Remote Sensing for Agriculture in the Era of Industry 5.0—A Survey

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***Abstract*—Agriculture can be regarded as the backbone of human civilization. As technology evolved, the synergy between agriculture and remote sensing has brought about a paradigm shift, thereby entirely revolutionizing the traditional agricultural practices. Nevertheless, the adoption of remote sensing technologies in agriculture faces various challenges in terms of limited spatial and temporal coverage, high cloud cover, low data quality, etc. Industry 5.0 (I5.0) marks a new era in the industrial revolution, where humans and machines collaborate closely, leveraging their distinct capabilities, thereby enhancing the decision-making capabilities, sustainability, and resilience. This article provides a comprehensive survey of remote sensing technologies and related aspects in dealing with the various agricultural practices in the I5.0 era. We also elaborately discuss the various applications pertaining to I5.0-enabled remote sensing for agriculture. Finally, we discuss several challenges and issues related to the integration of I5.0 technologies in agricultural remote sensing. This comprehensive survey on remote sensing for agriculture in the I5.0 era offers valuable insights into the current state, challenges, and potential advancements in the integration of remote sensing technologies and I5.0 principles in agriculture, thus paving the way for future research, development, and implementation strategies in this domain.**

Manuscript received 31 December 2023; revised 10 February 2024; accepted 23 February 2024. Date of publication 27 February 2024; date of current version 11 March 2024. This work was supported in part by the National Research Foundation of Korea (NRF) grant funded by the Korea government, Ministry of Science and ICT (MSIT), under Grant 2022R1A4A5034130 and Grant 2021R1A2C1008840, and in part by MSIT, South Korea, under the Information Technology Research Center (ITRC) support program IITP-2023-RS-2022-00156353 supervised by the Institute for Information and Communications Technology Planning and Evaluation (IITP). *(Corresponding authors: Yaodong Zhu; Jeongyeup Paek.)*

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Digital Object Identifier 10.1109/JSTARS.2024.3370508

***Index Terms*—Agriculture, automation, Industry 5.0 (I5.0), Internet of Things (IoT), precision agriculture, remote sensing, supply chain management (SCM).**

I. Introduction

FROM the earliest agrarian societies to the present day, agriculture plays a crucial role in sustaining human life. It basically includes the activities such as cultivating the soil, farming, and raising livestock for use by humans [1]. Agriculture is not just about the food production. It also has a significant impact on economic growth, rural development, maintaining biodiversity, shaping the cultural heritage, and in providing various ecosystem services such as water filtration, pollination, and habitat for wildlife. The way in which agricultural practices are carried out has evolved over time by incorporating various scientific advancements. Remote sensing technologies play a major role in today's agriculture, thereby enhancing the sustainability and productivity to a large extent. There are different types of remote sensing technologies that can be adopted in agriculture. This includes thermal imaging, multispectral imaging, radar, light detection and ranging (LiDAR), aerial imagery, satellite imagery, unmanned aerial vehicles (UAVs), etc. [2], [3].

Drones and satellites equipped with sensors significantly help in enhancing the efficiency and decision-making strategies in agriculture, thereby addressing the various challenges through data-driven insights. Different types of remote sensing sensors can be employed for specific functions in the agriculture arena [4], [5]. Synthetic aperture radar (SAR) sensors are typically used for monitoring the crop growth, moisture content in the soil, and also for efficient classification of crops. Similarly, multispectral and hyperspectral sensors and fluorescence spectroscopy and imaging sensors also can be employed for understanding the various attributes such as leaf area index, nitrogen content, etc. Visible RGB (VIS) sensors can be used for estimating the different geometric attributes. Yet another sensor is the near-infrared (NIR) that helps in analyzing the moisture content in soil, plant counting, and even for erosion analysis. Remote sensing technology along with other technologies such as Internet of Things (IoT), robotic systems, weather forecasting technology, and global positioning systems (GPSs) play a major role in precision agriculture as well [6], [7].

Remote sensing thus aids agriculture in a variety of aspects. One of the major applications is in monitoring the crops [8].

It can be regarded as the systematic process of observing, assessing, and collecting data about crops through the entire span of their growth cycle. The images collected using satellites can be used for the identification of stress factors, such as water scarcity, nutrient deficiencies, or pest infestations. Other applications include soil condition assessment, crop yield prediction, resource optimization, early detection of pests and diseases, environmental monitoring, global coverage, and time and labor savings.

Although remote sensing can help in various aspects of agriculture from crop monitoring to soil analysis and precision agriculture, the implementation is not without its challenges. Limited access to high-quality data is one of the significant challenges associated with the remote sensing technologies. As the data are complex, it needs expertise to understand and analyze the data. Hong et al. [9] proposed a subpixel-level HS superresolution framework that has the capacity to utilize the intrinsic properties of high spatial resolution multispectral images effectively for the fusion task. Cloud cover is another major challenge that may result in gathering inaccurate data due to the clouds [10]. Zhang et al. [11] proposed a CNN model for removing cloud cover interference. Another challenge is with regard to the lack of technical expertise in adopting these technologies in agriculture. Weather conditions, spatial and temporal resolutions of remote sensing data, data security, and privacy issues are all the other vital challenges concerning the adoption of remote sensing for agriculture. Extensive research has been carried out in the field of remote sensing to deal with the aforementioned challenges [12], [13], [14]. Industry 5.0 (I5.0) technologies also can significantly help in overcoming these challenges associated with the implementation of remote sensing for agriculture.

I5.0 is considered as a new production model where robots and machines work alongside humans. The key principles of I5.0 are sustainability, human centricity, and resilience [15]. The farmers and agronomists along with the artificial intelligence (AI) systems can efficiently analyze the remote sensing data that can help in generating more accurate interpretations, thus enabling informed decision making. Personalization is yet another advantage of adopting I5.0 in the agriculture domain. This will enable the farmers to get personalized recommendations based on specific farm requirements. Real-time decisions can be provided to the end users, thereby improving the responsiveness of the various agricultural practices. The agriculture sector can achieve greater sustainability, efficiency, and collaboration in farming practices by adopting the principles of I5.0 and fully embracing remote sensing technologies.

Several surveys have been carried out by researchers on the various Industry 4.0 (I4.0) and I5.0 technologies, different application domains, technical challenges associated with the implementation, and remote sensing technologies. Abbasi et al. [16] presented the state-of-the-art digitization technologies that could be adopted for agriculture. However, the survey was focused on I4.0 and not on I5.0. Yet another survey was conducted by Liu et al. [17], including a comprehensive analysis of the status, enabling technologies, and the potential challenges in adopting Agriculture 4.0. However, Raj et al. [18] conducted a study on the role of IoT in adopting the Agriculture 4.0 practices. Javaid et al. [19] also focused on the Agriculture 4.0 practices. Remote sensing technologies were also studied in the aforementioned surveys. However, only very few studies have been carried out so far on the role of remote sensing for agriculture in the I5.0 era.

Martos et al. [4] presented a study on remote sensing for Agriculture 5.0 in order to ensure the sustainability in agriculture. However, the focus was majorly on the important features of the remote sensing technologies such as the various data-retrieving approaches, electromagnetic (EM) wave bands, and the importance of AI for Agriculture 5.0. The key platforms such as the various sensors used and also on satellites and remotely piloted aircrafts (RPAs) were also discussed in this study. Nevertheless, the specific target application fields in agriculture were not dealt in depth. The technical challenges with respect to the I5.0 integration were also not presented. Guruswamy et al. [20] put forward a study on ensuring food security in the context of Agriculture 5.0. The role of remote sensing was not covered in this study. Another study was by Singh et al. [21] that focused primarily on the precision irrigation aspects using I5.0 technologies. A detailed review of the enabling technologies and potential applications in I5.0 was presented by Maddikunta et al. [22]. However, the study did not focus on the specific aspects of agriculture. The role of I5.0 technologies in crop data management was studied by Saiz-Rubio et al. [23]. Although few research works have been carried out on the use of I5.0 for general applications, none of them comprehensively addresses all of the technologies and various target application fields in the agriculture domain.

Table I presents a summary of the related surveys on remote sensing for agriculture in the I5.0 era. Even though several surveys on I5.0 and remote sensing for agriculture have been carried out separately, there is no survey focusing specifically on remote sensing for agriculture in the era of I5.0. This is the first work attempting to review remote sensing for agriculture in the era of I5.0, to the best of our knowledge. The significant contributions of this study are highlighted as follows.

1) The article presents a detailed discussion on the various remote sensing technologies used in agriculture, and the associated I5.0 enabling technologies such as data-driven data analytics, robotics, automation, etc.
2) The underlying inspiration for adopting the remote sensing technologies in various aspects of agriculture in I5.0 is also discussed in this survey.
3) A detailed analysis of the various applications of I5.0-enabled remote sensing for agriculture is provided along with the existing challenges and how I5.0 adoption may help in overcoming those challenges.
4) The article presents the several challenges that may arise during the integration of remote sensing for agriculture and I5.0 applications. The open research opportunities that may drive the researchers and industry toward future research in this interesting domain are also highlighted in this work.

The rest of the article is organized as follows: Section II highlights the importance of remote sensing for agriculture. The

TABLE I
SUMMARY OF LITERATURE SURVEY

Ref. No	I5.0 Technologies	Target Application Field in Agriculture			Role of Remote Sensing	Enabling Technologies	Technical Challenges	Research Directions	Remarks
		Manufacturing	Production	Supply chain					
[16]	N.A	Low	Low	Low	Medium	High	High	High	Focused mainly on the various digital technologies for agriculture 4.0
[17]	N.A	High	High	High	Low	High	High	High	Focused on I4.0 for agriculture
[18]	N.A	Medium	Medium	Medium	High	High	Medium	High	Focused mainly on Internet of Things for agriculture 4.0
[19]	N.A	High	High	High	Medium	High	Low	Low	Focused on I4.0 for agriculture
[4]	High	Low	Low	Low	High	High	Low	High	Focused mainly on remote sensing technology along with the key platforms such as satellites and remotely piloted aircrafts (RPAs), and the sensors used.
[20]	High	Low	Low	High	Low	High	Low	Low	Focused mainly on food supply chain using I5.0 technologies
[21]	High	High	Low	Low	Low	High	Low	Low	Focused mainly on precision Irrigation for field monitoring using I5.0 technologies
[22]	High	Low	Low	Low	Low	High	High	High	Focused on I5.0 as a whole
[23]	High	Low	Medium	High	Medium	High	Low	Low	Focused mainly on crop data management using I5.0 technologies
Proposed Work	High	High	High	High	High	High	High	High	

Low : Low Coverage   Medium : Medium Coverage   High : High Coverage   N.A : Not Applicable .

section also focuses on the various enabling technologies of I5.0 that can be adopted specifically for agriculture, and the motivation behind the integration of remote sensing for agriculture and I5.0 is also highlighted. Section III deals with the various applications of I5.0-enabled remote sensing for agriculture. Each section in Section III provides a brief introduction about the application, the existing challenges, and how the adoption of I5.0 technologies may help in terms of sustainability, human centricity, and resilience. In Section IV, we highlight the challenges and open issues of this I5.0 integration in agriculture and throw light into the possible research directions. Finally, Section VI concludes this article.

II. Background

A. Remote Sensing for Agriculture

Conventional agricultural methods depended on human and some domesticated animal strength to carry out tasks including field preparation, irrigation, harvesting, and monitoring. Simple tools such as hoes, sickles, and scythes were the mainstay of early agriculture [24]. However, using this tool required immense human effort and significant time, but with low yields. This sustained agriculture method is defined by local knowledge, labor-intensive tasks, less access to markets, low yields, and significant risks. Remote sensing technologies have transformed the field of agriculture, offering diverse and modern tools for monitoring and managing agricultural behaviors [25]. Thermal imaging allows for the detection of heat in crops and soil, providing valuable insights into water levels and disease occurrence [26]. Multispectral imaging captures data at different wavelengths, enabling detailed analysis of plant health, soil properties, and moisture levels [27]. Radar technology detects cloud patterns and provides data regardless of the weather, making it useful for analyzing soil moisture and estimating crop biomass [28]. LiDAR is useful in analyzing landscape and crop structures assessment based on its high-resolution 3-D mapping features [29]. Aerial imagery, captured by aircraft or drones, presents high-resolution images for complete field examination. Satellite imagery provides a broader view, essential for large-scale monitoring of crop health, land use, and environmental changes [30], [31]. UAVs collect agriculture data in a personalized and accurate manner, making them useful for specific investigations and continuous monitoring [32]. All of these technologies work together to achieve modern precision agriculture, assisting farmers and scientists in making accurate choices about effective and environmentally friendly farming practices. Table II presents the different types of remote sensing technologies used in agriculture. Fig. 1 depicts Remote Sensing in Agriculture.

Following the 18th century, during the steam power revolution, machinery began to take the place of human labor. This made it easier for small-scale farmers to meet the expanding food needs of the populace by producing food on a huge scale. The quick transition from steam to internal combustion engines improved agricultural productivity much further [60]. Later in the 20th century, the incorporation of machinery and electronics opened the door for specialized agricultural methods including GPS-assisted automated tractors, planting robots, automated irrigation systems, and analytical and monitoring instruments [61]. Apart from the boost in food production, the shift from traditional to commercial agriculture practices has noteworthy effects on society, including decreased labor requirements for human labor, large-scale farming, and meeting market demands [62]. Preprogrammed instructions are used by the automated machinery to carry out tasks mindlessly and without context awareness. Resources are used more efficiently and take less time when manual monitoring and analytical reasoning

TABLE II
DIFFERENT TYPES OF REMOTE SENSING TECHNOLOGIES USED IN AGRICULTURE

Sensing Technologies in Agriculture	Technology	Description	Applications in Agriculture	Advantages	Limitations
Thermal Imaging	Handheld Thermal Cameras [33]	Portable cameras that capture thermal images.	Used for checking crop temperature, identifying stressed areas.	Portable, user-friendly, immediate results.	Limited area coverage, manual operation.
	Fixed Wing Aircraft Thermal Imaging [34]	Thermal sensors mounted on aircraft.	Large area surveillance for crop health efficiency.	Can cover vast areas quickly, more flexible than satellites.	Expensive, weather-dependent, less frequent than UAVs.
	Vehicle-Mounted Thermal Cameras [35]	Cameras mounted on ground vehicles.	Used for row-by-row analysis of crops in large fields.	More detailed than aerial methods for specific areas.	Time-consuming, limited by field size.
	Thermal Imaging for Precision Agriculture [36]	Advanced systems integrating thermal images with GPS and GIS data.	Mapping field variability, optimizing inputs like ,such as water and fertilizers.	Highly accurate, aids in precision agriculture practices.	Requires sophisticated software and data analysis skills.
Multispectral imaging	Satellite Multispectral Imaging [37]	Satellites equipped with multispectral sensors.	Large-scale monitoring of vegetation, soil health, and water bodies.	Wide area coverage, consistent time-series data.	Lower resolution than close-range methods, affected by cloud cover, less frequent data.
	Fixed Wing Aircraft Multispectral Imaging [38]	Multispectral sensors on manned aircraft.	Large-area mapping for crop health and environmental monitoring.	Quick coverage of large areas, more frequent than satellite imaging.	Expensive, weather-dependent, less flexible than UAVs.
	Multispectral Imaging for Precision Agriculture [39]	Integrated systems combining multispectral data with GPS and GIS.	Field variability mapping, optimizing resource use, yield forecasting.	Enables targeted interventions, improves resource efficiency.	Complex data analysis, requires advanced software and expertise.
Radar remote sensing	SAR [40]	A form of radar that creates high-resolution images from radar data.	Soil moisture monitoring, crop type classification, biomass estimation.	High spatial resolution, all-weather capability, day and night operation.	Complex data interpretation, requires advanced processing techniques.
	Real Aperture Radar [41]	Traditional radar system with a fixed antenna size.	Surface roughness analysis, water body mapping, basic crop monitoring.	Simpler technology, lower cost compared to SAR.	Lower resolution than SAR, limited by antenna size and platform altitude.
	Airborne Radar Systems [42]	Radar systems mounted on aircraft.	Detailed local analysis of crop height, biomass, and soil properties.	Flexible deployment, higher resolution than satellite-based systems.	More expensive, limited by weather and flight regulations.
	Ground-Based Radar Systems [43]	Radar systems installed on ground vehicles or stationary platforms.	High-resolution soil moisture assessment, crop density analysis.	Extremely detailed local information, direct monitoring capability.	Limited area coverage, requires on-site installation.
LiDAR	Terrestrial LiDAR [44]	Ground-based LiDAR systems, either static or mobile.	Detailed survey of field topography, plant structure analysis, row and plant spacing measurement.	High accuracy, direct data collection, suitable for small-scale applications.	Limited area coverage, time-consuming for large fields, line-of-sight requirement.
	Mobile LiDAR [45]	LiDAR systems mounted on moving vehicles or handheld devices.	High-resolution mapping of crop rows, orchard management, soil surface modeling.	Flexible and suitable for detailed local analysis, rapid data collection.	Less accurate than static systems, affected by vehicle movement and speed.
	Satellite LiDAR [46]	LiDAR sensors on satellites.	Large-scale biomass assessment, forest canopy studies, regional topography.	Wide area coverage, provides consistent data over large geographical areas.	Lower resolution than airborne or terrestrial LiDAR, less frequent data acquisition.
	Bathymetric LiDAR [47]	LiDAR technology specifically for measuring water depth and underwater topography.	Mapping of water bodies in agricultural landscapes, irrigation planning, flood risk assessment.	Accurate water body mapping, essential for water management in agriculture.	Limited to clear water bodies, less effective in turbid or shallow waters.
Satellite imagery	Multispectral Imaging [48]	Satellites capturing images in multiple wavelengths of light.	Crop health monitoring, soil fertility analysis, water stress identification.	Broad coverage, suitable for various crop types, identifies vegetation health.	Limited resolution compared to airborne sensors, affected by cloud cover.
	Hyperspectral Imaging [48]	Captures a wide spectrum of light beyond visible and infrared.	Detailed crop analysis, disease detection, nutrient level assessment.	Provides detailed spectral information, useful for precise agriculture applications.	Large data volumes, complex data processing, more expensive.
	Optical Imaging [49]	Traditional camera systems capturing visible light.	General crop monitoring, land cover mapping, growth stage assessment.	Simple interpretation, high-resolution images, visually intuitive.	Limited by weather conditions, only operates in daylight.
Aerial imagery	Helicopter Imagery [50]	Cameras mounted on helicopters for aerial photography.	Precision agriculture, detailed topography mapping, emergency response in pest/disease outbreaks.	Highly effective, stable platform for high-quality images, quick deployment.	Expensive operation, limited flight time, noise can be disruptive.
	Balloon and Kite Imagery [51]	Low-cost alternatives using cameras attached to balloons or kites.	Small-scale farm analysis, educational and research purposes, localized monitoring.	Affordable, simple to operate, minimal environmental impact.	Limited by wind conditions, low altitude, less control over positioning.
	Hot Air Balloon Imagery [51]	Cameras mounted on hot air balloons for aerial photography.	Large plot analysis, landscape-level studies, vegetation mapping.	Quiet operation, offers steady and slow-moving platform.	Weather and wind sensitive, limited control, relatively low altitude.
	Paraglider and Paramotor Imagery [52]	Lightweight, motorized paragliders equipped with cameras.	Flexible aerial surveying, hard-to-reach areas, high-resolution site-specific data.	Highly effective, low-altitude flying, direct control by operator.	Requires skilled operation, weather-dependent, limited payload capacity.
UAV	Multispectral UAV Cameras [53]	UAVs equipped with cameras that capture images in multiple light wavelengths.	Crop health monitoring, nutrient management, pest and disease detection.	Detailed vegetation analysis, suitable for precision agriculture, relatively low-cost.	Limited flight time, requires clear weather conditions, data processing expertise needed.
	Thermal Imaging UAVs [54]	Drones equipped with thermal cameras.	Irrigation scheduling, water stress detection, monitoring plant health.	Effective for detecting changes in plant temperature, useful for water management.	Affected by environmental factors, lower spatial resolution compared to optical cameras.
	LiDAR UAVs [55]	UAVs equipped with LiDAR sensors.	3D mapping of farm topography, canopy structure analysis, crop height measurement.	High-resolution topographic data, precise elevation information, effective in various geography lands.	More expensive, heavier payloads, complex data processing.
	Hyperspectral UAV Cameras [56]	Cameras that capture a wide spectrum of light, mounted on UAVs.	Detailed crop analysis, disease detection, soil property assessment.	Provides extensive spectral information, allows for detailed crop health monitoring.	Generates large volumes of data, complex data analysis, higher cost.
	RGB UAV Cameras [57]	Standard color cameras mounted on UAVs.	Basic crop monitoring, growth stage assessment, visual inspection.	Simple to operate, provides intuitive visual data, lower cost.	Limited in detecting subtle crops, less informative than multispectral or hyperspectral imagery.
	Fixed-Wing UAVs [58]	UAVs with fixed-wing design for longer flight times.	Large area mapping, crop monitoring over extensive fields, erosion detection.	Longer flight duration, covers larger areas, more efficient for large-scale operations.	Requires larger area for takeoff and landing, less efficient than rotary UAVs.
	Rotary-Wing UAVs [59]	UAVs with rotary wings for precise maneuvering.	High-resolution imaging of specific areas, targeted pest and disease management.	Highly maneuverable, can hover over specific areas, suitable for detailed inspections.	Shorter flight times compared to fixed-wing UAVs, smaller coverage area.

are combined with automation. However, large-scale agriculture is hard for humans to intervene in, which makes labor even more necessary due to time constraints [63]. The science and technology of gathering data about the Earth's terrestrial, atmospheric, and aquatic ecosystems from their emitted and reflected EM radiation is called remote sensing. It is a type of geospatial technology used to monitor the physical characteristics of an object without coming into direct contact with it. It mainly uses a variety of sensors installed on airplanes, drones, satellites, or vehicles to gather information on the Earth's surface and atmosphere [64]. Precision farming uses automated methods, which are assisted by human interaction, and remote sensing as a supplement. In agricultural remote sensing, data regarding pest outbreaks, soil moisture, vegetation monitoring, irrigation levels, and the overall health of agricultural elements can be continuously sensed and provided to the automated machinery.

B. Technologies Driven by I5.0 for Agriculture

1) Data-Driven Data Analytics: Advanced data analysis algorithms enable us to create a virtual model that allows us to simulate the environment and test different strategies before implementing them in a real-world scenario. For example, farmers can experiment in the simulated environment with different fertilizers, and pest control mechanisms to optimize the resources and reduce risks [65].

Recognizing pests and plants for agricultural protection can be achieved with minimal data, making it a cost-effective solution for farmers. Li and Yang [66] proposed a method called "metalearning few-shot classification" that learns from just a few examples. This method "mimics" real-world scenarios by training on diverse data representing potential pests and plants. Using publicly available resources, we built a balanced database for effective training. Similar to this, sophisticated data analysis tools facilitate the examination of large datasets to provide new perspectives on difficult-to-understand systems. Object and feature classification, trend and pattern recognition, all depend heavily on data-driven data analysis. To benefit nontechnical users including end users and policymakers, data analysis tools assist in processing data and producing output in an easily understandable format.

Metalearning aims to create models that can quickly adapt to new tasks using minimal data. It focuses on using previous knowledge to increase learning efficiency and generalization. More interestingly, Tseng et al. [67] proposed TIML: task-informed metalearning for agriculture. The primary goal of this study is to investigate how model-agnostic metalearning (MAML) weights can be modulated, even when all tasks were selected from a single dataset. The experiments were carried out using the CropHarvest dataset. The experimental results show that the proposed TIML approach outperforms other algorithms on the CropHarvest dataset, with the highest F1 and AUC ROC scores. TIML consistently outperforms other algorithms across all tasks, including a difficult Brazil task with only 26 positive datapoints.

Another interesting research in [68] shows how metalearning, specifically MAML, can effectively learn from different datasets while preserving the unique information that exists in each dataset. The proposed model is a metalearning approach that uses a long short-term memory model to determine whether pixels contain a specific crop or not. The primary goal of this study is to determine the efficiency of the proposed model in different locations and creating crop maps for particular geographic areas with limited positive task labels. The experiments were conducted on three datasets: 1) Togo, 2) Kenya, and 3) Brazil. The experimental findings show that the proposed metalearning approach outperforms both random and pretrained baselines in different locations.

Few-shot learning in remote sensing agriculture allows the efficient training of models with limited labeled data, vital for sparse and dynamic agricultural landscapes. By making use of transfer learning and metalearning techniques, it simplifies rapid adaptation to new environments and crop types. A work proposed in [69] on few-short learning introduces a method called DLA-MatchNet for remote sensing image scene classification. It targets learning discriminative representations and an appropriate metric for remote sensing images, which is frequently overlooked by existing works. The attention technique was employed to discover discriminative regions and an adaptive matcher was used to address issues of large intraclass variances and interclass similarity. Experimental results on three public remote sensing image datasets show the effectiveness of the model in few-shot scene classification.

Another work done by Kim and Chi in [70] created a network called SAFFNet, a self-attention-based feature fusion network, for remote sensing few-shot scene classification. The authors underline the challenges in classifying new unseen scene categories in remote sensing applications and the significance of few-shot learning methods. SAFFNet integrates a self-attention feature selection module to select and reweight informative representations from images with different receptive fields for feature fusion. The proposed model is evaluated and assessed on publicly available datasets and compared to other few-shot approaches and multiscale feature fusion networks. Experimental results demonstrate that SAFFNet significantly enhances few-shot classification accuracy.

2) Robotics and Automation: Automation can reduce human labor's demanding nature and exposure to hazardous conditions, improving worker well-being and changing the appeal of agriculture as a job. Because robots can operate continually, they are more productive and efficient [71]. Cameras mounted on drones or land vehicles capture images of the crop and livestock that are used for further analysis and decision making. Vision-guided robots may carry out tasks autonomously, such as milking cows, which enhances sanitation.

Based on real-time data and forecasts, AI will suggest exact methods for harvesting, fertilizing, controlling pests, and irrigation. Farmers can make well-informed decisions about irrigation, fertilizing, and pest control because of the data that drones and sensors on robots collect about soil conditions, crop health, and water levels. Using real-time data, robots may apply water, fertilizer, and insecticides at different rates to maximize resource efficiency and reduce environmental effects [72].

3) Blockchain and Distributed Ledger Technology: On a blockchain, tampering with data is practically impossible, reducing the possibility of fake goods or incorrectly labeled substances and thwarting fraud involving agricultural products [73]. All parties involved, from farmers to merchants, have access to reliable information regarding food production, processing, and transportation, which promotes collaboration and prevents fraud. Transparency in supply chains helps avoid fraud in the case of access to subsidy products by guaranteeing that the required and eligible individuals receive subsidies. As a result, the actual farmers are encouraged and receive financial support. The transparency characteristic of blockchain would lessen fraud risk scenarios, which would benefit the actual user. Another similar case is manipulating data when claiming insurance for damaged objects, such as land, crops, and animals, after natural calamities [74].

4) Human–Machine Collaboration and Upskilling: The IoT devices concentrate on isolated items such as individual plants or animals or in compact spaces. This results in the need for frequent manual monitoring and adjustments to robot operations, which raises labor costs and increases the possibility of human error. Remote sensing and IoT are both essential to the collection and processing of data, although they function on different scales and have different goals. Robust remote sensing data streams are necessary to fine-tune and enhance robot algorithms for increased efficacy [75]. Large-scale coverage is offered by remote sensing, which offers a comprehensive picture of changing environmental conditions, weather patterns, and landscapes.

C. Motivation for the Integration of Remote Sensing for Agriculture and I5.0

Embracing I5.0 and remote sensing in agriculture gives a powerful chance to transform the sector, solving issues and realizing enormous potential. Remote sensing will continue to be essential in many agricultural domains by utilizing I5.0 technologies, improving human well-being, resource management, and decision making. With technological improvements, the future of remote sensing for agriculture seems bright.

Here are some key motivations for embracing this transformative approach.

1) Motivation 1. Advanced Sensing and Data Acquisition: Real-time data about crop growth, animal movements, environmental changes, weather, air and water quality, moisture content, pollutants, and other vulnerabilities are collected by satellites, drones, and integrated sensors in machinery and vehicles [76]. Biosensors can provide information on the stress level, deficits, and other possible insights of a plant or animal. Targeted insecticides can be applied by robotic devices that use vision sensors. Advanced remote sensing methods such as hyperspectral imaging are becoming more and more popular. Hyperspectral imaging systems can be used to find, classify, or measure the concentration of different components that are undetectable to standard cameras or the human eye during an inspection [77], [78].

2) Motivation 2. Resilience and Sustainability: Cobots are made for intimate human connection, in contrast to standard robots that are usually kept in cages or isolated work areas [79]. Examples of duties that Cobots can automate are feeding, keeping an eye on the health of the animals, and gathering information on behavior and productivity. Likewise, Cobots can help with accurate seed planting, delicately selecting and plucking fruits and vegetables, and classifying produce according to size and quality. With the use of COBOTS, farmers may create resilient agricultural practices and adjust to shifting weather patterns using remote sensing data-driven decision making. Utilizing real-time data enables farmers to adapt using various techniques, reducing the likelihood of disruptions and preserving food production [80].

3) Motivation 3. Empowerment and Human-Centric Approach: The focus of I5.0 is on the human-in-loop across all dimensions [81]. Therefore, combining remote sensing with I5.0 enables farmers to have access to remote sensing data, insights, and decision-making tools. Automation improves the quality of farmer's life and I5.0 technologies, such as Digital Twin, enable farmers to test out different scenarios leading to better decision making about the various agricultural components, which enhances risk management and reduces agricultural losses. A broader spectrum of users can utilize cobots because they are easy to operate even by those without extensive technological knowledge.

III. Applications of I5.0-Enabled Remote Sensing for Agriculture

The applications of I5.0-enabled remote sensing in agriculture span a wide spectrum, catalyzing transformative changes across key sectors. In the domain of supply chain monitoring, this I5.0 integration simplifies real-time tracking and optimization, improving the efficiency of agricultural logistics. Crop monitoring benefits from the adoption of advanced sensors, IoT devices, and AI algorithms, allowing farmers to obtain precise data on crop growth, health, and yield predictions, thereby optimizing cultivation approaches. Water management perceives developments through the intelligent use of remote sensing, helping farmers monitor and regulate water usage more effectively. Plant disease identification is reformed with the aid of sophisticated sensors and AI, allowing early detection and targeted treatment interventions. Precision agriculture makes use of I5.0 technologies to enhance decision-making processes, enhance resource utilization, and reduce environmental impact. Environment monitoring includes the tracking of environmental factors, contributing to sustainable farming practices. Soil health monitoring provides farmers with more details concerning soil conditions, fostering better-informed decisions for optimal crop growth. Agriculture education profits from immersive technology integration by offering students and practitioners hands-on experiences through virtual simulations. Finally, livestock management is augmented through remote sensing applications, allowing real-time tracking, health monitoring, and efficient herd management. These various applications collectively highlight the multifaceted impact of I5.0-enabled remote sensing, steering to a new era of precision, sustainability, and productivity in agriculture (see Fig. 4). This section discusses in detail about

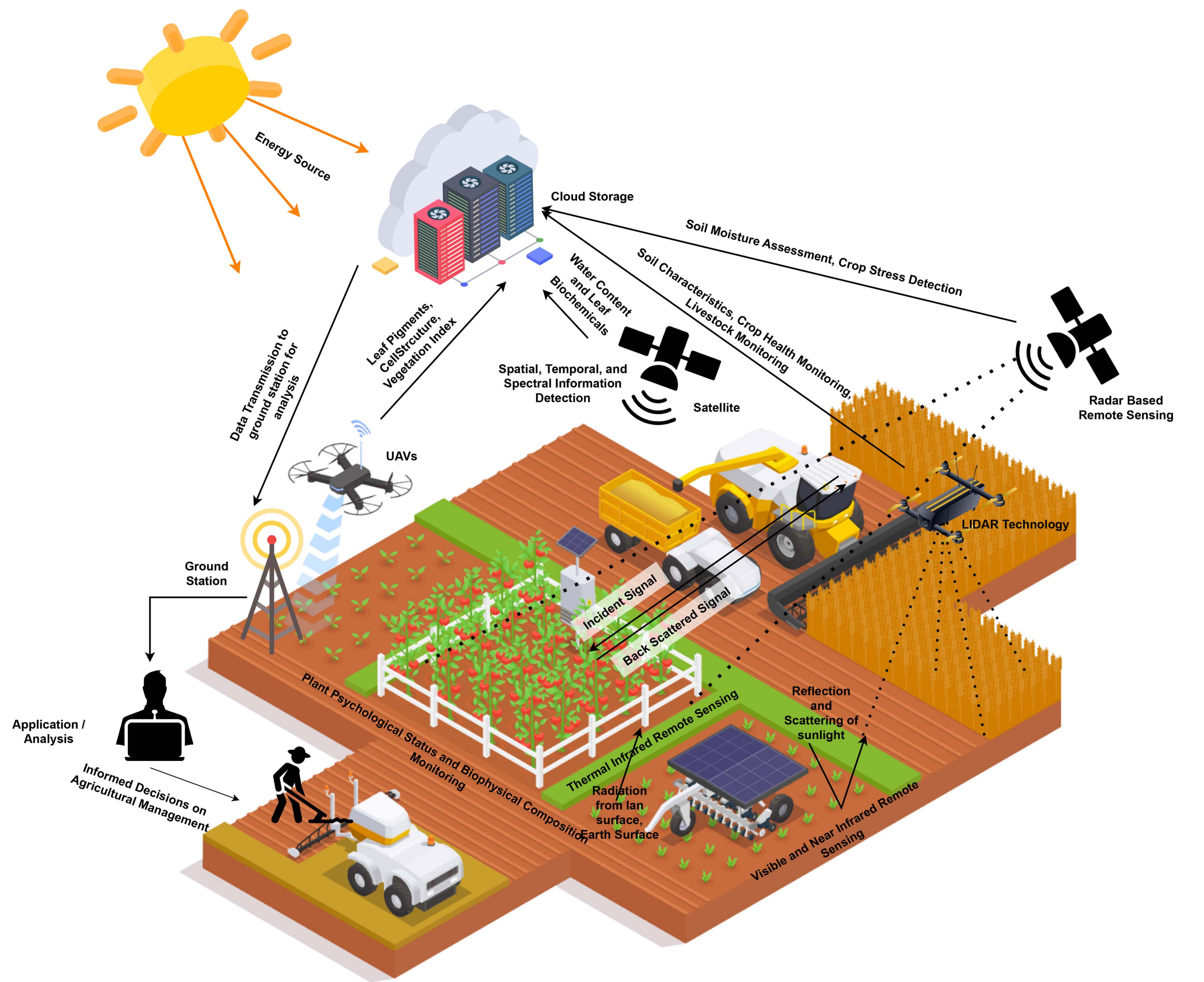

Fig. 1. Remote sensing in agriculture.

the impact of I5.0 on remote sensing for various applications in agriculture.

A. Supply Chain Monitoring

Agriculture and supply chain management (SCM) are intrinsically interconnected in a mutually beneficial relationship that supports the production and distribution of food and other agricultural products. Agriculture functions as the primary source of raw materials within the supply chain [82]. It provides crops, livestock, and various resources that lie as the backbone of numerous industries. SCM ensures that these agricultural products are efficiently, safely, and cost-effectively transported from farms to consumers. SCMs role in agriculture prolongs from improving production schedules and postharvest handling to managing distribution networks and obeying to quality and safety standards [83]. In essence, SCM acts as the channel between the fields and forks, allowing the agricultural sector to meet market needs, reduce waste, and improve overall sustainability [84]. This complicated relationship highlights the critical importance of effective SCM in confirming the success, reliability, and resilience of the agricultural industry. Here are some key phases of SCM in agriculture [17]: 1) planning and forecasting, 2) sourcing and procurement, 3) production and cultivation, 4) harvesting and delivery, and 5) monitoring and traceability.

Agricultural SCM faces a multitude of challenges [85] due to the sector's distinct characteristics and demands. Seasonal variability is very common in agriculture and is driven by aspects such as weather conditions and crop cycles, giving significant hurdles to SCM efficiency. Additionally, the easy decomposable nature of many agricultural products, such as fruits and dairy, requires rigorous efforts to maintain product quality and freshness throughout the supply chain. Stakeholder coordination, including farmers, processors, distributors, and retailers, can be complex, especially in rural areas. Unpredictable changes in crop yields and market demand contribute to SCM uncertainty [86]. This also affects production planning and inventory management. Sustainability issues and environmental regulations demand balancing profitability with environmentally

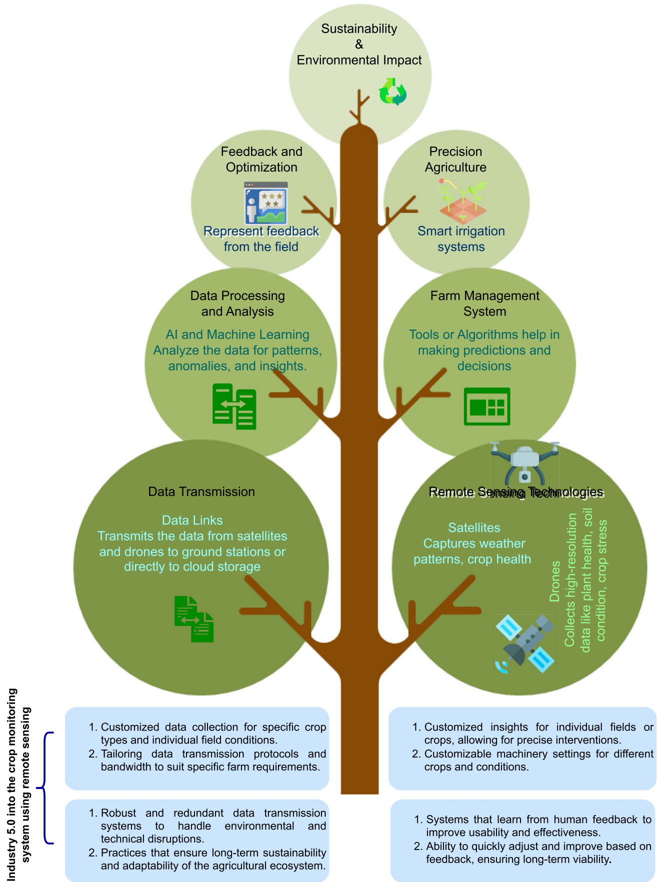

Fig. 2. Crop monitoring in agriculture using remote sensing and I5.0.

responsible practices. Compliance with stringent regulations related to food safety and quality is another ongoing challenge. Quality control and traceability systems are vital but complex and expensive to implement.

I5.0 integration has the potential to revolutionize the field of supply chain processes, focusing on collaboration between humans and machines [87]. The integration of I5.0, which typically involves cutting-edge technologies such as IoT, blockchain, DT, and AI, can use remote sensing data and has the potential to bring about a significant transformation in supply chain processes. The importance lies in the development of collaboration between human workers and machines to enhance efficiency, productivity, and sustainability in the supply chain, aligning with the core principles of I5.0 [88]. Here is how I5.0 can use remote sensing data to enhance agricultural SCM.

Remote sensing has become an innovative tool in agriculture, providing farmers with a wealth of information about their crops and fields from a bird's-eye view. Satellite imagery, drones, and IoT sensors can provide a wealth of data, such as crop health, soil moisture, nutrient content, etc., allowing farmers to monitor fields in real time.

AI has the potential to transform precision agriculture into agricultural SCM [89]. Advanced AI algorithms can integrate data from various sources to create a comprehensive picture of crop health. It can analyze remote sensing data to detect even minor changes in vegetation health, recognizing potential diseases before they are visible [90]. By examining historical and current data, it can predict issues such as nutrient deficiencies, allowing farmers to proactively address challenges and optimize crop yield. This collaboration involves not only the capabilities of AI but also the expertise of humans, who contribute valuable insights into local conditions and practices, aligning with the human-centric approach of I5.0. In [91], Shadrin et al. proposed a work that involves the development of a scalable smart agriculture system using wireless sensor nodes and machine learning (ML) for plant growth assessment.

Remote sensing data, when combined with advanced analytics using ML, can be used to predict crop yields [92]. These data are valuable for optimizing supply chain planning, including production scheduling and distribution. Another research effort [93] used ML to predict almond yield based on climate and orchard variables. The authors found that winter conditions and summer vapor pressure deficits significantly affect yield. The authors' findings aim to inform cultivators about adapting management practices for plant protection in changing climates. The data derived from remote sensing not only help in predicting yields but also bring them into line with a sustainable approach, a core principle of I5.0. Table III depicts the roles of I5.0 in the agricultural supply chain monitoring. Building trust and transparency in any process is another crucial ideology in I5.0. Blockchain integration in agricultural SCM has the potential to offer transparency and traceability features in the SCM process [94]. Blockchain, with its immutable and transparent ledger, improves trust by providing a tamper-proof record of the entire supply chain journey. Remote sensing data, combined with blockchain, can improve transparency and traceability aspect in the supply chain [95]. Consumers can monitor the journey of agricultural products from farm to table, confirming quality and authenticity. The proposed work in [96] focuses on evaluating the maturity level of blockchain technology within the agri-food supply chain. The work found that blockchain technology offers significant benefits, such as allowing stakeholders and consumers to access reliable information, tracking goods effectively, and dropping the need for third-party monitoring. The study also identified smart contracts, IoT, transaction records, and traceability tags as the significant elements that can improve the agricultural supply chain when integrated with blockchain technology.

B. Crop Monitoring

Crop monitoring in agriculture comprises the systematic observation and assessment of crops throughout their growth cycle to improve productivity and make informed decisions. This process uses a combination of technology, data analysis, and traditional agricultural methods to monitor various aspects of crop health [97]. This includes growth patterns, disease occurrence, and resource utilization. Recent technologies such as remote sensing, satellite imagery, drones, and sensors provide real-time or near-real-time data, allowing farmers to detect problems with the crops early [8]. This real-time information about the field also helps to make timely interventions and enhance overall crop management. By making use of these tools, farmers can make

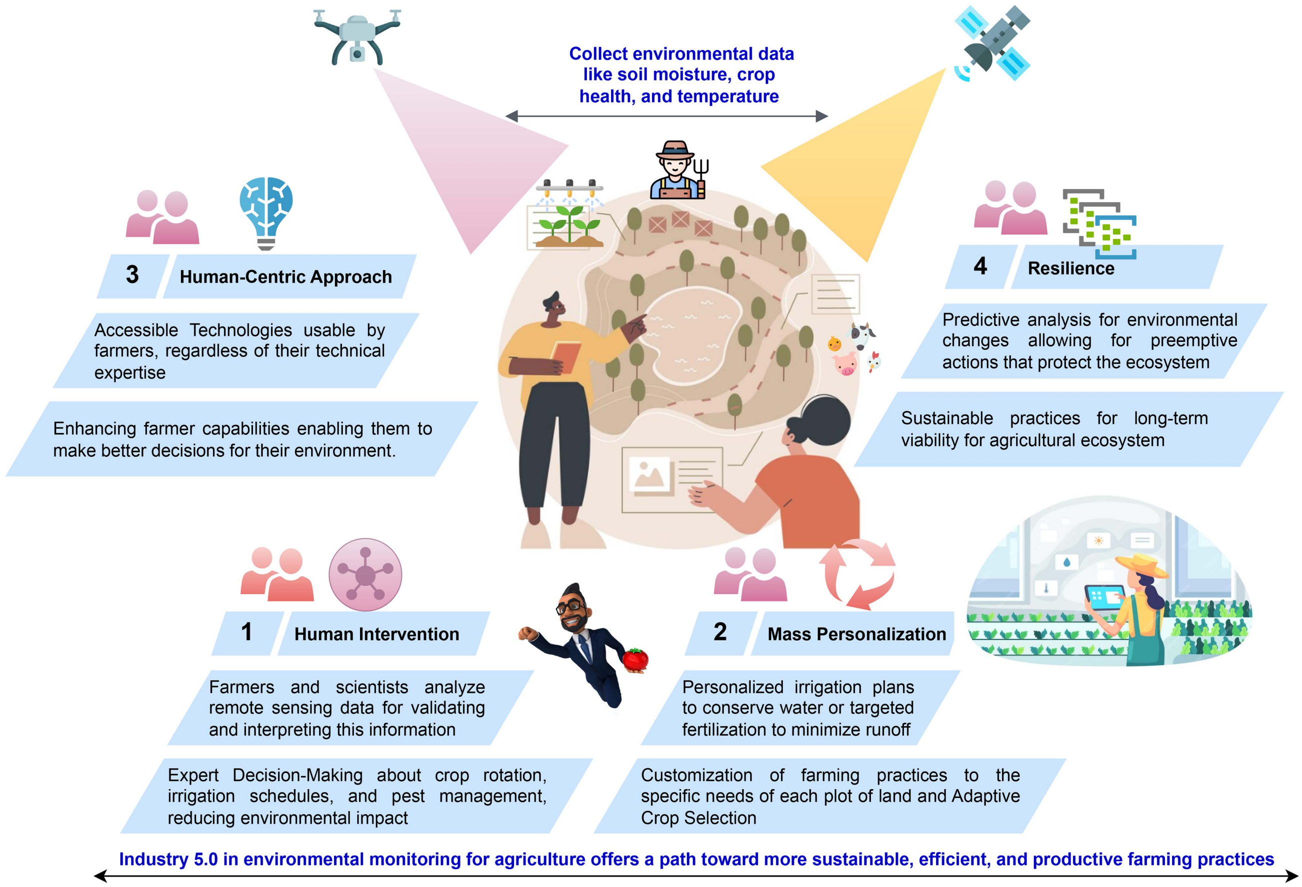

Fig. 3. Environmental monitoring in agriculture using remote sensing and I5.0 principles for sustainable farming.

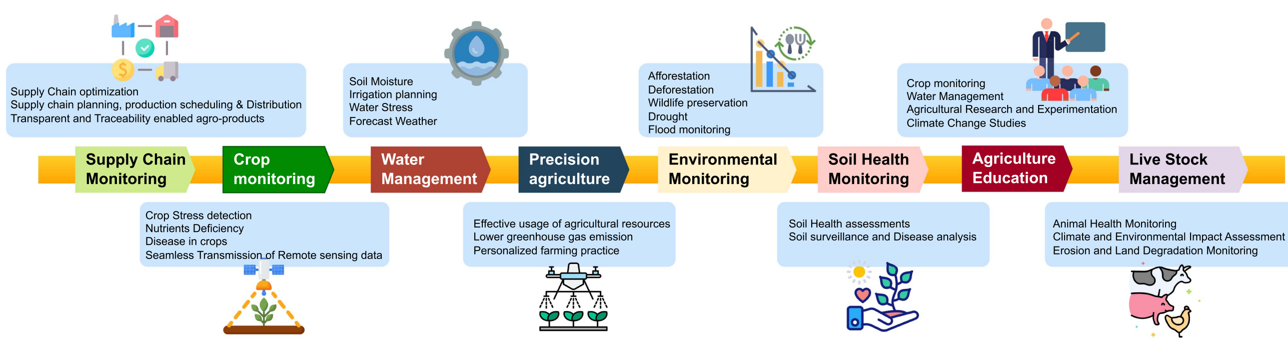

Fig. 4. Applications of I5.0-enabled remote sensing for agriculture.

data-driven decisions to improve crop yield, resource efficiency, and sustainability in modern agriculture [98].

A large volume of data generated by various monitoring methods, such as satellites, drones, and sensors, specifically managing and analyzing the data generated efficiently carries a significant challenge for farmers, and demands advanced data processing and interpretation skills [99]. Deploying monitoring technologies, such as satellite imagery and precision agriculture tools, can be expensive [100]. The lack of the necessary infrastructure and reliable connectivity for seamless data transmission is a big challenge. Limited internet availability in rural areas can restrict or delay real-time monitoring and timely response to crop-related issues [101]. The collection and sharing of agricultural data raise concerns about privacy and security [102]. Farmers may not be willing to share sensitive information about their crops, soil, and practices, and be scared of unauthorized access or misuse of data. Changeable weather patterns, including extreme events such as storms, droughts, or floods, can have a serious impact on the effectiveness of crop monitoring. These changes can introduce uncertainties and affect the accuracy of predictive models.

Satellite sensors, including multispectral and hyperspectral, can capture data on crop health by measuring the reflectance of different wavelengths [103]. This remotely sensed data uses

TABLE III
ROLES OF I5.0 IN THE AGRICULTURAL SUPPLY CHAIN MONITORING

Supply Chain Stage	Human Intervention	Mass Personalization	Human-Centric Approach	Resilience
Farm Production	Farmers use remote sensing data to customize their methods of agriculture.	Customizing crop production based on micro-climate and fertility of the soil.	Educating farmers with the latest technologies and keeping them at the center of the process.	Diverse farming techniques for dealing with climate change and market changes.
Data Analysis and Decision Making	Analysts and farmers work together to analyze data for better crop management.	Personalized solutions for each farming operation based on data analysis.	Technology improves farmers performance by delivering useful insights.	Rapid response to changes in the environment and consumer demands.
Harvesting	Supervisors control automated harvesting systems to ensure both productivity and quality.	Customized harvesting methods optimized by artificial intelligence for various crops.	Automation improves employees by reducing their workload.	Automated systems respond to various harvesting conditions to ensure uninterrupted production.
Postharvest processing	Supervising automated processing for quality control and handling unknown exceptions.	Customizable machinery for processing different crop categories.	Increases worker productivity and reduces strain from repetitive tasks.	Quickly adapt to changes in item type and quantities.
Logistics and Distribution	Logistics managers optimize routes and handle circumstances using IoT and GPS data.	Customized delivery routes and schedules based on real-time demand.	Makes logistics more efficient, reducing environmental footprint and cost.	Robust supply chain against disruptions with real-time tracking and adaptive logistics.
Retail and Market Delivery	Retailers and distributors connect with consumers and understand their needs using technology.	Blockchain for traceability, allowing consumer choice based on preferences and values.	Ensures transparency and trust in the supply chain, enhancing consumer confidence.	Transparent supply chain better equipped to handle market shifts and trends.
Feedback Loop	Farmers use consumer and retailer feedback for informed decision-making.	Adjustments in production to meet specific market demands based on personalized feedback.	Focus on end-user needs and preferences, informing the entire supply chain.	Dynamic, responsive, and resilient agricultural system through continuous feedback.

vegetation indices such as the normalized difference vegetation index, which provides insights into plant health, biomass, and growth [104]. ML can be employed to analyze these data to identify areas of stress, nutrient deficiencies, or diseases in crops [105], [106], [107]. Interesting work in [108] involves using the DLR Earth Sensing Imaging Spectrometer (DESIS) to predict crop health. It comprises the classification of major crops in the USA using DESIS data and ML algorithms, focusing on corn, soybeans, and winter wheat. This collaborative approach makes use of human expertise, the core principle of I5.0, with machine capabilities to make timely interventions to monitor crop health.

In addressing the challenge of securely sharing sensitive information related to farming and soil conditions, blockchain technology has evolved as a robust solution [109]. Blockchain provides a secure and decentralized method to store and manage remote sensing data. Farmers can have greater control over who accesses their information and can grant or restrict permission through smart contracts [110]. This aligns with I5.0's importance on secure and controlled access to data and technology integration [111], confirming that sensitive information remains protected while still promoting collaboration and data sharing among authorized stakeholders. The work in [112] summarizes a model for better traceability and tamper-proofing of remote sensing data changes. It aims to integrate blockchain technology with remote sensing data sharing to confirm decentralized, secure, and reliable data storage. The model comprises a multichain structure, utilizing a public chain to store open data and a summary of federated chain blocks. Fig. 2 depicts crop monitoring in agriculture using remote sensing and I5.0.

The absence of high bandwidth connectivity poses a significant problem in linking with remote sensing devices, presenting a critical challenge in agriculture in the era of I5.0. Addressing this problem is essential for simplifying the smooth transmission of data from various remote sensing devices, including satellites, drones, and ground-based sensors. Overcoming this challenge allows real-time monitoring capabilities, permitting farmers to promptly receive updates on vital factors such as crop conditions, pest infestations, and environmental dynamics. Sharma et al. [113] proposed a work that involves the design of a compact antipodal structured antenna for future 5G broadband applications and upcoming remote sensing satellite links. The stable performance of the proposed antenna has made it suitable for deployment in application devices. This integrated approach encourages I5.0's emphasis on seamless connectivity, developing a more interconnected and responsive agricultural system. Ranjha et al. [114] demonstrate a technique for achieving ultrahigh reliability for short-packet communication in UAV-assisted agricultural systems for effective remote sensing of crops. The approach uses iterative methods based on perturbation theory to improve the system parameters, with simulation results verifying the proposed algorithm's effectiveness. The work aims to allow ultrareliable low-latency communication in highly challenging remote sensing scenarios. Sharifi et al. [115] focus on field border extraction from satellite images using a convolutional neural network that performs multiple semantic segmentation tasks. The model offers high efficiency in detecting field borders accurately at both pixel and object levels. The proposed approach involves the use of ResUNet-a architecture with multiple convolutions to classify features on several scales. The work highlights the importance of contextual knowledge at different levels to improve the accuracy of border extraction. Shafi et al. [116] make use of IoT, and ML focused on crop health mapping using low-altitude remote sensing. Data collected from drone imagery and IoT sensors was gathered and used for crop health classification. ML algorithms were applied to classify crop health using the fused data. Different classification models were used and evaluated, with a model M4 outperforming the rest.

C. Water Management

Water management plays a vital role in achieving sustainable agriculture [117], serving as a serious component of the growth and productivity of crops. Efficient water management in agriculture comprises the careful planning, distribution, and utilization of water resources to optimize crop yields while minimizing waste. As the global population continues to increase, the demand for food production increases, highlighting the importance of responsible water management practices [118]. Farmers and policymakers face the challenge of balancing the demands of agriculture with the necessity of preserving water resources for future generations. Effective water management not only confirms the economic viability of farming but also contributes to environmental sustainability by avoiding the impact of water shortages and promoting resilience in the face of changing climate conditions [119]. By integrating I5.0, which prioritizes human collaboration and emphasizes the interconnection of various stakeholders, stakeholders can work together to develop and implement innovative solutions for sustainable water use in agriculture. Thus, understanding and implementing sound water management practices are mandatory for achieving food security and promoting sustainable agriculture.

Water management in agriculture faces significant challenges, including water shortage made worse by factors such as climate change and population growth, leading to increased competition for limited water resources [120]. In addition, water quality issues arise due to pollution from agricultural excess and industrial discharges, raising threats to crop health, soil fertility, and ecosystems [121]. Inefficient water use, often arising from outdated irrigation practices, contributes to wastage and irregular distribution, further increasing competition for water. Climate change introduces increased variations in weather patterns, with increased frequency and severity of droughts and floods disrupting traditional water management approaches [122]. Handling these challenges requires a comprehensive method integrating advanced irrigation technologies, sustainable practices, and adaptive strategies to confirm the careful and sustainable use of water resources in agriculture, promoting the sustainability and resilience of I5.0.

Microwave and infrared sensors on satellites can calculate soil moisture content, helping farmers and water managers make informed decisions about irrigation planning [123]. Deployed ground sensors and satellite data can be analyzed using ML to provide real-time information on soil moisture levels across large agricultural areas. Das et al. [124] proposed a work that involves the development and evaluation of an ML approach for the joint modeling of carbon and water fluxes in drylands of the western US using satellite data. The work explicitly contains soil moisture in the model and introduces new vegetation indices for capturing dryland seasonality demonstrating a form of human–machine collaboration through the integration of advanced technologies in agriculture.

Remote sensing data can be used to assess the efficiency of irrigation systems by monitoring changes in soil moisture before and after irrigation. Sensors capable of capturing thermal infrared radiation are deployed on various platforms, including satellites, drones, and hand-held devices [125]. Thermal infrared imagery can help identify areas with water stress, aligning with I5.0's resilience ability in agriculture by allowing farmers to adapt irrigation practices accordingly. The work proposed in [126] involves the use of UAVs for precision agriculture applications such as tracking crop health, estimating nutrient status, yield, and crop water demand. Thermal sensors deployed in the UAVs were used to monitor the surface temperature of the crops before and after irrigation to identify plant water stress in crops. It supports water management by allowing farmers to make timely and effective irrigation decisions.

Satellite or drone-based sensors can gather data on soil moisture levels, crop health, and weather conditions [127]. AI algorithms can analyze the remote sensing data to create predictive models for soil moisture dynamics [128]. These models allow automated irrigation scheduling by taking factors, such as current soil moisture, crop water requirements, and upcoming weather conditions. Another interesting work in [129] uses an AI algorithm to estimate crop behavior in terms of crop coefficient (Kc) and growth stages at the plot level. The work demonstrates improved Kc and growth stage estimation compared to experimental Kc protocols, which can help design dynamic irrigation management and allocate water between plots in real time.

D. Plant Disease Identification

Plant disease identification in agriculture helps in the identification of crop-damaging diseases. Plant disease identification in agriculture is an important part of the farming process because correctly and quickly identifying diseases can lead to proper treatment, controlling disease spread, and minimizing crop damage. Plant disease identification helps in crop yield improvement, food security, and the reduction of agricultural economic losses [130]. Identifying a crop's history based on previous disease occurrences and applying advanced disease prevention practices can reduce future disease risk. Plant diseases can be avoided by following appropriate agricultural practices such as crop rotation, proper irrigation, and sanitation. Plant disease can be identified by spots on leaves or fruits, undersized growth, color changes, and other abnormal changes in the plant's exterior parts [131]. To provide effective treatment, it is important to identify the germs that cause the disease, such as fungi, bacteria, and viruses. As medical technology advances, samples of the affected plant are sent to a lab for microscopic examination for a more accurate diagnosis. Recent technological advances, such as imaging technology, remote sensing, and AI, are being useful in identifying plant diseases [132].

Remote sensing technology aids in the monitoring of plant diseases and pests by identifying plant health from a distance, which is primarily useful for large-scale monitoring. This technology provides efficient surveillance for large agricultural areas by minimizing time-consuming tasks [133]. Agriculture experts can easily identify the specific location and severity of disease and pest infestations in crops by analyzing data from remote sensors, which is important for understanding the severity of the problem and responding appropriately. Remote sensing technology uses live agriculture data, such as optical data, to detect changes in plant health that are not visible to the naked eye. It also utilizes fluorescence and thermal parameters, which are important in detection and monitoring processes [134]. High-resolution images provide detailed information about the landscape, which enables an analysis of environmental factors that can influence disease and pest spread. As a result, this technology is critical not only for identifying current plant health issues, but also for continuously protecting crops from future threats [135].

Although remote sensing technology can help in identifying plant diseases and pests, it has some limits. One of the most significant challenges is the limited identification of certain diseases and pests, particularly those lacking unique, distinct features that can be detected by remote sensors [136]. This is particularly challenging for soil-borne and root diseases, which frequently cause systemic changes in the metabolism of a crop. These changes can be minor and complex, making remote sensing technologies difficult to identify. Another significant challenge is ensuring the accuracy and reliability of remote sensing data. Accurate and reliable data are required for efficient crop preservation, but gaps in sensor performance and outside factors can affect data accuracy. Furthermore, existing sensor characteristics may limit their ability to detect specific diseases and pests, emphasizing the importance of future sensor development [137]. I5.0 plays an important role in plant disease identification. The human-centric approach, which is considered as an important principle of I5.0, helps in plant disease identification by leveraging human knowledge. Accurate disease identification cannot be accomplished solely through advanced technology. Skilled humans must be involved in dealing with complex or ambiguous scenarios, assessing the significance of symptoms, taking environmental factors into account, and determining the status of plant disease conditions [4]. I5.0 aids in adaptive learning by allowing farmers to interact with AI systems and provide feedback. Based on this feedback, the AI systems learn and improve, thereby helping in disease identification. The collaborative characteristic of I5.0, which combines human expertise and machine productivity, aids in providing efficient and environmentally friendly solutions for plant disease identification [4]. The use of I5.0 helps in the achievement of sustainable economic practices by reducing waste and excess production by recognizing and dealing with plant disease spread. Precision agriculture practices, when combined with remote sensing and AI, can indicate exactly where and how much treatment is needed, thereby reducing chemical usage and the impact on the environment. Predictive analysis aids in the prediction and preventive management of plant diseases, thus minimizing the need for large amounts of chemical medication and protecting the ecological balance [138]. Table IV explains the I5.0 principles for identifying plant diseases, emphasizing the importance of technology and human expertise, customized solutions, user-friendly designs, and sustainable practices.

TABLE IV
I5.0 PRINCIPLES FOR PLANT DISEASE IDENTIFICATION

I5.0	Plant Disease Identification
Human Intervention	1. Expert involvement in interpreting data and making decisions. 2. Feedback from farmers and agronomists to refine AI algorithms and improve disease identification accuracy.
Mass Personalization	1. Personalized diagnosis and treatment of plant diseases at the individual plant or field level. 2. Precision agriculture techniques for specific interventions based on the exact needs of each plant or area within a field.
Human-Centric Approach	1. Technologies designed to augment human capabilities, making systems intuitive and enhancing farmers understanding of plant diseases. 2. Collaborative solutions that combine human expertise and machine efficiency for effective disease management.
Resilience	1. AI systems adapt and learn over time with inputs from human interactions, improving disease identification under varying conditions. 2. Sustainable agricultural practices reduce chemical treatments, ensuring ecological balance and farming system resilience.

E. Precision Agriculture

Precision agriculture improves agricultural productivity and farming techniques by monitoring and controlling environmental variations using modern technology [139]. This method increases productivity by optimizing the use of resources such as water, pesticides, and fertilizers based on environmental conditions. It also reduces waste, reduces environmental impact, and lowers costs by making better use of resources [140]. Precision agriculture makes use of data from drones, satellites, and sensors to make decisions and monitor crop health. Precision agriculture aids in the detection of plant diseases and nutrient deficiencies at an early stage. Furthermore, precision agriculture provides a robust system for dealing with weather-related changes, ensuring environmentally friendly and productive agriculture. Precision agriculture aids in the monitoring of many parameters, including crop irrigation, best sowing stages, and harvesting. Precision agriculture also provides accurate crop status information that can be acquired via ground and air sources.

Remote sensing provides an important role in precision agriculture by providing important information for improved agricultural management. Remote sensing is useful for optimizing inputs for agriculture, increasing crop production, and reducing input waste [103]. Remote sensing applications in agriculture provide crop surveillance, irrigation management, precise nutrient deployment, disease and pest control, and crop yield estimation. The use of high-definition satellite imagery has increased its application in the agriculture field. Furthermore, the use of UAVs has improved the effectiveness of remote sensing [141]. Remote sensing technology ensures best agricultural practices by providing accurate information, resulting in more efficient and environmentally friendly farming methods, emphasizing its important role in precision agriculture [142]. The integration of wireless sensor networks (WSN) and UAVs improves crop monitoring, agricultural yields, production modeling, future predictions, and effective decision. The WSN-UAV-based IoT framework provides advantages such as real-time data collection and analysis, as well as 3-D modeling of sensor data. Crop monitoring using UAV images can achieve a variety of outcomes, including water level monitoring, pesticide levels, and identification of diseases. In [143], Abioye et al. proposed a predictive controller model for precision irrigation based on discrete Laguerre networks. The proposed model employs embedded devices in an IoT platform to monitor water consumption at the appropriate time, quantity, and location by monitoring the weather as well as controlling soil moisture levels and crop response. When compared to existing approaches, the proposed approach reduced water usage by 30% over 21 days.

Although remote sensing technology in precision agriculture offers advantages, it also has some limitations. Interpreting and analyzing the huge quantity of agricultural data generated by remote sensing devices necessitates human expertise [144]. Obtaining high-resolution and accurate information for specialized agricultural needs is one of the most challenging tasks in precision agriculture using remote sensing technologies. Purchase and maintenance of modern remote sensing technology, such as high-resolution satellites and UAVs, can be expensive, especially for small-scale farmers [145]. Environmental factors such as cloud darkness, which can blur satellite imagery, and changing weather conditions, which can affect data accuracy, might create a negative impact on remote sensing efficiency. Integrating remote sensing data into traditional farming systems is a major problem [146]. This integration necessitates not just technological data processing and analysis skills but also human knowledge and intervention. Farmers and agricultural professionals must be able to analyze data in the context of their own farming techniques and situations. This needs a combination of scientific expertise and practical agricultural knowledge, emphasizing the significance of training and assistance in the efficient use of remote sensing in agriculture. The challenges involved in integrating remote sensing into precision agriculture highlight the vital role of human involvement and experience. Farmers and agricultural workers need both scientific expertise and practical application skills to properly use remote sensing data [147]. This is where I5.0 can make a huge contribution. There is a chance to improve agricultural productivity and sustainability by integrating remote sensing technical improvements with the human-centric approach of I5.0. This integration can lead to more productive, efficient, and environmentally friendly agricultural practices [111].

I5.0 can significantly improve precision agriculture by addressing its limitations. The human-centric Approach improves precision agriculture by combining human expertise with cutting-edge technologies such as AI and remote sensing, ensuring that data analysis and decision making are guided by real-time agricultural expertise [148]. When human knowledge expertise is applied to remote sensing data in agricultural tasks, personalized and successful farming practices occur. Training farmers and agricultural professionals on how to use advanced technologies results in efficient farm management. This method ensures that precision agriculture is not completely reliant on technology but also makes use of human expertise and inputs [149]. In I5.0, sustainability plays an important role in improving precision agriculture by encouraging environmentally friendly and resource-effective practices [117]. Precision agriculture benefits from I5.0 by emphasizing the efficient use of resources such as water, fertilizers, and pesticides, reducing waste and environmental harm. Precision agriculture contributes to lower greenhouse gas emissions by reducing resource overuse and meeting sustainable development goals. I5.0, sustainable precision agriculture methods guarantee the long-term health and fertility of the soil, saving ecosystems for future generations [21]. This sustainable approach in precision agriculture using I5.0 focuses on protecting the environment and preserving resources, resulting in more environmentally friendly and productive farming. Mass personalization, an important concept in I5.0, significantly improves the efficiency, sustainability, and productivity of precision agriculture. Customizing agricultural practices and approaches to meet the specific needs of individual farms allows for more effective and resource-efficient operations. This personalized approach aligns with the goals of sustainable farming, guaranteeing that agricultural practices are both environmentally friendly and financially feasible. Table V presents precision agriculture utilizing remote sensing and I5.0 to create a sustainable, efficient, and resilient agricultural system.

TABLE V
PRECISION AGRICULTURE UTILIZES REMOTE SENSING AND I5.0 TO CREATE A SUSTAINABLE, EFFICIENT, AND RESILIENT AGRICULTURAL SYSTEM

Feature	Description
Remote Sensing Technologies	Satellites are equipped with high-quality cameras for environmental and crop health monitoring. UAVs provide complete, real-time information about crop health and environmental factors.
Data Analysis and AI	Cloud computing is used to store and process large amounts of data collected from remote sensing. AI and ML algorithms analyze data to optimize agricultural processes like resource allocation and disease management.
Human-Centric Approach	Farmers use technology to gain insights, which improves understanding and decision-making. Training and education programs are designed to provide farmers with the necessary skills to use modern technology efficiently.
Mass Personalization	Customize inputs like such as water, pesticides, and fertilizer based on observations. Customized Farm Management techniques are used for crop-specific irrigation, pest control, and nutrient management.
Sustainability and Environmental Protection	Resource efficiency technologies minimize water consumption and greenhouse gas emissions. Soil health and crop sustainability practices promote long-term sustainable farming and productivity.
Resilience	Scalable approaches for handling weather forecasts and changing conditions. Systems respond to continuous data collection and farmer feedback, improving accuracy and efficiency.
Integration and Training	Integrating technology with traditional farming systems, as well as providing farmers with the knowledge required to analyze and apply data insights to improve their farming practices.
IoT Framework	Real-time data collection using IoT devices enables continuous monitoring. IoT data is used for monitoring and predictive analytics, which helps with decision-making and future planning.

F. Environmental Monitoring

Environmental monitoring in agriculture is critical for increasing crop yields, ensuring resource sustainability, and reducing the effects of climate change and environmental damage caused by farming operations. Environmental monitoring helps in monitoring soil health conditions such as nutrient levels, pH levels, moisture, and temperature. Monitoring all of these parameters helps to understand the soil's capacity and assists in making decisions regarding fertilization, irrigation, and crop rotation [150]. Environmental monitoring methods are used to track climate conditions such as temperature, rainfall, humidity, and wind patterns. These data are essential for scheduling sowings, irrigation, and crop protection during bad weather. Environmental monitoring in agriculture helps in determining the quality and quantity of irrigation water. Monitoring water sources ensures that crops get enough water without wasting it and reduces excessive irrigation, which can help to prevent soil degradation [151]. Diseases and pests that harm crops are being monitored for their presence and spread, enabling early use of pesticides. Environmental monitoring aids in determining how air quality affects crop health. This helps in the identification of harmful pollutants that harm crops and reduce their quality.

Environmental monitoring in agriculture is enhanced by technologies, such as remote sensing, UAVs, and satellite imaging. Remote sensing technologies provide detailed information on land topography, soil structure, and the plant life that is currently growing in afforestation. Remote sensing and satellite imaging can be used to identify appropriate areas for planting, track the progress of newly planted areas, and assess forest health periodically. These sensing devices provide accurate mapping and analysis, which is essential for successful afforestation activities [152]. Remote sensing and satellite imagery enable real-time monitoring of deforestation. They detect changes in forest areas, identify illegal logging locations, and assist in ensuring that forest conservation policies are followed. UAVs aid in the provision of high-resolution images of specific areas, allowing for close monitoring and quick response to deforestation activities.

Remote sensing technologies play an essential role in wildlife conservation as they provide accurate environmental monitoring [153]. Satellite and aerial imagery provide information about changes in land usage and habitat fragmentation, which is important in understanding how agricultural practices affect wildlife. Conservation approaches can be developed to protect species in danger and preserve biodiversity by monitoring changes in the environment [154]. Satellite imaging and UAV technologies are useful for gathering information during monitoring droughts and floods. They monitor weather patterns, soil moisture levels, and water availability across large areas and provide important forecasting information. These data assist farmers in making irrigation, crop selection, and land management decisions, reducing the impact of extreme weather on crop yields [155].

Although the use of remote sensing has advantages in environmental monitoring, some challenges must be addressed. One of the challenges of using remote sensing in environmental monitoring is data privacy and security, as the large amount of data provided by remote sensing can raise ethical concerns about the use as well as confidentiality, particularly in areas resided by local people [156]. Obtaining an appropriate spatial and temporal resolution is an enormous challenge [153]. Although high spatial resolution can capture accurate images, it may not be practical for constant monitoring. Remote sensing generates massive amounts of data, which may be challenging to maintain, analyze, and evaluate. Remote sensing data analysis and interpretation require specialized human expertise [157]. Data degradation and noise effects are common challenges in imaging processes, resulting in inconsistent and low-quality images. These issues can be caused by a variety of factors, such as sensor limitations, environmental conditions, and computational techniques, requiring advanced noise reduction and data correction strategies to ensure accuracy and reliability in image analysis and interpretation. Effective mitigation involves utilizing sophisticated algorithms and preprocessing techniques to improve data integrity and usability [158].

Incorporating local expertise and viewpoints into remote sensing operations is critical. It is a significant challenge to make remote sensing data accessible and understandable to people without expertise, including local farmers [159]. Fig. 3 depicts environmental monitoring in agriculture using remote sensing and I5.0 principles for sustainable farming.

I5.0 helps in accomplishing the goal of sustainability in remote sensing and satellite imaging for environmental monitoring. Remote sensing and satellite imaging are employed for monitoring deforestation, monitoring ocean health, and observing atmospheric changes [160]. The incorporation of I5.0 helps in reducing environmental impact while improving data collection for environmentally friendly practices [22]. Data analysis experts must be involved to understand the complicated remote sensing data. These professionals are skilled at analyzing complex data and converting it into formats that the general public can understand [161]. Human–machine collaboration is emphasized in I5.0 during environmental monitoring. Sensors collect data, AI systems analyze satellite data, and then human decisions are made based on the analysis [162].

Human collaboration ensures that technology and human intervention achieve effective environmental monitoring goals. This approach not only improves monitoring efficiency, but guarantees that the knowledge obtained is relevant, accurate, and useful in real-world scenarios. Mass personalization and mass customization are important principles of I5.0 that aid in environmental monitoring in areas, such as afforestation, deforestation, wildlife preservation, and drought and flood monitoring. These principles enable personalized solutions to be used in specific environmental conditions and needs, enhancing the effectiveness of monitoring [163]. Mass customization in afforestation and deforestation allows for the creation of specialized drones and satellite imaging technologies that may be customized to different types of forests and geographical locations. These devices may be customized to monitor certain tree species and detect illegal deforestation.

Conservation measures become more efficient when these technologies are customized for specific ecosystems. For wildlife preservation, I5.0 helps in providing customized tracking systems and sensors that cater to the specific habits and needs of different wildlife species [20]. This personalization ensures that monitoring efforts are nonintrusive and highly effective, leading to better understanding and protection of animal populations. It also facilitates the development of personalized conservation strategies that address the unique challenges faced by each species. This approach not only increases the effectiveness of conservation measures but also ensures that these efforts are customized to the specific needs and challenges of various wildlife preservation efforts [164]. When dealing with natural disasters such as droughts and floods, mass personalization enhances the effectiveness of monitoring and response systems. Weather patterns, soil moisture levels, and water flows in specific regions can be closely monitored using customized sensor networks and forecasting techniques. This approach improves the accuracy of early warning systems [165]. AI integration in remote sensing [166] discusses the use of deep learning methods for semantic segmentation in land cover classification in urban environments. It targets both individual environments and multiregion/urban city scenarios. The work involves the development and application of multimodal AI models to process and understand diverse remote sensing data for land cover segmentation. The study highlights the importance of generalization ability across different urban environments and addresses the challenges and potential future solutions in the field chosen.

G. Soil Health Monitoring

Soil health monitoring in agriculture is a methodical and extensive process that entails regular assessment and analysis of diverse soil properties and indicators to assess the overall fertility, structure, and biological activity of the soil. This proactive strategy is essential for fostering sustainability and productivity in farming, offering crucial insights into nutrient levels, microbial diversity, and potential soil limitations [167]. The significance of soil health monitoring lies in its ability to guide precision agriculture, empowering farmers to optimize resource management, boost crop productivity, and mitigate environmental impacts [168]. The article also discusses the need for soil health monitoring, highlighting its pivotal role in optimizing crop productivity, minimizing environmental impacts, and fostering sustainable resource management. Additionally, this survey delves into the multifaceted benefits, including informed decision-making for farmers and land managers, improved nutrient management, and enhanced soil structure.

The challenges encountered in soil health monitoring for agriculture are several and intricate. According to Silva et al. [169], the limited accessibility and affordability of advanced monitoring technologies pose significant hurdles, a sentiment echoed by Usman et al. [170], who highlight the spatial and temporal variability of soil properties as additional obstacles to obtaining accurate and representative data. The complexity of soil ecosystems, emphasized by Reddy et al. [171], necessitates nuanced models to capture dynamic interactions while Bagnall et al. [172] point out that the lack of standardized protocols contributes to inconsistencies in data interpretation. Ethical concerns regarding data privacy and ownership, as discussed by multiple sources, further complicate the collection and sharing of soil health information. To establish an effective and sustainable soil health monitoring process, addressing challenges such as integrating stakeholder input, ensuring long-term commitment, and overcoming resource constraints is important.

Challenges arise from the limited spatial and spectral resolutions of remote sensing data, creating difficulties in capturing fine-scale variations in soil properties as highlighted by Debangshi et al. [173]. Moreover, atmospheric interference, including clouds and aerosols, can impede the reliable acquisition of data, thereby impacting the accuracy of soil health assessments according to Deshpande and Inamdar [174]. The complexity of calibrating and validating remote sensing models for soil health parameters persists due to the dynamic nature of soil properties and the requisite ground truth data, as observed by Pande and Moharir [103]. Additionally, the high initial costs associated with obtaining and maintaining remote sensing technology may serve as a deterrent to widespread adoption, particularly in resource-constrained agricultural settings as noted by Sadenova et al. [175]. Overcoming these challenges is crucial to unlocking the full potential of remote sensing for soil health monitoring and advancing sustainable agricultural practices.

I5.0 has the potential to revolutionize soil health monitoring in agriculture by harnessing remote sensing data and integrating cutting-edge technologies for data acquisition, processing, and analysis. The application of agricultural remote sensing, utilizing sensors such as SAR, NIR, LiDAR, and multispectral imaging, allows for nondestructive, large-scale observation of crops and soil conditions. Martos et al. [4] highlight that this approach provides high-resolution data, facilitating accurate assessments of soil health. To address challenges associated with model calibration and validation, as noted by Chmielewski et al. [176], these technologies significantly enhance the precision of soil health assessments. Moreover, the deployment of remote sensing technologies, particularly through UAVs and robotic process automation (RPAs), has demonstrated promise in soil analysis and disease surveillance, aligning with the principles of Agriculture 5.0 outlined by Reid and Castka [177]. This technological integration supports sustainable agricultural resource management. The synergy of remote sensing and data analytics not only boosts the efficiency of soil health monitoring but also contributes to the overall sustainability and productivity of agricultural practices. I5.0 emphasizes the development of cost-effective solutions and widespread accessibility of technologies, ensuring that even farmers in resource-constrained settings can adopt remote sensing tools for soil health monitoring. This inclusive approach fosters a more sustainable and productive agricultural landscape, aligning with the vision presented by Diaz-Gonzalez et al. [178].

H. Agriculture Education

Agricultural education encompasses structured and methodical guidance, instruction, and training provided to students, farmers, or individuals keen on delving into the realms of agriculture, spanning the science, business, and technology associated with both animal and plant production. This educational framework also extends to the management of the environment and natural resources. Its significance in contemporary society and for future generations is underscored for various reasons, such as increasing self-sustainability, stimulating interest in agriculture, promoting sustainable and responsible agricultural practices, enhancing food security, etc. [179], [180].

Agricultural education faces challenges associated with persistent stereotypes and misconceptions about the field, limiting its attractiveness and recognition. The stereotype that agriculture solely involves traditional farming practices can restrict the scope of agricultural education [181]. The lack of motivation to establish agricultural education programs is another challenge, as the misconception that agriculture is not a viable career path leads to a lack of interest in offering these programs [182]. Difficulty in aligning agricultural education courses with key graduation requirements can impede student enrollment. This challenge highlights the need for flexible curricula that meet both educational standards and the evolving needs of the agricultural sector [183]. Teachers must have the minimum enrollment needed to continue teaching their course content, which can be challenging in some cases [181]. Addressing these challenges is essential for the continued success and relevance of agricultural education programs and the overall well-being of the agricultural sector.

I5.0 enables the use of remote sensing data in agriculture, which provides extensive coverage and highly accurate information about land cover, land use changes, and soil erosion, allowing for precise monitoring and management of soil health attributes [165]. These data can be correlated to soil health attributes measured in the field, further enhancing its reliability and effectiveness in soil monitoring [4]. Remote sensing in agriculture has been used to guide the application of fertilizer, pesticides, and other farm inputs, with benefits such as improved crop yield and reduced environmental impacts [184]. The integration of I5.0 and remote sensing into agricultural education programs allows students to gain a deeper understanding of the interconnectedness of various agricultural practices and the impact of these practices on the environment, ultimately leading to more informed and effective future farmers and leaders in the agricultural sector [185]. By incorporating remote sensing data into agricultural education programs, students can gain a deeper understanding of the importance of agriculture and natural resource management [186]. The use of remote sensing technology in agricultural education has the potential to revolutionize the agricultural sector by promoting sustainable practices, enhancing food security, and developing a strong connection between urban and rural communities [165], [185].

I. Livestock Management

Livestock management in agriculture involves the care and handling of domesticated animals for the production of meat, milk, eggs, and other by-products. It encompasses various aspects such as basic husbandry, animal health and nutrition, pasture management, organic farming, economic sustainability, and sustainable food systems [187]. Livestock management is essential for sustainable agriculture and offers several benefits, including providing income, food, manure, fuel, and transport, contributing to the global value of agricultural output, supporting the livelihoods of smallholders and agribusiness, and promoting sustainable agriculture practices [188]. Proper livestock management practices can ensure that feed nutrients are not wasted, feed efficiency is optimized, and animal welfare is maintained. Livestock management is crucial for the production of high-quality food, the economic sustainability of farming communities, and the overall development of sustainable agriculture practices [189].

Livestock management in agriculture faces several challenges that need to be addressed to ensure the sustainability and profitability of livestock farming. Proper animal feeding and management practices are essential for optimizing feed and nutrient use, preventing waste, and avoiding overfeeding [190]. Nutrient management on livestock farms is crucial to ensure that inputs such as feed, animals, and bedding are balanced with outputs such as meat, milk, and manure. When inputs exceed plant and animal requirements for nutrients, losses can occur, leading to excess nutrients stored in the soil, which may result in environmental issues such as nutrient leaching and soil surface runoff [191]. In addition, livestock management requires skills, such as basic husbandry, nutrition, communication, preparation, adaptation, and evaluation [192], [193]. Clear communication and adaptation are essential for managing livestock, as producers need to adapt to fluctuating markets, variable seasonal factors, and declining terms of trade [194]. Furthermore, environmental sustainability is a significant challenge in livestock management, as the sector must balance the need for agricultural output with the environmental impact of livestock farming, including greenhouse gas emissions, land degradation, and water consumption [195]. Addressing these challenges requires a collaborative effort from farmers, researchers, industry stakeholders, and policymakers to develop innovative solutions and best practices for sustainable and profitable livestock management in agriculture.

The adoption of I5.0 technologies, such as remote sensing data, can significantly enhance livestock management in agriculture [196], [197]. Remote sensing technology provides valuable information on animal welfare, grazing lands, and environmental sustainability, which can assist in monitoring herd movement, vegetation conditions, water availability, and weather [198], [199]. It can also be used to develop quantitative risk management strategies. The incorporation of sensor technology, encompassing on-animal sensors, environmental monitoring tools, and remote sensing, has the capacity to transition livestock operations from a conventional, reactive, knowledge-driven model to a proactive, data-centric decision-making approach [200], [201], [202]. The substantial potential lies in employing remote and on-animal sensing to enhance both the production and welfare of grazing livestock while also significantly improving landscape management.

IV. Challenges and Future Directions

Despite the advancements brought out by the I5.0 industrial revolution, still challenges persist in the realm of agricultural remote sensing. This section investigates the challenges that persist, exploring the complexities and hurdles faced even after the integration of I5.0 technologies in agricultural remote sensing. Fig. 5 depicts the challenges and future directions in integrating remote sensing and I5.0 technologies in agriculture.

A. Security and Privacy Concerns

1) Threats Related to Data Security: Sensitive data obtained from the field have the potential threat of unauthorized access from hackers or market competitors. While transmission of remote sensing data, there is a possibility of interception by malicious intruders, leading to data breaches. For instance, data transmission between sensors, networks, and platforms may not have sufficient encryption, making it vulnerable to interception and unauthorized access [203].

2) Threats Related to Network Security: The communication channels used for transmitting remote sensing data may be vulnerable to cyber-attacks. This may lead to data manipulation or disruption of services. Lack or weakness in the fundamental infrastructure supporting remote sensing systems can be exploited to compromise data integrity and availability [204].

Fig. 5. Challenges and future directions in integrating remote sensing and I5.0 technologies in agriculture.

3) Threats Related to Device Security: Data collected from farms through deployed sensors, networks, and cloud platforms in the era of I5.0 are highly vulnerable to hacking, malware, and ransomware attacks, potentially losing control over data integrity, confidentiality, and availability [205]. Security vulnerabilities in these devices may lead to unauthorized access to sensitive information. For instance, sensors deployed in the field may encounter the risk of physical accessibility, making them vulnerable to tampering, damage, or theft, eventually leading to compromised data accuracy and possible disruptions to the system [206].

4) Threats Related to Privacy: Farmers face potential issues with the ownership and control of their data. This includes risks associated with location tracking and the collection of personal information [207]. Informed consent becomes crucial to address privacy worries, confirming that farmers are sufficiently informed about the gathering and utilization of their data. Development in spatial resolution of satellite imagery can create a risk of privacy violation. This means that remote sensing satellites through high spatial resolution technology can provide information to a wide range of people in real-time, leading to crucial privacy protection issues for remote sensing data [208].

5) Future Directions: Making use of I5.0's technologies can help mitigate security threats in remote sensing. Employ robust cloud security schemes, including data encryption, access controls, and frequent security audits. Deploying edge computing to process sensitive data closer to the source can help mitigate the movement of data. This can aid in improving data security. In addition, integrate blockchain to create an immutable record of data transactions to add additional layer of security. Establish clear privacy policies and regulations for the collection, storage, and use of agricultural data. Implement anonymization and aggregation methods to protect individual farmer information [209]. Implement suitable security measures that address the interconnected nature of I5.0 systems. Conduct complete risk assessments and adopt a holistic approach to security.

B. Real-Time Data Processing

1) Threats Related to Investment and Returns: The challenges in constructing IoT infrastructure for continuous monitoring and real-time processing, mainly in open-field agriculture, include the significant tradeoff between massive investments and low returns in rural areas [210].

2) Threats Related to Accumulation, Storage, and Processing of Massive Amounts of Data: Another crucial challenge is technology adoption, which will give rise to an increase in data volume and complexity in management. Additionally, the challenges in data storage, computation, and data management related to I/O operations and applications will become serious issues in remote sensing [4]. For instance, a remote sensing system has to accumulate thermal imaging sensor data for various studies related to agriculture, such as crop stress, water and nutrient deficiency, and herbicide resistance. This sensing system monitors crop acreage change, yield, production, growth, drought, and other agro-information and communicates it to government ministries and other agricultural sectors. This indicates that the real-time process threats pertain to the challenges related to the accumulation, storage, and processing of large volumes of remote sensing data for agricultural monitoring and management.

3) Threats Related to Technology: Traditional satellite remote sensing systems face challenges in meeting the real-time processing and intelligent service demands for satellite remote sensing imagery [126]. This includes challenges such as the inability to meet the massification and real-time application needs of satellite remote sensing imagery and the urgent need to develop intelligent satellite systems to resolve these issues.

4) Threats Related to Cloud Cover: Cloud cover obstructs the transmission of EM radiation, diminishing the ability of remote sensing systems to capture clear images or data. The presence of cloud cover introduces interference that compromises the accuracy and reliability of remote sensing measurements by attenuating or distorting signals received from the Earth's surface. Interesting work [211] discusses advancements in cloud detection for remote sensing images. They introduce RD-UNet, a deep learning model, showing superiority over current methods. Another research effort [212] focuses on cloud removal in remote sensing images using deep learning methods. Traditional methods such as exemplar-based and information cloning show inconsistencies in feature reconstruction. The proposed method, GAN-CA, U-Net, Shift-Net, and SAR-opt-GAN, outperforms traditional methods in reconstructing ground objects accurately.

5) Future Directions: The development of intelligent remote sensing satellite systems in I5.0 is vital to address on-orbit processing and intelligent service issues. Additionally, I5.0's technological advancements in cloud computing and wireless technologies are expected to help process remote sensing data quickly after acquisition, ultimately combining automation and computational resources to create intelligent technologies for AI and real-time processing for decision-making tools [4]. Edge intelligence can be deployed to meet the effective real-time processing requirements of typical applications for future intelligent remote sensing satellites [213].

C. Data Variety and Standardization

1) Threats: Multimodal data fusion in remote sensing presents numerous challenges [214]. One challenge is the integration of data from diverse sources and sensors, which may have varying resolutions, spectral ranges, and spatial and temporal coverages. Another challenge is the requirement for methods to integrate and analyze the different types of data in a way that maximizes supplements and provides a much better description of the context captured [215]. Additionally, addressing unforeseen problems and exploring the capabilities of the data provided in the framework of contests can also be crucial challenges.

Satellite-based sensing includes data with the following characteristics multisource, multiscale, high-dimensional, dynamic-state, isomer, and nonlinear [216]. These data are high-dimensional with many spectral bands and long-time-series data, which offers challenges for analysis. The dynamic state of the data includes changes in the Earth's surface and the movements of satellites. There is a requirement to consider scale effects in data analysis and processing due to the multiscale characteristic.

Spectral variability is another crucial challenge in remote sensing. The work in [158] focuses on remote sensing, image analysis, and data fusion. It includes the use of ML, signal processing, and data science for global urban mapping. The researchers have created models for spectral variability and endmember extraction, with a special application focus on global urban mapping. The work also comprises the use of Gaussian fields to satisfy certain conditions, and the development of perturbed linear mixing models to account for spectral variability.

These challenges demonstrate the complexities and opportunities for research in the field of multimodal data fusion in remote sensing.

2) Future Directions: Multimodality in remote sensing and data fusion can be handled by addressing challenges related to data acquisition from different sources coming in different formats, such as the need for converting data into common formats for processing, validation of results, and computational load. Addressing this challenge requires a multidisciplinary approach involving expertise in remote sensing, cutting-edge technologies, and domain-specific knowledge. Current research and advancements in these areas contribute to the development of more effective solutions for multimodal remote sensing applications.

D. Interoperability Issues

Interoperability issues arise in agriculture, particularly when remote sensing and I5.0 are integrated. Some of the most important issues must be addressed for successful agricultural practices.

1) Standardization of Data and Protocols: Agriculture tools and remote sensing technologies are frequently manufactured by different companies, each working with unique exclusive processes and standards. This lack of standardization makes it difficult to guarantee proper integration and successful data exchange between devices and platforms [217].

2) Complex Data Management and Data Analysis: The huge volume of data generated by remote sensing technologies necessitates advanced data processing techniques and analysis tools. Integration of these tools with I5.0 tends to be challenging. This causes problems with effectively utilizing data for decision making and has an impact on the accuracy of results produced by remote sensing data [218].

3) Real-Time Data Processing and Optimal Response: Data generated by satellite imagery, UAVs, and remote sensing devices requires quick analysis and responsiveness in the I5.0 environment, which is important for effective agricultural management. This quick data processing enables timely monitoring of crop health, soil conditions, and environmental factors in I5.0. Considering advances in I5.0, current systems struggle with real-time data handling and quick decision-making [219].

4) Future Directions: Standardization of data and protocols can be accomplished through collaborative efforts between technology vendors, standardization organizations, and agricultural stakeholders. Manufacturers of agricultural tools and remote sensing technologies must collaborate to develop common standards. This collaboration would guarantee that their products are interoperable and can communicate efficiently. Farmers and agricultural businesses should engage actively in the standardization approach. Handling complex data management and achieving optimal responses can be solved by using advanced analytics and ML algorithms to efficiently process and analyze large volumes of remote sensing data. Edge computing can be used to process data while reducing latency and bandwidth. To manage the massive volume of data, automated tools for data cleaning and preprocessing can be used.

E. Data Accuracy and Calibration

The integration of remote sensing and I5.0 in agriculture poses several challenges in achieving data accuracy and calibration.

1) Sensor Calibration and Validation: It is essential to ensure that remote sensing devices are accurately calibrated. Calibration is required to ensure that the sensors produce accurate data because it has a significant effect on the quality and reliability of the data collected [220]. Sensors can crash or be damaged over a period of time, reducing their accuracy. Calibration and validation of sensor data must be done regularly because it can affect accuracy and generate incorrect data.

2) Data Fusion and Integration: Data integration from various sensors (e.g., satellite, UAV, and ground-based sensors) can be challenging [221]. It is challenging to integrate the data from these sensors into a precise model as they may have different resolutions, scales, and measurements.

3) Environmental Influences: External factors such as weather conditions, atmospheric interference, and seasonal changes affect the accuracy of agricultural remote sensing data [222]. These factors generate noise and distortions, which have an impact on the reliability of the data collected.

4) Future Directions: Sensor calibration depends on sensor type, usage intensity, and the environment to which the sensors are exposed, so a regular sensor calibration schedule is essential. Setting up automated calibration systems, which can continuously monitor sensor performance and update calibration parameters in real-time to ensure accuracy. Remote calibration techniques must be provided for sensors that are difficult to access, such as satellite sensors. Applying advanced data fusion algorithms to effectively integrate data from multiple sources. Geospatial information systems aid in the integration and analysis of spatial data from various sources. Developing and using sensors that are resistant to environmental influences. The use of advanced image processing techniques such as image sharpening, contrast adjustment, and AI-based filtering techniques helps in improving the quality of images that are affected by environmental conditions.

F. Connectivity and Latency

Integrating remote sensing with I5.0 in agriculture poses several challenges, particularly in terms of connectivity and latency.

1) Limited Network Infrastructure: Many agricultural areas, especially those in remote or rural areas, have inadequate network infrastructure [223]. Large amounts of data generated by remote sensing technologies are difficult to transmit due to a lack of infrastructure.

2) High Bandwidth Requirements: Remote sensing technologies, such as drones or satellite imagery, generate huge amounts of data [224]. Real-time data transmission necessitates high-bandwidth networks, which might not be feasible in all agricultural regions.

3) Latency Issues: It is essential for precision agriculture to capture real-time data, send, and process data in a shorter amount of time [225]. However, due to the physical distance between the sensors (in the field) and the data processing centers, there may be a huge latency delay. This delay may have an impact on decision-making processes that rely on real-time data.

4) Future Directions: Deploying satellite internet enables network coverage in inaccessible regions where traditional connectivity is unavailable. It provides a solution for delivering remote sensing data from fields to data processing centers. The use of low Earth orbit satellites offers lower latency and higher bandwidth than conventional geostationary satellites, making them useful for agricultural remote sensing applications. Data compression techniques can be used to reduce the amount of data that must be transmitted. Since the data are compressed, less bandwidth is required for transmission, making it useful in remote areas with limited network capacity. Upgrading network infrastructure to 5G and beyond, enabling faster data transmission. Edge computing facilitates data processing and analysis at the edge of the network. Only essential and processed data will be sent to central servers. This method significantly reduces the amount of data that must be transmitted across the network.

G. Regulatory Compliance

1) Risk Management and Environmental Regulations: The integration of advanced technologies in agriculture requires careful management of risk and adherence to environmental regulations, which can impose compliance costs and burdens on farmers. Future directions in this area may involve the development of new technologies and processes that minimize environmental impact and promote sustainable farming practices.

2) WTO Rules and Regulations: Compliance with World Trade Organization rules and regulations poses a demanding challenge for countries, affecting the agro-industry and agricultural production. Future directions in this area may involve the development of new trade agreements and frameworks that support the integration of I5.0 technologies in agriculture.

3) Food Safety and Quality Standards: The use of robotics and advanced technologies in food processing necessitates adherence to complex food safety and quality standards, adding to the regulatory challenges faced by I5.0 in agriculture. Future directions in this area may involve the development of new technologies and processes that improve food safety and quality while reducing compliance costs for farmers.

4) Labor Laws and Regulations: The increasing use of automation and robotics in agriculture requires careful consideration of labor laws and regulations to ensure fairness for workers and compliance with evolving work practices. Future directions in this area may involve the development of new regulations and frameworks that support the integration of I5.0 technologies while protecting workers' rights [117].

5) Data Privacy and Security: The integration of digital technologies in agriculture raises concerns about data privacy and security, necessitating the development of robust regulations to protect sensitive information. Future directions in this area may involve the development of new data privacy and security frameworks that support the integration of I5.0 technologies while protecting farmers' and consumers' data [226].

H. Skill and Knowledge Gaps

1) Skewed Focus and Limited Awareness: There is a skewed focus toward commercial agriculture, and limited awareness and understanding of the vast opportunities in agri-business, leading to a lack of interest in agricultural careers and study directions. The future direction is to change perceptions through public–private collaboration and government intervention.

2) Data-Driven Development and Career Paths: The industry faces challenges in data-driven development and the need to develop career development paths that align with the requirements of I5.0. Future direction focuses on developing training programs that focus on data analytics, ML, and other I5.0 technologies that can equip the workforce with the necessary skills [117].

3) Soft Skills and Development: The importance of soft skills, now addressed as the soft skill gap in the labor market, is increasingly recognized under the conditions of I5.0. Focused efforts on developing soft skills are needed. Incorporating soft skill development into agricultural education and training programs can help bridge the soft skill gap and prepare the workforce for effective human–machine collaboration [227].

4) Integration of Broader Skill Set: There is a need to integrate a broader skill set into discipline-specific agricultural degrees to meet the specific challenges posed by I5.0. This includes skills beyond traditional agriculture, such as data-driven development and human–machine collaboration. In the future, integrating a broader skill set into agricultural degrees, including skills from fields such as data science, automation, and AI, can prepare graduates for the interdisciplinary demands of I5.0 [117], [228].

5) Public–Private Collaboration and Government Intervention: Effective public–private collaboration and government intervention are essential to reduce skill gaps and change perceptions about agricultural careers. Private industry involvement is crucial for providing the required skills, experience, and funding. In future, encouraging collaboration between the agricultural industry, government agencies, and educational institutions can facilitate the development of relevant training programs and address skill gaps.

6) Industry–Academia Linkage: Close collaboration between the agricultural industry and academia is crucial for developing relevant training programs that impart the skills demanded by I5.0. In the future, promoting continuous learning and upskilling opportunities for the agricultural workforce can ensure that they remain adaptable and proficient in the face of technological advancements.

I. Costs and ROI

1) High Initial Investment: The adoption of I5.0 technologies, such as AI, IoT sensors, and automation systems, requires a significant upfront investment, which can be a barrier for many agricultural businesses, especially small and medium-sized farms. Governments can provide financial incentives, grants, and subsidies to encourage farmers to adopt I5.0 technologies. This can help offset the high initial investment costs and reduce the financial risks associated with these technologies.

2) Uncertain Return on Investment: The return on investment (ROI) for I5.0 technologies in agriculture is often uncertain and can vary depending on factors such as the specific technology, the size and type of farm, and market conditions. This uncertainty can make it difficult for farmers to justify the initial investment. Collaboration between the agricultural industry, government agencies, and research institutions can facilitate the development of affordable and accessible I5.0 technologies tailored to the specific needs of the agricultural sector.

3) Lack of Technical Expertise: Implementing and maintaining I5.0 technologies requires specialized technical expertise, which may not be readily available in the agricultural sector. This can lead to additional costs for training and support. In the future, investing in education and training programs can help farmers and agricultural professionals develop the technical skills and knowledge necessary to implement and manage I5.0 technologies effectively [229].

4) Data Security and Privacy Concerns: The use of digital technologies in agriculture generates large amounts of data, raising concerns about data security and privacy. Ensuring the protection of sensitive data can involve additional costs and resources.Encouraging data sharing and collaboration among farmers, researchers, and technology providers can help accelerate the development of more effective and efficient I5.0 solutions for agriculture [230].

5) Limited Infrastructure: The successful implementation of I5.0 technologies often relies on reliable and high-speed internet connectivity, which may not be available in all agricultural areas. This lack of infrastructure can hinder the adoption of these technologies. Expanding access to reliable and high-speed internet connectivity in rural areas is crucial for enabling the adoption of I5.0 technologies in agriculture [20].

V. Case Studies

Brazil's coffee supply chain was equipped with a remote sensing-based monitoring system to deal with issues related to efficiency and quality control [231]. It collects extensive data on crop health and field conditions through spectral sensors, drones, and satellite photos. Real-time tracking, precision farming, production forecasting, quality assurance, and transparency are some of the benefits obtained through this system. Through the use of sustainable techniques, the results demonstrated a remarkable decrease in resource usage, noticeable increase in production, greater consistency of quality, and improved brand recognition.

Another case study that demonstrates how environment monitoring can be enhanced through the adoption of technology integration is how grape health is getting tracked in California's Napa Valley with remote sensing that combines data from drones and satellites [232]. It handles issues such as nutrient shortages, disease outbreaks, and water stress. Cost-effective and sustainable practices are made possible by remote sensing, which also makes precision agriculture, yield prediction, and early detection and reaction possible. However, issues such as cloud cover and data interpretation continue to persist, highlighting the necessity for knowledge and reliable infrastructure.

A precision agriculture experiment was conducted in a Spanish vineyard with seven treatments involving different water regimes and fertilization methods [233]. The vineyard, planted with the Bobal grape variety, had a specific irrigation system and soil type. Aerial images were taken using a drone with multispectral capabilities to assess crop health. Weather conditions and water status were monitored to adjust irrigation schedules. The yield was measured at harvest time to evaluate the impact of the treatments on grape production.

Another case study made by researchers used satellite and airborne sensors of varying resolutions to study coastal wetlands [234]. They tracked changes in vegetation, hydrology, and land cover over time. The study focused on mapping and monitoring long-term trends and short-term changes in wetlands. Recommendations suggested using medium-resolution sensors for large areas and high-resolution sensors for critical areas. Multispectral imagery was preferred, with hyperspectral imagery for specific cases. Airborne digital camera imagery helped interpret satellite images. LiDAR and hyperspectral imagery combined improved wetland species discrimination and understanding of topography. The study observed changes in land cover, buffer degradation, wetland loss, invasive species expansion, and biomass change. The study highlighted the importance of site visits in conjunction with remote sensing for accurate mapping of coastal wetlands.

Another research study has made an effort to optimize nitrogen utilization in winter wheat fields of small to medium size in Switzerland [235]. Employing remote sensing technology, particularly UAVs equipped with multispectral cameras, allowed for the capture of detailed crop field imagery. Various indices were analyzed. Among various indices examined, the normalized difference red-edge index (NDRE) demonstrated the strongest correlation with both nitrogen uptake and crop nitrogen status. Utilizing NDRE values in conjunction with soil nitrogen mineralization data and established fertilization guidelines, personalized nitrogen fertilization maps were created. These maps provided precise guidance for applying nitrogen fertilizer at variable rates across the fields. By adopting this tailored approach, nitrogen input was reduced by 5% to 40% compared to conventional fertilization methods, all while maintaining crop yield levels.

VI. Conclusion

Based on the comprehensive survey presented, it is evident that remote sensing technologies have immense potential to transform and enhance agricultural practices in the era of I5.0. I5.0 marks the next phase in industrial development, characterized by the amalgamation of cutting-edge technologies including AI, to create highly intelligent and interconnected systems. Our survey demonstrates how advanced technologies such as AI, ML, and Big Data analytics can be integrated with remote sensing data to provide actionable and timely insights to various agriculture stakeholders. The implementation such technologies will revolutionize remote sensing in agriculture facilitating more accurate, timely, and data-oriented decision-making processes, thus leading to more efficient and sustainable agricultural practices, ultimately enhancing productivity and ensuring food security.

However, for widespread adoption across the agriculture sector, some key challenges need to be addressed. These include lack of awareness among farmers, high costs and complexity of solutions, lack of technical expertise, concerns around data privacy and security as well as compatibility issues arising from the use of multiple data formats and systems. Overcoming these barriers through collaborative efforts between technology providers, research institutions, governmental agencies and farming communities will likely accelerate adoption. Overall, the smart integration of advanced I5.0 technologies and agricultural remote sensing has the potential to make farming more efficient, sustainable, and productive. Realizing this potential will play a crucial role in addressing rising food demands and environmental pressures in the future.

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