can be used for any problem, which is also true in machine learning problems. Every method has different capabilities for different problems. One of the most essential techniques in machine learning to process a massive amount of data is deep learning (DL) [82]. DL uses Artificial Neural Networks (ANNs) to identify patterns within the data, thereby

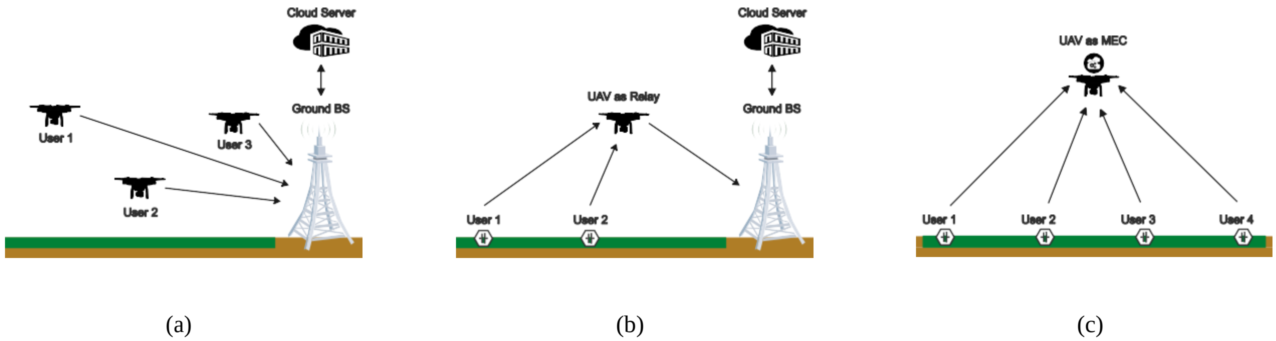

Fig. 6: (a) The scenario UAVs have computation task, (b) The scenario UAVs as a Relay, (c) The scenario UAV act as a MEC.

facilitating machine learning processes. The DL technique effectively processes unstructured data such as images, video, and sound. In the agricultural remote sensing context, it often collects data in the image form (e.g., satellite imagery) that align with the DL strength. Table II provides examples of use cases where enhanced DL techniques are employed to process satellite data for field and crop classification. Furthermore, considering the two types of data that are typically produced: 1-dimensional (1D) data (e.g., soil moisture readings) and2-dimensional (2D) data (e.g., satellite imagery). Relevant algorithms have been classified based on these data dimensions in table IV.

B. Emergence of Digital Twin

Sensing is one of the crucial parts and an enabler of digital twin technology. By acquiring real-time data, digital twin technology develops a digital representation that can simulate, analyze, and optimize real-world counterparts. This system needs a combination of hardware, software, and data toperform a virtual simulation representing the physical entities. Implementing digital twins may be an opportunity as the next step after developing a reliable sensing infrastructure. Work in [83] conduct a review on the state of the art ofdigital twin technology in agriculture. Implementing digital twin technology can improve several agricultural use cases (e.g., Crop and livestock monitoring and optimization).

In the context of the airborne network, authors in [84] propose an architecture of an air-ground network poweredby digital twins. Two kinds of digital twins represent theground equipment and drones, reducing the communication cost between drones and ground devices, and increasing the system's efficiency. Furthermore, by leveraging digital twin technology, the system designer can efficiently evaluate a large-scale IoT network before deploying it to the real world.

C. Smart Agriculture Research Projects

Agriculture 4.0 is rapidly expanding through numerous initiatives worldwide. This section examines some Agriculture 4.0 projects by the European Union, the United States, and China to understand the current trends and efforts when implementing airborne sensing technology in the Industrial 4.0 project.

1) European Union: The European Union (EU) has traditionally prioritised supporting and developing its agricultural sector, as agriculture is a significant part of the EU's economy. The EU's Common Agricultural Policy (CAP) supports farmers, promotes sustainable agriculture, and ensures a stable food supply. Based on The Community Research and Development Information Service (CORDIS) platform[1] there are several smart agricultural projects conducted in Europe:

FLOURISH [85]: This project aims to fill the gap between agricultural robots' current and desired capabilities by developing an adaptable robotic solution for precision farming. This project started from March 2015 to August 31, 2018, with a total funding of up to €4.7 Million. This project used multi-copter drones and a multi-purpose Unmanned Ground Vehicle (UGV). This combination between drones and UVG provides a complete system that can survey a field from the air, perform the intervention on the ground, and provide detailed information for decision support.

FOODIE [86]: This project aims to develop an open and inter-operable agricultural platform hub on the cloud for spatial and non-spatial management for farming production. This project started from March 1, 2014, to February 28,2017, with a total funding of up to €5.9 Million. This project implements terrestrial and non-terrestrial sensor data, suchas satellite imagery, to simulate yield production based on satellite data.

MISTRALE [87]: This project aims to address soil moisture management in agriculture using Global Navigation Satellite Systems reflected signals (GNSS-R). This project is from January 1, 2015, to June 30, 2018, with a total funding of up to €3.3 million. Using GNSS-R, the project maps the soil humidity to optimize water resource management for the agricultural context. This project also embedded a GNSS-R receiver into a small Remotely Piloted Aircraft System (RPAS) to increase the sensing accuracy.

2) United States: The United States government, through USDA (United States Department of Agriculture), pays attention to the agricultural sector by providing funding for research, development, and infrastructure projects, as well as support for farmers and rural communities. On the other hand, some technology companies, such as Microsoft, are also experimenting with emerging technology to improve the agricultural sector. An example of such projects are:

[1]cordis.europa.eu

GRAPEX [88]: Grape Remote Sensing Atmospheric Pro- file Evapotranspiration eXperiment (GRAPEX) is a highly collaborative and interdisciplinary project that is supportedby NASA, USDA, and E&J Gallo[2]. GRAPEX is a remote sensing experiment that started in 2014 to improve irrigation management in California vineyards. This project develops a multi-scale remote sensing evapotranspiration (ET) toolkit for grape-growing regions. This project produces twenties papers that consist of two volumes. The first volume is about the application, uncertainties, and sensitivities in the measurement and remote sensing of vineyard ET. The second is remote sensing methods for monitoring vine water status and stress, root zone soil moisture, and management applications. One of the published paper by Kisekka et al. combine the sensing technology between imagery data from Landsat satellite and in situ soil moisture data from the field [89].

FarmBeats [90]: FarmBeats is a project by Microsoft that started in 2014 intending to enable data-driven agricul- ture. This project used some technologies, including sensors, drones, tractors, cameras, satellites, and weather stations, to acquire data from the field. This project provided a platform that process and combines the data using some technique (i.e., Artificial Intelligent) to fill the gap in the data and predict likely outcomes from the data. All these data collection and processing enabled practical use cases such as developing a very hyper-local weather prediction, building 3D orthomosaics, and aerial time-lapses of the farm.

3) China: China's government and research institutions such as the Chinese Academy of Science (CAS) and the Chinese Academy of Engineering (CAE) have implemented various policies and projects to improve the country's agricultural sector. Some of these projects are:

Smart agriculture model in Ruian, Zhejiang Province [91]: The project of triune integration between agricultural production, supply and marketing, and credit access was initiated in 2006. By 2020, the project adopted a modern agriculture platform (MAP) that integrates into the triune system with the help of Syngenta Group[3]. Some technologies integrated with MAP systems are remote sensing, big data, cloud computing, IoT, Blockchain, and AI. by leveraging these technologies, the system can provide worry-free agricultural scenarios, which include subsidy, loan, planting, and selling. Furthermore, by implementing robots in the field, this project reduced the cost by US$1200 per hectare.

Smart Agriculture Strategy for China 2035 [92]: In 2021, the Chinese Academy of Engineering (CAE) developed a smart agriculture strategy for China 2035. Four categoriesbecome the key technologies in this strategic planning. These technologies are smart service, smart decision-making, Intelli-gent control, and smart perception. Currently, China has to implement automatic navigation, smart plant factories, and UAVs for agricultural applications with the help of BeiDou technologies[4]. Furthermore, the long-term goal is to establisha technology system combining key technologies such as "*AI + big data + new-generation communication technology + Internet of Things (IoT) + Beidou satellite navigation*".

[2]www.gallo.com
[3]www.syngentagroup.com
[4]beidou.gov.cn

IV. Challenges

The use of airborne sensing technology has the potential to revolutionize agriculture in the age of Agriculture 4.0. However, to successfully implement the technology need to consider some potential challenges. This section will discuss the challenges from agricultural perspective and technological perspectives. The challenges faced by the agricultural sector perspective will help to understand how airborne sensing technology contributes to solving the problem. On the other hand, from the technological perspective will provide some consideration when implementing the technology.

A. Limited Resources

One challenge the agriculture sector faces is optimizing the output with limited resources. In general, there are two primary resources in the agricultural context. The first one is land. The land is a critical resource for agriculture, providing space for raising crops and livestock. However, access to land can be limited due to various factors, including ownership patterns, land tenure systems, and land use policies. The second vital resource for agriculture is water. Water is essential for agriculture as it is necessary for crops' growth and livestock maintenance. However, access to water can be limited due to physical and economic factors. Other resources necessary for agriculture, such as fertilizers, pesticides, and irrigation equipment, may also be limited due to economic constraints or inadequate infrastructure.

1) Precision Agriculture: One approach commonly used to manage limited resources in agriculture is Precision Agriculture [93]. Precision agriculture is a farming approach that utilizes advanced technologies to increase efficiency, reduce waste, and improve crop yields by tailoring inputs such as fertilizers and pesticides to the specific needs of individual plants or fields. Precision agriculture relies on data collection and analysis to make informed decisions about crop management, and it can significantly improve agricultural operations' sustainability and profitability. Work in [94] specifically explored UAV-based applications for precision agriculture. According to their research, the several applications of UAVs in precision agriculture include weed mapping management, vegetation growth monitoring and yield estimation, vegetation health monitoring and disease detection, irrigation management, and corps spraying. However, the most common application of UAVs in precision agriculture is to monitor crop growth.

Furthermore, on the technological aspect, some resource needs to be managed, such as energy consumption. Usually, we face this problem when deploying LAP UAVs in a large agricultural field. In addressing this problem, an optimization approach can be used to manage the limited resource in UAVs to achieve the desired QoS.

2) Resources optimization on LAP UAVs: UAVs' limited resource consumption can be managed as a scheduling problem or workload distribution. Dynamic availability of resources plays an essential role in improving the performance of offloaded services. Various resource allocation schemes have been adopted to ensure optimal utilization of resources in order to improve UAV network performance and meet the increasing demand for computationally intensive applications due to uncertainty in the field with resource-constrained devices. Resource allocation is a crucial challenge for UAV networks to meet the minimum QoS in the field, especially in large areas of implementation due to UAV battery and trajectory limitations.

1) Energy Efficiency: The first constraint that needs to be optimized is the energy consumption for the whole system. In this system, we can see the subset of this energy optimization as the tasks that consume energy. Some of these tasks are the calculation of resource allocation, online task scheduling, the live location of the drone, and calculatingthe number of drones under a delay constraint (e.g., slowoffloading velocity). Therefore, the solution space of energy optimization problems is often vast and complex, with multiplelocal optima. One promising approach to addressing this issue is Evolutionary Algorithms (EAs). EAs are population- based heuristic search methods that work without needinggradient information. However, EAs may have some issues when the number of sensors and UAVs increases, which makes the problem have a large-scale search space with a mixed decision variable and also needs to include the correlationbetween UAVs deployment and task scheduling. To tackle thisissue, work by Wang et al. proposed ToDeTaS that works in two layers of optimization which used EAs to optimize the number of deployed UAVs (i.e., Upper layer) and optimized the scheduling problem as an integer problem at the lower layer that improves the algorithm efficiency [95]. In another noteworthy contribution to this field, Shi et al. delves into energy efficiency optimization within the context of satellite-aerial-terrestrial networks (SATN). Addressing the limitations of existing works that often focus on resource optimization while overlooking relay strategy optimization among multiple UAVs, they proposed an innovative solution: an iterative algorithm. This algorithm, which leverages coordinate ascent and Lagrangian dual decomposition methods, was designed to optimize relay selection, power allocation, and UAV deployment jointly. The study's extensive simulation results underscored its effectiveness, highlighting its potential for significantly improving system energy efficiency and optimizing relay selection and power allocation decisions. This work's novelty and promising results further underline the potential of algorithm-based approaches in enhancing energy efficiency in SATNs [96].

2) Computation Efficiency: In the implementation of UAV-MEC systems, optimization of computation power is crucial. The work in [97] addresses this by proposing a compu- tation efficiency maximization strategy. This strategy aims to maximize central processing unit (CPU) frequencies and energy consumption while minimizing user offloading time and optimizing the position and mobility of UAVs. To solve this problem, the study calculates transmitted power and CPU frequencies using the Lagrangian Duality Method. Furthermore, the Sequential Convex Approximation (SCA) method addresses determining the optimal UAV trajectory. Similarly, [98] presents an approach that optimizes the system's en-ergy consumption and computation bits. This is achieved by managing users' transmit power, optimizing the allocation of spectrum resources, and setting the most efficient trajectory for UAVs.

3) Delay Minimization: Another problem is an operational delay, a significant concern for optimization. An existing approach to address this issue is described in [99], which aims to minimize the maximum delay (min-max) by optimizing user scheduling binary variables, offloading task ratio, and trajectory of UAVs under discrete binary constraints to enhance the overall performance. The authors employed the Penalty Dual Decomposition (PDD)-based algorithm consisting of two loops. In the inner loop, variables are updated using the Concave-Convex Procedure (CCCP) algorithm, while the Augmented Lagrangian (AL) multiplier and penalty factor are updated in the outer loop. Building on this understanding,recent work by Mao, He, and Wu presents an innovative approach to delay minimization in the context of a space- aerial-assisted mixed cloud-edge computing framework. Here, unmanned aerial vehicles (UAVs) provide low-delay edge computing services to IoT devices, while satellites ensure ubiquitous access to cloud computing [100]. The authors striveto minimize the maximum computation delay among IoT devices by jointly scheduling association control, computation task allocation, transmission power and bandwidth allocation, and UAV computation resource and optimizing deployment position. To tackle the formulated problem, they leveraged block coordinate descent and successive convex approxima- tion, creating an alternating optimization algorithm with guar- anteed convergence. Extensive simulation results from this study showcased a significant delay reduction compared to existing benchmark methods, further highlighting the potentialof such joint optimization strategies in minimizing operationaldelay. UAV computing is discussed for supporting 6g networks and industry 4.0/5.0 [101] and disaster management [102].

4) Load Balancing: Another method for improving the entire UAV-Enabled MEC system is load balancing. By evenly distributing the computational load across various machines, load balancing minimises bottlenecks and ensures efficient system functioning. According to one study in [103], load balancing issues can be resolved by concurrently optimizing job scheduling and UAV deployment under coverage restrictions. The author optimized the scheduling of jobs offloaded in multi-UAV scenarios using Deep Reinforcement Learning, which decreases transmission delay. In line with this approach, a different study proposes a federated deep Q-network (DQN)-based task migration strategy that considers both load and energy deviation among UAV MEC servers to enhance energy-efficient load balancing in UAV-Enabled MEC systems [104]. This strategy uses DQN to create a local model for migration optimization for each server, and federated learning forms a more efficient global model by capitalizing on the standard spatial features among adjacent regions.

B. Climate Change

Climate change has the potential to significantly impact agriculture, as changes in temperature, precipitation, and extreme weather events can affect the growth and yield of crops

TABLE V: HAP and LAP Characteristic Related to Communication.

Characteristic	Low Altitude Platform (LAP)	High Altitude Platform (HAP)
Range	Limited	Long
Latency	Low	High
Cost	Low	High
Power	Low	High
Jamming susceptibility	High	Low

and the health and productivity of livestock. Rising temperatures can increase water stress for plants and promote the growth of pests and diseases. Changes in precipitation patterns can also majorly affect agriculture, with floods and droughts posing challenges for farmers. Extreme weather events, such as heatwaves, hurricanes, and wildfires, can devastate agriculture, damaging crops and infrastructure and reducing production. The current climate condition is increasingly concerning as in the [105] which studies the effect of climate change in China, it shows that it is expected that the Total Factor Productivity and yield will decrease linearly by 2.6% and 4.4% during the whole year. If we are not finding a way to improve this condition, it could cause another crisis related to food security. Addressing this problem, this section will generally explain some approaches, such as facility agriculture and Climate-smart agriculture, to adapt to the current climate condition.

1) Climate-smart Agriculture (CSA): Climate-smart agriculture is a farming practice that aims to increase agricultural productivity and adapt to climate change's impacts while reducing greenhouse gas emissions and increasing carbon sequestration. It is a holistic approach considering agriculture's economic, social, and environmental aspects. In 2022 USDA invested more than $3.1 billion for 141 projects in climate-smart commodities [106]. On another side of the world, work in [107] evaluates several cropping systems in the North China Plain (NCP) considering the CSA approach. In the sensing technology context, there are several efforts to implement a climate-smart approach. Innovations such as energy harvesting [108], on-demand sensing [109], and battery-free device [110] may improve sustainability when deploying a sensing technology. Combining these technologies, work in [111] proposed a new sustainable power supply scheme called PowerEdge. Moving the energy supply distributed may support the sensing technology deployment in a vast agriculture field.

C. Terrestrial to Airborne Communication

Another challenge from the technological deployment perspective is communication between terrestrial and airborne networks. When deploying a conventional IoT sensor network, it is necessary to consider the obstacle that may disturb the network communication. On the other hand, airborne networks have the advantage of providing better communication by providing LoS connection. However, a challenge, such as three-dimensional interference, still needs to be overcome. Addressing this problem, work in [112] proposes an interference management approach using mean-field game theory in a dense drone small cells (DSC) network. By controllingthe altitude of each DSCs, this work achieves a better down- link communication quality and considers the interference introduced by other DSCs. Furthermore, work by Wang et al. addressed more complex conditions when the interference and the traffic demand change frequently. Using a machine learning-based approach (i.e., affinity propagation and K-means), they mitigate an inter-DSC inference and optimize the position to receive better signal quality [113]. Another problem that must be considered in designing communication between airborne and terrestrial sensing networks is the distance between two or more machines. In the conventional terrestrial system, one solution to extend the communication range is to use a relay between two machines. However, due to the mobility constraint in the terrestrial device, the relay device is mostly deployed in a fixed location. On the other hand, airborne technologies (i.e., UAVs) enable a more mobile relaying strategy that provides short-range LoS communication links [114]. Moreover, it is essential also to consider the characteristic of different types of airborne platforms, namely Low Altitude Platforms (LAPs) and High Altitude Platforms (HAPs) in Table V. These attributes can significantly influence the design and performance of such systems.

LAPs, such as drones, provide the advantage of rapid deployment and adaptability to specific areas of interest. They are also relatively affordable compared to HAPs, making them more accessible to smaller farms or resource-constrained regions. However, LAPs present some limitations, includ- ing a restricted range due to their limited flight endurance.This constraint may necessitate multiple flights with frequent recharging or battery replacement to cover larger agricultural areas. Moreover, LAPs are more susceptible to jamming. On the other hand, HAPs have the capability to cover large agricultural areas, providing wide-scale monitoring and data collection. However, deploying and maintaining HAPs can require a significant investment, which may pose challenges for small farms or less developed regions seeking to adopt HAP technology. Moreover, due to their long-range deployment, HAPs may exhibit higher latency, which could delay data transmission and impact real-time decision-making processes in agricultural management.

V. Opportunities

Leveraging the technological capabilities of airborne sensing, data processing, and virtual optimization trends and addressing the challenges from both the agricultural and technological perspectives leads to a new opportunity for improving the current agricultural system. This section will explore the potential of combining these elements and propose innovative ideas that build upon the findings from previous sections. The aim is to provide a comprehensive understanding of the opportunities and potential solutions for improving the agricultural landscape through airborne sensing technology.

A. Sensing Synergies

In our exploration of satellite-airborne sensing technologies, as detailed in Section II, we scrutinize the spectrum of satellite-airborne sensing technologies such as LAPs, HAPs, and satellites, as illustrated in Fig. 7. The utility of these technologies varies with altitude; LAPs excel in high-resolution imaging for precise, local agricultural assessments, while satellites facilitate expansive coverage, crucial for gathering data in remote regions. Despite the broad reach afforded by satellites' high-altitude positioning, challenges like cloud cover can impede data acquisition, which can compromise data quality.

Addressing this, a multi-tiered sensing strategy emergesas a solution employing HAPs and LAPs to complement satellite observations by operating beneath cloud coverage, thus filling the observational voids and improving the overall sensing quality. This integrative approach not only counters the limitations of satellite data but also significantly boosts efficiency by ensuring continuous and reliable data flow. Bridging the gap further, the synergy between terrestrial sensors and their non-terrestrial counterparts enables a multi-dimensional analysis, enhancing the granularity of our agricultural insights. Adopting the idea on [115], the synergy between each sensing technology can be categorized into four strategies (Fig. 8).

1) Data Comparison: This strategy compares the data between different data sources. The data from different sources will not affect each other interpretation, and the result will be compared to gain new insight. This strategy is categorized as weak synergy because it only compares the result (e.g., using visualization) without affecting each other interpretation of the data.

2) Multi-scale Explanation: This strategy combines different data sources to obtain more detailed information. This strategy will combine the result between different data models to develop an interpretation. Expanding the idea in [115] that combined the detailed view of a UAV and the global view from a satellite makes it possible to combine other data sources' use cases with the same logic combined between local and global sensing data.

3) Model Calibration: Bringing the local and global combination to the next level, the Model calibration strategy combined the data in the model level to calibrate the result. For example, more specific local data with more detailed features can improve the global data model output. However, this strategy is not combining the data directly into one model but as a collaboration between 2 or more data sources to improve one model (e.g., improving the data label based on a more specific data source).

4) Data Fusion: Combining data into one model is themain idea for the data fusion strategy. In this strategy, itis possible to combine multi modalities data (e.g., Image,sound, temperature) into one model to gain a more in-depth representation of the actual condition. One promising approach to this problem is multimodal machine learning [116].

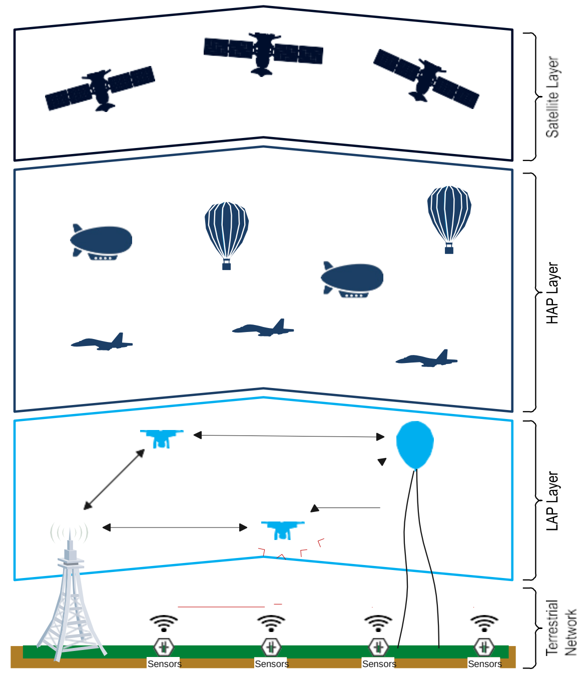

Fig. 7: Terrestrial and airborne network architecture.

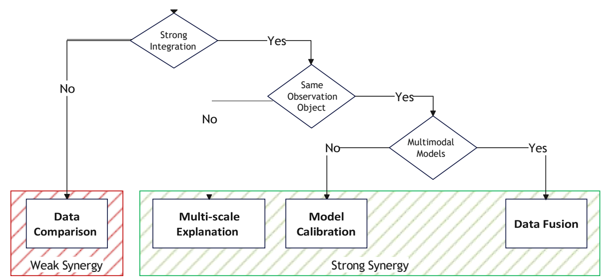

Fig. 8: Synergy strategies.

B. Intelligent Sensing

Data processing processes such as ML commonly start after sensing technologies acquire data. However, work in [117] proposed a concept to merge computation and machine learning-based statistical analysis of signal into the sensing technology hardware to optimize sensing performance. Their proposed intelligent sensor design consists of four steps. First, the intelligent sensor will begin with the sensing data acquisition. Next, these data will be used to train a machine-learning model as part of the sensing system. The model will then be evaluated by calculating the cost function, which will be compared to the ground truth sensing data. This optimization part will reduce non-informative or less helpful features in the data. Finally, the sensing hardware will be redesigned based on the statistical analysis of the previous phase.

In the context of agricultural remote sensing (e.g., satellite imagery), which usually has a vast data set, we may need to reduce the complexity of the data to gain insight more efficiently. Intelligent sensing provides the capability to optimize the data by selecting only essential features (i.e., reducing data noise) that can reduce the overall computational expenses of the system [118].

C. From Sensing to Virtual Optimization

A reliable sensing infrastructure that provides accuracy, high-resolution, and real-time data collection with cost-effective adoptions will enable effective virtual optimization by integrating the data into virtual simulation approaches such as digital twin (DT) or predictive modelling [119]. Processing multi modalities data in sensing technologies needsto consider a strategy to integrate it. Work in [120] investigates multi-modalities in digital twins using a knowledge graph as heterogeneous information networks (HINs). Furthermore, integrating HINs with powerful data processing approaches such as DL needs to transform the graph or network structure into a low-dimensional vector space using an approach like network embedding. Another perspective on implementing digital twin technology is explored by Hu et al. that examines the potential of developing a Driver Digital Twin (DDT) as the enabling technologies for intelligence vehicles [121]. In the context of smart farming, there is an opportunity to develop a digital twin of a farmer based on a multimodal interface that can provide comprehensive sensing and feedback. Furthermore, handling multimodal information may need to leverage multimodal fusion that consists of three fusion levels, i.e., feature-level, model-level, and decision level [122].

Developing a virtual system optimisation also needs to consider the virtualization of the hardware and network sides. Software-defined networking (SDN) and network function virtualization (NFV) technologies can be used to developa network design and structure that can be simulated and implemented virtually [123]. Leveraging these technologies will enable new services to be quickly deployed and tested, increasing infrastructure flexibility and network service adaptability.

D. Climate Resilience and Satellite-Airborne Sensing Technologies

Airborne sensing technologies play a crucial role in addressing the impacts of climate change on agriculture. The changing climate patterns, including shifts in temperature, precipitation, and extreme weather events, pose significant challenges to agricultural productivity and food security. Farmers and policymakers can better understand and respond to the challenges by harnessing the capabilities of satellite and airborne sensing technologies. Airborne sensing technologies provide valuable data for monitoring climate-related parameters that impact agriculture. For example, satellite remote sensing data can help assess the spatial and temporal distribution of temperature, rainfall, vegetation indices, precipitation, vegetation health,and soil moisture levels [124]. The information enables farm- ers to make informed decisions regarding irrigation manage- ment, crop selection, and pest control measures. By integrating satellite imagery with data from airborne platforms such as drones or tethered balloons, finer-scale and near-real-time monitoring can be achieved, offering localized insights for climate-resilient agriculture [125].

In addition to data collection, airborne sensing technologies facilitate the development of predictive models and decision support systems to enhance climate resilience in agriculture. Machine learning algorithms applied to the collected data can help identify patterns, predict crop yields, and detect anomalies related to climate stress [126]. Such models aid in opti- mizing resource allocation, implementing adaptive practices, and mitigating climate-related risks for farmers. Moreover, integrating airborne sensing technologies with other technologies, such as IoT devices and data analytics platforms, enables continuous monitoring of environmental parameters at various scales [127]. This comprehensive approach enhances the understanding of climate change impacts on crop growth, soil conditions, and water availability. Using this knowledge, stakeholders can design climate-resilient strategies, improve resource management, and promote sustainable agricultural practices.

Furthermore, airborne sensing technologies support adaptive decision-making in agriculture. By continuously monitoring climate variables, farmers can make timely and informed decisions regarding irrigation management, crop selection, and pest control strategies [128, 129]. For instance, satellite data and ground-based sensors can provide real-time infor- mation on soil moisture content, helping farmers optimizeirrigation schedules and conserve water resources in water- stressed regions. Similarly, aerial platforms with multispectral or hyperspectral sensors can detect early signs of crop stressor disease, enabling proactive interventions and preventingyield losses. Mitigation strategies for climate change can also be enhanced through airborne sensing technologies. By providing detailed information on greenhouse gas emissions, land use changes, and vegetation dynamics, these technologies contribute to assessing and monitoring carbon sequestration efforts in agricultural landscapes [130]. The data can support implementing and evaluating climate-smart agricultural practices, such as agroforestry, precision nutrient management, and conservation agriculture, which aim to reduce greenhouse gas emissions [131, 132, 133, 134, 135] and enhance carbon sinks in agricultural ecosystems.

In recent years, several case studies have demonstrated the effectiveness of airborne sensing technologies in enhancing climate resilience in agriculture. For instance, a study in [136] showcased using drones with thermal imaging sen- sors to assess crop water stress in drought-affected regions.By detecting variations in canopy temperature, the drones provided early indicators of plant water needs, allowing for targeted irrigation and water management strategies. This approach optimised water usage and mitigated the potential yield losses caused by drought conditions. Another initiative by [137] utilized satellite remote sensing to monitor changes in vegetation dynamics and land cover in response to climate change. By analyzing multi-temporal satellite imagery, the study highlighted the shift in agricultural practices towards more climate-resilient crops and land management strategies. The insights gained from this monitoring approach guided policy interventions and supported adaptive decision-making at regional scales. Furthermore, airborne sensing technologies have been integral in precision agriculture applications for climate resilience. In [138], drones equipped with hyperspectral sensors to detect early signs of crop diseases and pests were used. By identifying stress indicators in the plant's spectral signature, the drones enabled timely interventions, preventing the spread of diseases and reducing yield losses. This targeted approach minimized pesticide usage and promoted sustainable farming practices. As we continue to grapple with the impacts of climate change, the adoption and further development of these technologies present an unprecedented opportunity to secure our food systems and foster a more sustainable, resilient future for agriculture.

VI. Research Challenges and Insight Gained

After exploring the technologies of airborne agricultural sensing (Section II), the current trends (Section III), challenges (Section IV), and opportunity (Section V) related to it, the insights we gained are as follows:

- The airborne network can be utilized to enable more flexibility to the sensing network. However, the opportunity this technology provides also comes with limitations on each airborne technology (i.e., LAP, HAP, Satellite), such as limited energy capacity and high noise sensing data. Addressing this problem, the synergy between technology is a promising solution to gain the full potential of these technologies.
- The synergies between each airborne technology show us some new exciting collaboration patterns between global and local sensing perspectives. We may gain unexpected insight by combining global and local sensing perspectives compared than interpreting them separately. Furthermore, applying it to multimodalities data processing or virtual optimization will potentially provide a more accurate optimization objective.
- Advancements in airborne sensing technologies offer significant opportunities to enhance agricultural productivity while tackling climate change challenges. These technologies provide crucial data for informed decision-making, offer real-time monitoring when integrated with platforms like drones or IoT devices, and support cli- mate change mitigation strategies. However, their fullpotential can only be realized when effectively integrated into physical machinery for proper field intervention. Adopting and developing these technologies presents a promising path towards a more sustainable and resilient agricultural future amidst climate change.
- Airborne technologies may become a reasonable initial adoption as a key enabler of Agriculture 4.0 due to their scalability, which can be easily implemented across large agricultural areas (Fig. 9). However, current technological adoption may need some level of technical expertise. Therefore, examining a more efficient way of adopting this technology from the farmer's perspective becomes essential.

Conducting this study, we also face some challenges, some of are as follows:

- Reviewing an emerging technology and its application in a specific domain, such as agriculture, requires a balanced perspective between a technical understanding of the technology and the problem faced in the domain. Therefore, some parts in section IV discuss some problems in the agricultural domain perspective.
- To accurately recommend further improvements by leveraging the current state of airborne technological capabilities and limitations in sections II, III, and IV and synthesize an idea in section V, a dedicated and systematic brainstorming session may be necessary.

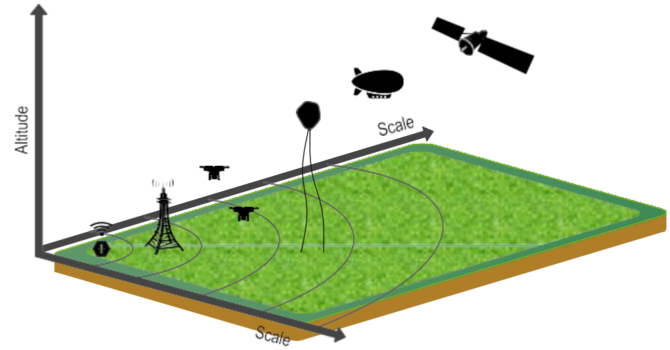

Fig. 9: Scalable satellite-airborne technologies initiate Agriculture 4.0 adoption.

VII. Future Research Direction

Airborne sensing network collaboration, robust data processing, and reliable integration between various technologies provide several opportunities to enhance agricultural productivity. However, the development of a robust sensing architecture presents a multitude of challenges. One such challenge is developing a resilient methodology for multi-modalities data processing. Data processing techniques like machine learning can still encounter performance bottlenecks when applied to multi-modalities optimization problems. Addressing this challenge could lead to a more comprehensive understanding of the agricultural environment and conditions through the combined input of multiple sensing technologies.

A related direction for future research is the exploration of efficient and effective collaborations between sensing technology and robotic intervention in the field. The increased urgency to maintain productivity in the face of a dwin- dling farming workforce, compounded by extreme weather conditions, underscores the potential value of this research. However, technological advancement alone is not sufficient. There is a critical need to improve the cost efficiency of adopting these technologies to ensure they are accessible and practical solutions to real-world problems.

Following this line of thought, we propose several key areas of focus for future research:

1) Data Fusion and Integration: Investigating techniques for seamless data integration and fusion from satellite and airborne platforms with ground-based sensors and IoT devices. The fusion approach can create comprehensive datasets for precise decision-making and enable more profound insights into agricultural systems.

2) Enhanced Data Processing and Analytics: Advancing data processing techniques, including artificial intelligence, machine learning, and data fusion algorithms, to efficiently analyze vast amounts of remote sensing data and derive actionable information for precision agriculture and climate monitoring.

3) Climate-Resilient Adaptation Strategies: Developing and implementing climate-resilient agricultural practices based on the insights obtained from satellite and airborne data, including targeted approaches for water management, pest control, and crop selection optimized to withstand climate variations.

4) Multi-Scale Monitoring: Exploring the integration of satellite and airborne technologies to provide multi-scale monitoring, combining regional and global perspectives with detailed local observations to understand agriculture's response to climate change comprehensively.

5) Climate Change Impact Assessment: Continuously assessing the impact of climate change on agriculture usinglong-term remote sensing data to monitor trends, shifts incropping patterns, and ecological changes, aiding in climate change vulnerability assessments.

In navigating the future of agricultural sensing technologies, we identified that the trajectory is moving towards a holistic, integrated approach. At the core of this evolution is the fusion and integration of data across various platforms, including satellite, airborne, and ground-based sensors. This integra-tion is pivotal for developing comprehensive datasets that enable precise, informed agricultural decision-making. Further, enhancing data processing and analytics through advancedAI and machine learning techniques is essential, especially when handling multi-modalities from broad sensing tech- nologies. These advancements will be crucial for developing climate-resilient agricultural strategies grounded in data-driveninsights. Additionally, combining wide-ranging perspectives from regional to local scales, multi-scale monitoring will offer a more nuanced understanding of agriculture's response to climate change. Finally, continuous assessment of climate change impacts through long-term remote sensing will be key to adapting agricultural practices and ensuring food security in a changing world. Together, these directions aim to forge a future where agricultural systems are highly efficient, resilient, and adaptable to climatic variations.

VIII. Conclusion

Adopting key technologies such as airborne sensing technology in Agriculture 4.0 presents an economically viable and flexible means of harnessing its benefits and improving climate resilience. The present review has explored airborne sensing technology, unpacking its enabling technologies, trends, challenges, and opportunities from both agricultural and technological perspectives. The integrated approach of merging airborne sensing technologies with IoT devices and data analytics platforms has been stressed, emphasizing the need for comprehensive and continuous monitoring at various scales. The integration approach lead to a deeper understanding of climate change impacts on crop growth, soil conditions, and water availability, thereby enabling the design of climate-resilient strategies, improved resource management, and the promotion of sustainable agricultural practices. We also underscored the potential of airborne sensing technologies to facilitate mitigation strategies for climate change by monitoring greenhouse gas emissions, land use changes, and vegetation dynamics. By adopting the proposed strategies and technologies, farmers potentially achieve significant cost savings, increase increased crop yields, and contribute to the broader trend of sustainable, data-driven, and climate-resilient farming practices. With the scalability and quick deployment capability, airborne sensing technologies offer a promising pathway to lower the barrier to entry of Agriculture 4.0 adoption and improve climate resilience. Furthermore, the potential impact of adopting airborne sensing technologies on global food security is immense, as more efficient and sustainable agriculture practices are crucial for meeting the growing demand for food in a rapidly changing and climate-impacted world.

Acknowledgments

This work has emanated from research conducted with the financial support of the Science Foundation Ireland under Grant number SFI/12/RC/2289 P2

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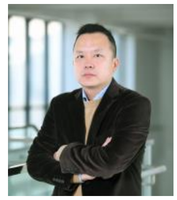

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