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RESEARCH ARTICLE

Remote Sensing and Decision Support System Applications in Precision Agriculture: Challenges and Possibilities

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ABSTRACT As the world's population rises, there will be a greater need for food, which will have repercussions on the environment and on crop yields. Increased production, efficient resource allocation, climate change adaptation, and diminished food waste are the four cornerstones of Agriculture 4.0's vision for the future of farming. Agriculture 4.0 makes use of cutting-edge data systems and Internet technology to acquire, analyze, and organize massive amounts of farming facts such as weather reports, soil conditions, market demands, and land usage to better guide farmers' decisions and boost their bottom lines. As a result, research on agricultural decision support systems for Agriculture 4.0 has gained significant momentum. Crop monitoring and yield forecasting are two applications where remote sensing has proven useful, and these two areas are intrinsically linked to variations in soil, weather, and biophysical and biochemical factors. Multi- and hyper-spectral data, radar, and lidar imaging are just some of the remote tools that could be employed for crop monitoring and yield forecasting. This paper's goal is to examine some of the difficulties that can arise in the future while using agricultural decision-support platforms in the context of Agriculture 4.0. Addressing these identified obstacles may help future researchers create better decision-assistance systems. This research examines the possibilities, benefits, and drawbacks of each method, as well as how well they work in various agricultural settings. Furthermore, these methods are demonstrated in a variety of strategies that can be effectively employed. In this research, we take a look at some remote sensing techniques developed to increase farm profits while minimizing their impact on the natural world. This research shows how remote sensing information can be used to predict crop yields, evaluate plant nutrient needs and soil nutrient levels, calculate plant moisture levels, and manage weed populations, among other applications.

INDEX TERMS Agriculture 4.0, decision-support platforms, remote sensing, soil nutrient levels, crop yields.

I. INTRODUCTION

Information about an object can be gathered by a technique called "remote sensing," which does not require physical touch. In remotely sensed, data is transmitted using radiation, which passes through empty space at the speed of light in a variety of different wavelengths. Remotely sensed data makes extensive use of visible light (VIS), near-infrared (NIR), shortwave (SWIR), thermal (TIR), and microwave bands. Although derived from remote sensing devices just record

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whatever radiation is reflected or released by the items being studied, active sensors actually produce radiation of their own, which interacts with the target under study and is then reradiated to the survey tool.

The term "remote sensing" denotes to a collection of techniques that rely on satellites and other forms of space-based technology, as well as ground-based remarks for increased precision and accuracy [1]. Visible, infrared, thermal, RADAR, and microwave remote sensing are built on the electromagnetic spectrum to assess how electromagnetic radiation interacts with Earth's surface [2]. Field sensors [3], UAVs [4], aircraft [5], LIDAR and RADAR sensors [6], [7], cameras, and sensors mounted on orbiting satellites are only some of the technologies for remote sensing used in agriculture. By delivering comprehensive, timely, repeatable, and cost-effective information on the Earth's surface, remote sensing photographs can be used to map and track changes to the planet's topography. It's also used for things like reconnaissance and defense purposes, as well as in agrometeorological, forest, and soil research, crop production, glacier, ice, and ocean management, geological exploration, mapping, land use and environmental control, and more. Space-based satellite images are increasingly valuable for gathering spatiotemporal meteorological and agricultural information and updates to supplement the conventional approaches, while air-based and earth systems have restricted use and save time only in limited situations.

The principle of remote sensing is to evaluate the earth's features using the electromagnetic spectrum. Because vegetation, bare soil, water, and other similar things typically respond differently in these wavelength zones, they are utilized to differentiate between them. Passive and active remote sensing are the two main categories in the field. Sensing from a distance using only the sun's kinetic energy (passive). This can only occur, for instance, when the sun is shining and making the Earth visible. The lighting for the activity is provided by their own energy source. The sensor releases radiation that is aimed toward the object of study. The target's radiation reflection is picked up and analyzed by the sensor. It doesn't matter what time of day it is or what season it is, they can always get measurements. Like, say, a laser or radar.

Renewable and dynamic agricultural resources are crucial. Over 70% of Indians rely only on agriculture for their income, and it accounts for almost 35% of the country's GDP. Since there is little room for expanding farmland, boosting agricultural output has taken center stage. This calls for careful and effective management of the planet's precious soil and water supplies. The last two decades have seen the use of remote sensing techniques expanded into new areas of agriculture, such as the monitoring of crop growth. There needs to be accurate and thorough data on things like land cover, forest area, soils, geological information, wasteland, agricultural crops, surface and subterranean water resources, and natural disasters like drought and flood. With seasonally specific data on crops, land used, and yield, the country can take corrective action to fulfill shortages and apply corrective assistance and procurement programs.

Tools on the ground include an infrared thermometer, a spectral radiometer, pilot balloons, and radars. Aircraft in the air serve as distant sensing equipment. Based on satellite technology: In order to analyze and understand remotely sensed data, high-powered computers are used for digital image processing. Due to the high cost and limited use of ground and air-based platforms, space-based satellite technology has proven useful for expanding the scope of remote sensing's reach. When compared to the conventional approach, remote sensing offers numerous benefits while conducting surveys of agricultural resources. Synoptic views, rapid surveys, change detection through repeated coverage, reduced costs, improved precision, and the ability to integrate hyperspectral data to provide more context are just a few of the benefits.

When weeds are present in an ecological system, they contest with the crop for resources, including light, nutrients, water, and gas exchange, lowering crop output and excellence [8], [9]. Potential herb deprivation for agricultural production includes the type of plant, its density, its emergence timing and length, and the fact that plants and crops may emerge at the same time, increasing competition for scarce artificial fertilizers [10], [11].

II. LITERATURE REVIEW

In the twenty-first century, sustainable farming production relies heavily on precision agriculture (PA) [12], [13]. There are a variety of definitions for PA, but they all boil down to the same thing [14]. To advance crop manufacture while decreasing water and nutrient economic loss and adverse environmental effects, PA entails a management strategy that employs a suite of valuable data, connectivity, and data analysis methods in the decision-making process [15], [16]. Other terms that are used interchangeably with PA include information-based control, site-specific cultivation practices, goal agriculture, variable rate invention, and grid agriculture. PA is used not only for farming crops but also for horticulture, viticulture, grazing, and animal management [17].

Environmental parameters such as water value, air eminence, radiation, noise contamination, etc., are monitored using a wide variety of sensors and Internet of Things (IoT) devices; [18] provides a critical analysis of these technologies and offers suggestions for improving their effectiveness. The study suggests certain unusual tasks to accomplish in order to successfully install environment monitoring systems using sensors, the IoT, and AI. In [19], the authors provide a detailed discussion of the technological, physical, and implementational developments that have led to today's state-of-the-art sensors. This might serve as a helpful guide while researching and deciding on a sensor.

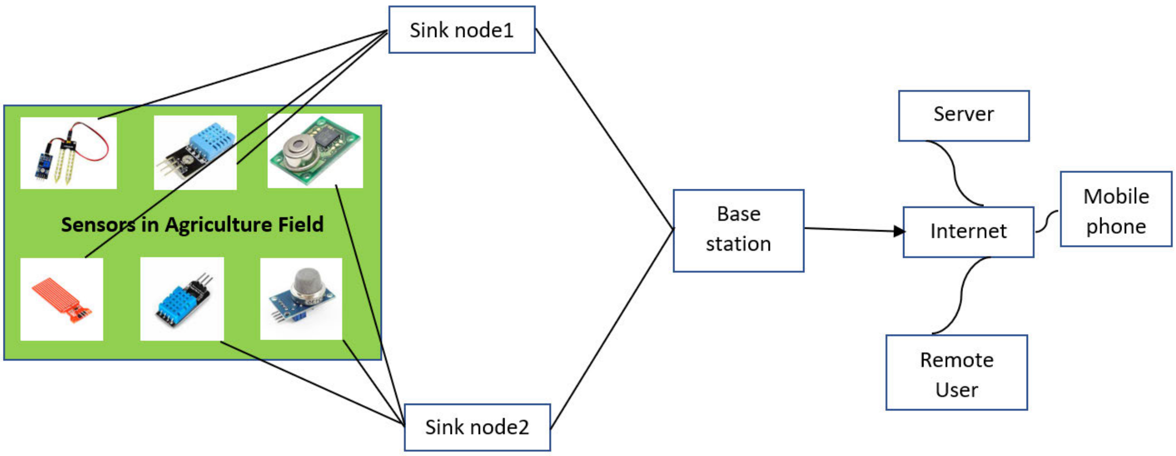

FIGURE 1. Sensor nodes in agriculture.

In [20], [21], [22], [23], [24], and [25], several aspects of IoT, including their designs, implementations, problems, and privacy concerns, are covered. While trying to determine which form of IoT would work for a certain application while also fulfilling the needs of the end user, it is critical to have a thorough understanding of all of these features. In [26], the use of edge computing was proposed as a method for creating efficient IoT applications. In [20], [21], [22], and [23], various sensor networks used for deploying sensors and IoT-based applications are described. In [24], the authors explore how miniaturized pervasive sensors can be used for intelligent applications across a variety of domains, allowing for more portability and adaptation in their deployment. There is also talk of agricultural and distant sensing sensors. In [21], [25], [26], [27], [28], [29], and [30], the authors provide a thorough overview of IoT and its applications, with a particular focus on how to best use IoT in the field of remote sensing.

Researchers have used a variety of approaches to the issue of crop categorization using spectral information [31], [32]. To better categorize Brazil's sugarcane crops, a system based on a regression model was developed. The EO-1 satellite was used to gather this HSI data [33]. The method suggested in [34], which was actually applied to Hyperion remotely sensed data, is a hybrid of Support Vector Machine (SVM) and linear spectral models. Also, in Guangzhou, litchi crops were categorized in this way. Using the Hyperion data, the Spectral Angular Mapper (SAM) classifier was used to categorize crops in the Karnataka region [35].

For quite some time, researchers have been aware of the requirement to map land and soil use datasets for the purpose of achieving sustainable supervision of natural resources on a local, provincial, and national scale [36], [37]. It is crucial to have knowledge of the soil's mechanical, microbiological, and chemical qualities in order to create and implement crop methodologies, which are essential components of PA. Some of these crop management strategies include irrigation, permeability, and nutrient management. In a similar vein, land use mapping can assist in evaluating the effects of pre-existing administration and strategy on a scale ranging from regional to national. Even before 1958, when the phrase "remote sensing" was first established [38], there was already a conventional method of applying remote sensing techniques in agricultural settings. For instance, aerial photography was utilized in the 1930s and 1940s in the United States to record the soils, land usage, and crop conditions at that time [39]. Nonetheless, these traditional approaches to soil mapping and property use classification (for example, low-altitude imagery and ground personnel) often involve substantial fieldwork and laboratory investigation, both of which are time-consuming and costly [40]. The development of remote sensing satellites in later years made it possible to map land uses at scales that ranged from regional to national to worldwide with greater accuracy and efficiency.

III. MATERIALS AND METHODS

A. REMOTE SENSING WITH SMART SENSORS

More and more sensors are being embedded into machine parts to give inventors and operators data on the features of organizations' active (field) loading, as well as recurrent biotic and abiotic stresses. According to ecological and economic sustainability standards, technical advancements can be achieved by analyzing data from sensors put on the earth, in harvests, and in animals. Major advancements are made in the areas of physical and non-contact proximal discovery.

Sensors that are either moved vertically and horizontally in the soil or remain in one place can capture a wealth of useful data. With the advent of nanotechnology, sensors are getting even smaller. Not only can information be gathered from animals by inserting microchips into their bodies, but nano-sized sensors might also be used to collect crop data. That way, it's possible to track how various environmental factors affect the internal health of living things. Devices positioned above the soil, in the soil, or the lab under prescribed light circumstances can determine soil moisture content,

TABLE 1. Sensors in remote sensing for agriculture.

Sensors	Usage
Optical Sensors	Evaluate soil quality using spectral analysis
Electrochemical Sensors	Soil Nutrient Detection
Mechanical Soil Sensors	Measures the force needed to enter the soil medium
Dielectric Soil Moisture Sensors	checks soil moisture conditions
Location Sensors	Find the proximity, length, and elevation of any point
Electronic Sensors	To ensure the proper functioning of the apparatus
Airflow Sensors	The force required to inject a fixed volume of air into the ground at a given pressure
Agriculture Sensors IOT	Data is collected and recorded at regular intervals, including measurements of ambient temperature, soil moisture at different depths, rainfall, weather conditions, chlorophyll, wind direction

texture (dispersal of particle sizes), chemical makeup, and other physical aspects using tests based on hyperspectral reflectance, made possible by nanotechnology (own reference) as shown in Fig. 1. UGV (in this instance, small-smart robotics), drones, aircraft, and spacecraft equipped with Normalized Difference Vegetation Index (NDVI) cameras can be used to estimate crop yields. Hyperspectral and NDRE (Normalized Difference Red Edge) cameras can be used to improve the estimations' precision. Artificial neural networks (ANNs) and principal component analysis (PCA) have been used to develop color-based maturity assessments for crops (fruits).

Gloves with built-in sensors for touch pressure, images, inertia assessment, location, and RFID (Radio Frequency Identification) are used to categorize fruits [41]. Because of this, losses are cut down during hand harvesting while production speeds up. In addition, the groundwork is laid for a crop to be classified in accordance with its direct quality, making it possible to prevent loss-making classification down the line. Connecting Internet-of-Things devices with unmanned aerial vehicles combines two cutting-edge tools. With the use of computer vision and good grasping gear, the drone can also be used to pick fruit. Robots that can fly autonomously have been used to harvest fruit. The role of natural pollinators is being taken over by artificial bees. There is potential for UAVs equipped with sensors for sight and smell to be utilized in the future as a pest-free alternative to the usage of insecticides. Table 1 shows the usage of sensors in agriculture for remote sensing.

B. WSN IN AGRICULTURE

The computerized analysis and evaluation of multiple input characteristics simultaneously require extensive databases. Soil moisture, soil temperature, soil nutrient content, leaf temperature, relative humidity, air temperature, rainfall, vapor pressure, and available sunlight are only some of the physical and environmental characteristics that may be monitored with a wireless sensor network. The physical, chemical, and environmental factors are tracked by a WSN's dispersed sensor nodes. With the use of sensors, wireless technology, and processing tools, WSNs can accurately measure a wide range of physical properties. After being processed, the parameters are sent across a gateway and into a centralized database, where the user can access and evaluate the information from a remote location. The various sensors that make up a WSN-based system are connected to electrical hardware via an array of data processing tools. In addition, the electronic components feature wireless technology modules, which modulate the observed data and send it over a network using a predetermined protocol. In WSN, these terminals are known as motes. Several wireless sensors are interfaced with each mole, and the exact sensors used will vary between applications. Each sensor can be set to either a continuous or discrete mode. We present the most important aspects of WSNs that make them a viable instrument for automation in agriculture in Table 2.

Precision agriculture relies on extensive sensing of environmental conditions at the ground level, and WSN is seen as a potential technology that can help update data collecting in the agricultural field and facilitate the automation of agriculture systems. Precision agriculture, which makes use of WSN technologies, is becoming increasingly popular because of its positive effects on agricultural productivity in a variety of contexts. With WSN, farmers might learn more about their farms and find the optimal approach. WSN can monitor soil moisture and temperature, manage irrigation, and help farmers make better decisions. Hence, collecting data, monitoring the environment, and analyzing that data are the primary motivations for WSN implementation in agricultural settings.

Several protocols, such as Zigbee, Bluetooth, and Wi-Fi, have been created by researchers to facilitate communication between sensor nodes and the deployment of WSNs. Zigbee is one of the best options for precision agriculture

TABLE 2. The advantage of WSN in agriculture.

Advantage	Description
Intelligent decision-making capability	The nature of WSNs is multi-hop. This function extends the network's useful lifespan over a wide area by improving the network's energy efficiency. With this function, a network of sensors communicates with one another to reach a consensus [42].
Dynamic topology configuration	Sensor nodes usually stay in "sleep mode" to conserve battery power. Topology management lets sensor nodes decide together. The network topology should have the fewest active nodes to improve network longevity.
Fault-tolerance	Faulty sensor nodes make WSN deployment difficult. Unexpected node placement may split the network, affecting its performance. In response, sensor nodes might "self-organize" by constantly modifying the network structure.
Context-awareness	Sensor nodes learn about their surroundings through physical and environmental data. Sensor nodes then make context-aware judgments.
Scalability	WSN protocols work in any network, regardless of size or node count. This functionality expands WSN applications.
Node heterogeneity	WSNs usually have homogeneous sensor-connected devices. In many realistic circumstances, electronics are diverse in processing and computation power, memory, sensor, transceiver unit, and mobility abilities.
Communication failure tolerance in severe environments	WSNs endure extreme weather conditions due to their many applications in open agricultural situations. The WSN protocol stack can tolerate environmental-induced network communication outages.
Autonomous operating mode	WSNs have autonomy and adaptability. This capability is crucial in agricultural applications, enabling easy and improved operation.
Information security	WSNs store raw field parameters. WSNs prohibit unauthorized users and detect anomalies to secure sensing data.

applications since it allows for periodic data updates in areas such as irrigation control, water quality monitoring, and fertilizer and pesticide tracking. Zigbee, a wireless protocol that is low-cost, flexible, dependable, and easy to implement, streamlines the monitoring of a wide range of environmental factors, such as soil health, weed disease detection, crop growth, and agricultural product quality. Zigbee can be effectively implemented in the precision agriculture industry. One such application is a smart irrigation system built on the Zigbee network protocol. The system's actuator node is designed to respond to changes in soil moisture detected by the system's sensor node, which monitors soil water levels. Zigbee's capacity to overcome the limits of wire connection and facilitate greenhouse management development also demonstrates its value in protected agriculture. Greenhouse monitoring and control can benefit from the incorporation of Zigbee-based WSN systems because they are simple to maintain and increase automation and efficiency. WSN allows for real-time monitoring and regulation of greenhouse environment parameters like humidity, temperature, light, and air pressure, improving plant development, increasing yield production, and decreasing the severity of damaging natural catastrophes on farms. The reduced power consumption and extended communication range of WSN could prove invaluable in greenhouses for health monitoring and prediction, fertilizer supply assurance, and cost-effective precision agriculture [43].

C. MODERN, CREATIVE, AND SUSTAINABLE FARMING

Sustainable agro-innovation is only measured if it satisfies ecological opportunities, such as being ecologically friendly, helping to increase biodiversity on and about the field, being climate neutral or mitigating the negative belongings of climate modification, and narrowing the gap between rich and poor nations by eliminating hunger and guaranteeing that all people have admission to clean water [44]. Economic studies in terms of novelty, new skills, or operations should be conducted only after these conditions have been met and then only on a global and local scale. This is the bedrock upon which all moral and ethical norms rest. So, in industrialized nations, the explosive increase in livelihoods that was forecasted is impossible to achieve; convergence should begin; otherwise, we will broaden the disparity in living conditions between advanced and developing nations, which could have unanticipated implications.

In contrast, the innovation process requires various considerations in industrialized and poor countries. By expanding output, the First Industrial Revolution and the three that followed served to supplant man's physical strength. This is the result of progress in science and technology. The second machine age, which began in the last decade, is characterized by artificial intelligence's gradual but steady assumption of the function of decision-maker. There is a "threat" that AI will not act in our best interest in this area as well. Many ethical and moral problems, such as local and international conflicts of interest, are also brought up.

The exploitation of developing nations is still widespread, stymying progress in many sectors. While rapid technological advancement has many positive outcomes, it also has two major drawbacks. It isolates people living in developed nations from nature and widens the separation of wealth and poverty. Development and Least Developed Countries (LDCs) have a growing population, which means there is a pressing need to increase food production in a sustainable manner. The industrialized world has learned the hard way that increasing yields at the expense of environmental damage is not the way forward [45]. The advanced nations will continue their trend of rapid technological advancement and groundbreaking new discoveries. The repercussions of climate change, which are largely generated by affluent nations, are felt most acutely by poor nations. Hence, reducing economic gaps between industrialized and developing countries is a key criterion for sustainable growth worldwide.

Today, thanks to the Internet of Things (IoT) [46], smart sensors that can exchange data with one another and the outside world are being used in industrialized nations' farms [47]. In addition to humans, robots, Drones, aircraft, and satellites all contribute to the data collection process. Data for IoT systems will rely heavily on distant sensing, especially in low-income regions. With the use of cloud computing [48], artificial intelligence [49] processes the data.

IV. CHALLENGES IN THE AGRICULTURE MANAGEMENT SYSTEM

A. IRRIGATION DECISION SUPPORT SYSTEM

The precision irrigation procedure necessitates a water application system that can precisely regulate the amount of water supplied to a field's various irrigation management units in a given amount of time. Continuous motion systems have been the primary focus of research and development for variable-rate water application systems. Databases with geo-referenced data describing irrigation management units are used to regulate water claims on continuous move systems. To adjust the amount of water delivered to each management unit, you can adjust the sprinkler's flow rate or the ground's speed in a continuous movement system. Fig. 2 depicts the irrigation decision support system.

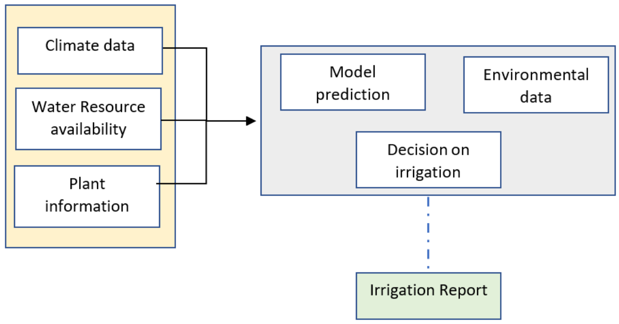

FIGURE 2. The Irrigation decision support system structure.

Sprinkler nozzles typically employ pulse modulation to allow for a wide range of application rates. Normally, opened solenoid valves are used to regulate water distribution to certain sprinkler heads or zones. A solenoid controls the water flow at a sprinkler location to accomplish a set application depth within a given cycle time. Pulse cycles are measured in terms of the cycle time, which is the number of times the solenoid valves must flip (either to the on or off phase).

Unmanned Aerial Vehicles (UAVs) have found widespread use in a variety of contexts thanks to the evolution of sophisticated robotics, and this is especially true in the field of agriculture. The on-board decision-making approach seeks to pinpoint the specific locations of infected crops so that appropriate actions, such as the application of herbicides, can be carried out. Toxic damage to the fields can be largely mitigated with the careful application of herbicides. Meanwhile, using UAVs for spraying missions increases productivity because of the increased efficiency of the workers. The Observation, Orientation, Decision, and Action (OODA) loop depicted in Fig. 3 serves as the conceptual foundation for the method provided. The technique depicted in Fig. 3 uses inputs such as ultrasonic sensor readings and camera images and received orders to compile data during the observation phase.

Once UAVs have gathered this information, they will begin their mission and proceed in a straight line to their destinations. Mission execution is where the UAV's onboard computer checks to see if the vehicle is on the right track. If a UAV's altitude [50] is determined to be too high, the decision-making component will issue an order for the vehicle to lower its altitude until it is within the predetermined range. Meanwhile, the decision-making part is in charge of revisiting previously visited waypoints to track progress in the objective. Imaging, approaching waypoints, and spraying herbicides are all examples of actions that fall under this category. UAVs are required to return to base after completing

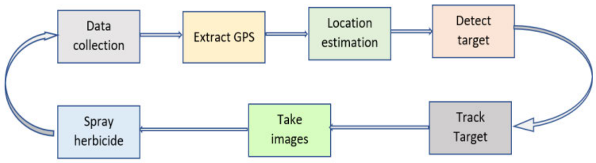

FIGURE 3. On-board decision-making approach.

a mission and switch to observation mode. Several flights served to validate the onboard decision-making strategy. UAVs have been shown to be able to hover above their intended destinations upon arrival, according to the results of recent experiments. The proposed method successfully directs UAVs to all of their waypoints.

Here, we take a look at the current state of precision irrigation study and equipment by reviewing published works, land-grant university extension materials, commercial offerings, and US patents. We zeroed in on four key areas of difficulty in precision irrigation decision-support systems:

(a) data accessibility and scalability;
(b) assessment of plant water stress;
(c) model uncertainties and limits, and
(d) producers' engagement and motivation.

Then, we discovered openings to tackle those four problems:

Increase the widespread implementation of decision-support systems for precision irrigation by,

(a) using satellite integration results with high time and spatial granularity in conjunction with inexpensive sensing devices.

(b) explicitly analyze the connection between soil water availability, atmospheric water demand, and plant physiological management to optimize irrigation decisions by mechanistic measurement of 'plant water stress' as triggers;

(c) use data-model fusion techniques to place constraints on process-based machine-learning models at the field level for scalable solutions; and

(d) Provide adaptable, user-friendly tools, and encourage more monetary and policy backing from governments.

B. REMOTE SENSING-BASED CROP MONITORING

For effective decision-making and to forestall food market disruptions and speculation, timely and accurate temporal-spatial and qualitative data on crop conditions is essential. Observing these characteristics is crucial for tracking crop performance. Biophysical characteristics [51] of crops are used as surrogates for environmental factors. For this reason, these measures have been used to analyze agricultural growth status and the effects of agroclimatic conditions, pests and diseases, water trees, and management methods on crop growth and to aid in the development of early warning systems. The detrimental effects of abrupt shifts in aberrant weather conditions on crops are complex, interconnected, and typically associated with particular crops, growth phases, and

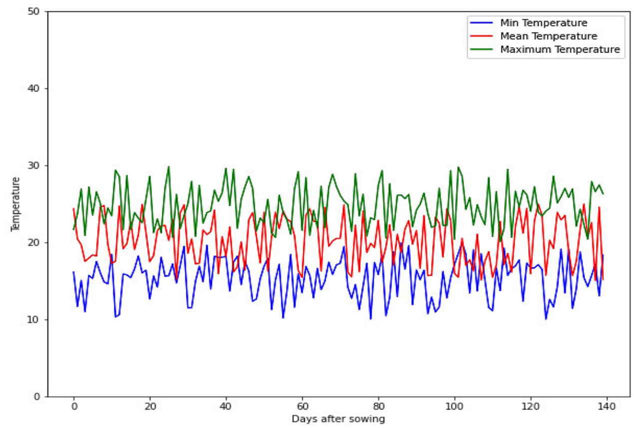

FIGURE 4. Sample recorded temperatures (T) from crop monitoring.

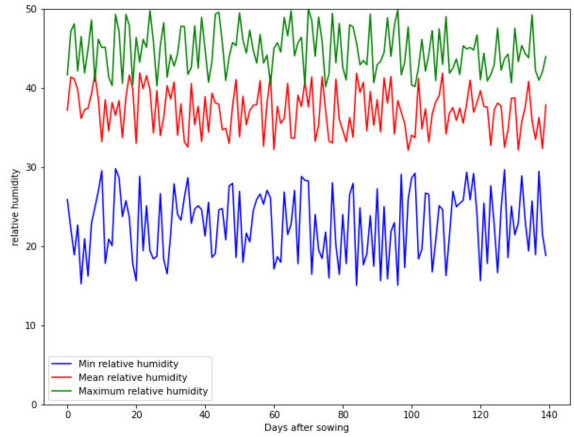

FIGURE 5. Sample-related humidity (RH) from crop monitoring.

genetic types. Nonetheless, in areas where winter harvests are farmed through the dovetail joints stage, frosts and stress brought on by low weather and/or cold shocks are frequently recorded despite winter crops' greater cold resistance compared to the growing season. Quantitatively classified methods and criteria can infer differences in yield, area, and production from pointers and/or metrics used primarily for assessing crop conditions, stress, and drought severity. These evaluations don't separate the stresses and disturbances from the indicators and/or metrics used to gauge the state of crop growth. Hyperspectral data, light detection and ranging (LiDAR) data, and optical data in grouping show promise for effectively enhancing the potential to produce early cautions and discriminating the origins of regional agricultural stress and the degree of the stress in terms of consequences on ultimate yield. Nevertheless, due to their limited coverage areas, enormous footprints, or low resolutions, these satellites are currently incapable of meeting operational needs. Fig. 4 and Fig. 5 illustrate the most significant climatological crop growth metrics that were obtained from the data: temperatures (T) and relative humidities (RH) are being measured (no rainfall occurred during the drying periods).

In addition, remote sensing data has been used to make forecasts about crop yields, crop stress assessment, and yield modeling. The ability to quickly identify plant diseases and to plan for accurate management estimates are crucial for maintaining agricultural production. Potential uses of remote sensing in agriculture include yield estimation and pest/drought detection. Strong vegetation has a higher reflectivity in the near-infrared region and a lower reflectance in the visible region. Plants that have been impacted by illness show an increase in perceptible band reflectance and a decrease in infrared area reflectance. In practice, this concept can be used to differentiate between healthy and diseased harvests.

As plants become sick, they may absorb less sunlight due to changes in their internal structure or because of a decrease in the amount of chlorophyll they produce, both of which are symptoms of the disease. Because of assimilation fluctuation, infected plant reflectance varies. Scientists are able to identify the stress potency of green foliage by comparing the ranges of infected and healthy plants.

1) CHALLENGES IN MONITORING CROP CONDITION

Most global, regional, and national Crop monitoring systems use the same approaches for real-time crop condition analysis, with a focus on maps showing how measures deviate from their norms to examine geographical differences or on temporal development to depict crop growth dynamics. Nevertheless, changes in crop factors may cause the differential technique to be biased and prevent it from providing accurate judgments. In order to successfully lessen uncertainties in crop condition monitoring, it is necessary to determine a proper benchmark product and an appropriate remotely sensed product at a reasonable spatial resolution. For example, as the health of irrigated crops and rainfed crops differs greatly, particularly during the dry terms (and in drought-prone locations), each type of crop might be monitored separately based on the irrigation practices in place at a given site. However, current crop condition monitoring approaches still rely heavily on low-resolution satellite measurements; such data frequently cover multiple crop production in coarse pixels and can rarely suggest the circumstances of independent crops, except in large parcels. Medium- to high-resolution crop health monitoring is now possible thanks to the growing accessibility of Sentinel-2-like satellite data, but this requires a massive amount of data dispensation. Furthermore, high spatial-resolution data could lead to other problems, such as geolocation mismatch and ground cover impressions. Users should have the option to pick data at the spatial scale most suitable to their monitoring needs.

C. CHALLENGES WITH ACCURATELY ASSESSING THE ROLE OF NUTRIENTS, DISEASES, AND PESTS IN CROP STRESS

If bad weather isn't to blame for crop stress, then nutrient deficiency, pathogens, or pests probably are. After water, a lack of nutrients has been identified as a major worldwide stressor. CCC and leaf nitrogen content (LNC) inversion algorithms have been established to identify nutritional stress in wheat and other crops. It has been proven that the red-edge groups, which are distinct bands situated between some of the red and near-infrared bands, are much more responsive to chlorophyll concentration than any of the several visible-band VIs reported to correlate to chlorophyll or nutrient content. The red-edge band's benefit in identifying nutritional status or total chlorophyll has been repeatedly shown. However, it works best for dense crops. Chlorophyll can be seen in images captured by the Sentinel-2 satellites thanks to the presence of three red-edge bands in their spectral range.

Disease and pest types can be identified, the severity of infection can be evaluated, and distribution can be mapped at the plot or regional level using a variety of criteria that have been created over the years. However, prior knowledge of the local diseases, pests, and other pressures that occur in the field is required. Because many of the symptoms and plant damage associated with agricultural pests and viruses can also be produced by other variables, such as nutrition shortages, it is problematic to proactively accomplish consistent and exact assessments in places where there is a lack of prior knowledge. The photochemical reflectance index (PRI), for instance, has traditionally been used to sense water pressure, frost pressure and destruction, and nitrogen content and stress, in addition to wheat yellow rust. Differentiating between stressors and their origins, as well as quantifying their many manifestations, requires the development of novel indicators and metrics.

D. CHALLENGES IN AI-BASED FIELD MONITORING

The potential applications of the aforementioned robotic principles in agricultural settings require additional study. The authors are confident that the increasing need for intelligent, compact machines will spur rapid advances in robotics. Both the efficiency of small farms and the diversity of their crops and animals should improve as a result of this. Autonomous robots are useful because they can act independently of a human programmer. Managers' expectations can be formulated at the same time, and the robot will account for them while making decisions (such as whether a crop is ready to be picked or not). They get to determine what constitutes an acceptable crop in terms of yield, shape, color, and size. AI, or in this case, digital, artificial image processing, is necessary for such endeavors to be accomplished.

Self-propelled or integrated with self-propelled equipment, field data-gathering robots need to have their current prices lowered if they are to become commonplace. For industrial robots in the field, Arduino and Raspberry Pi are the two most essential computing systems. Proximal sensors mounted on smart-small robots collect data in areas that cannot be detected by other methods, such as drones, airplanes, or satellites, during a certain vegetative time. Clever, compact robots have the potential to bring revolutionary change to the field. It's important to bring attention to the prospect of constant monitoring of microclimate features. The lack of 5G is now

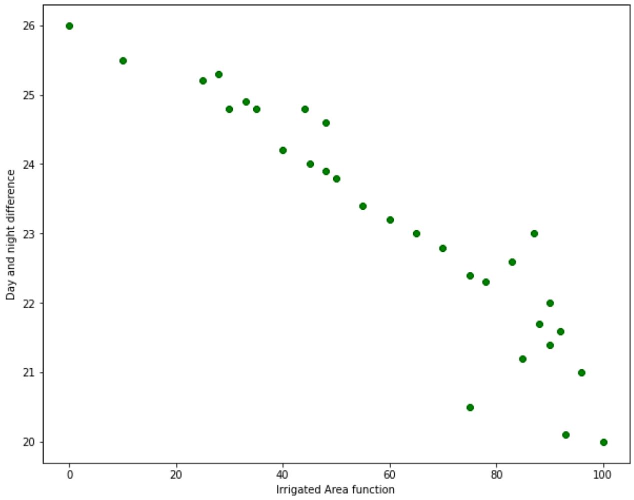

FIGURE 6. Sample association between the diurnal variation in land surface temperature (day minus night) and the sub - pixel luminosity of the irrigation region.

one of the biggest obstacles to the digital transformation of agriculture. But its effects on the quality of life need more explanation. The deployment of a robotic workforce should be prioritized because of the various economic benefits it provides. Some of these advantages involve but are not restricted to, the systematic gathering of information on the soil, vegetation, and natural landscape in the outdoors. The potential of Machine-to-Machine communication, the New Machine Era, and entirely independent fertile land manufacturing hinges on this.

Fig. 6 demonstrates that as the difference in temperature between the lowest and highest land surface temperatures diminishes, the intensity of irrigated crop production increases. This is because the presence of vegetation and moisture enhances the regulation of radiative warmth. Using thermometers that are attached to the land's surface and operating at perception level frequencies, this data can be used to map the extent of irrigated land immediately.

The extensive usage of robots has resulted in the elimination of many different types of employment, which has a significant impact on policymakers. The first step is to reconsider the potential benefits of AI as a decision-making system for fostering human cooperation. However, we need to look into what tools and resources may be employed to improve the efficacy of retraining. An important factor here will be the knowledge gained from past interactions between humans and artificial intelligence. Agricultural equipment simulators are becoming increasingly important in the classroom. Generalized retraining of the human population is the next emerging field. We have difficulty in that there may be a lack of faith in robots as we increasingly rely on advanced technology, especially in the workplace (and AI). But, if society establishes proper guidelines for robots, we may take use of their many benefits.

There are a lot of problems that need fixing in the smart manufacturing and farming industries; AI technologies like CPS (Cyber-Physical Systems), Big Data, the Internet of Things, and cloud computing could be the answer. There are high hopes that robot technology will advance in the agricultural sector. Often in manufacturing facilities, the product is in motion while the intervention robot remains stationary. Yet, robots are mobile in agriculture, for example, in crop production, unlike in animal husbandry. Autonomous robots have manipulators that allow them to move on their own. Robots for gathering data can constantly check their findings with IoT-connected soil or plant sensors and relay that data to a central IoT database.

E. SPECIFIC CHALLENGES OF AGRICULTURE IN THE INDIAN SCENARIO

There are issues with agricultural WSN systems in the Indian context that are distinct from those faced globally. Listed below are some of the unique difficulties India faces today.

A key barrier to these applications in LMICs is the high cost of the sensors and accompanying systems. The most difficult aspect of developing a WSN-based system for farming in India is the wide range of climatic conditions and soil types present across the country. The characteristics of the program must be adjusted so that it works correctly in various geographical settings. India's divided farmland presents a unique problem that necessitates a well-thought-out deployment architecture for wireless sensor network (WSN)-based agricultural applications like irrigation control. The average amount of land owned by an Indian farmer is smaller compared to the rest of the world. This necessitates a shift towards more compact and individualized solutions. To be successful, implementing automation in the agricultural sector will require careful planning that takes into account the varied topography of the land and the specific needs of individual farmers.

F. SPECTRAL DATA CHALLENGES

A significant challenge for remotely sensing irrigated areas across diverse geographical locations is selecting spectral bands or indices that encompass the largest amount of information relevant to agriculture and linking this data to complex forms of irrigation activity. Find vegetated areas in agricultural fields with the use of satellite-derived indices but pinpoint the cause of temporal and spatial variations in biomass, such as irrigation or precipitation, with more difficulty. When just supplementary irrigation is used, further difficulties may occur. Center pivot irrigation fields have a distinctive shape, but this detail is not immediately apparent and cannot be easily included in automated image classification.

To address these difficulties, it is necessary to first identify the distinctive features of irrigated areas, in particular, the features that can be monitored using remote sensing. The "greenness" of plants is one such quality. Almost everyone agrees that the NDVI is useful for keeping tabs on crops,

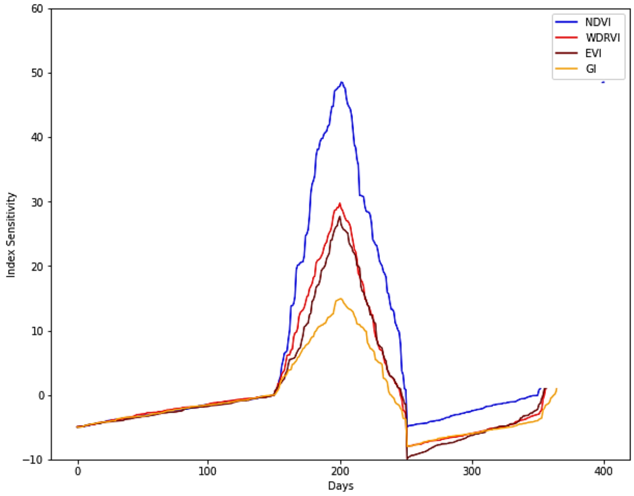

FIGURE 7. Sample Relative Sensitivity Index (RSI) values for four vegetation indices (NDVI, EVI, GI, and WDRVI) in response to the presence of irrigation. Each index was calculated as the mean response from a random sampling of roughly five different websites.

whether or not they're being watered by a sprinkler system. In semi-arid regions with a single irrigation period and straightforward land cover types, the NDVI signal related to irrigation makes it possible to identify irrigated lands. However, in many other parts of the world, there are multiple irrigation periods and a variety of crop types with varying schedules. It's possible that the NDVI signal linked to irrigation is weaker in these areas. Mapping these areas might be aided by the use of high-frequency NDVI observations from satellites like MODIS, which could then be used to establish when to take high-resolution pictures of the area. Yet, in areas where the same crop variety is cultivated with and without irrigation during the same growing season, identifying irrigated from non-irrigated crops can be challenging. It is possible that the temporal NDVI profiles of irrigated and non-irrigated crops in these areas follow the same trend. The NDVI variance among irrigated and non-irrigated fields is tiny and likely irrelevant, despite the fact that irrigated fields tend to be greener than non-irrigated ones because of the accessibility of moisture. As a result, it's possible that a more complex index is needed to make this division.

Comparisons were made between the normalized difference vegetation index (NDVI), the green normalized difference vegetation index (GNDVI), and the expanded vegetation index (EVI2), and a brand-new index was developed as a result of these comparisons. The following are the formulae for NDVI, GNDVI, and EVI2:

$$\mathrm{NDVI} = \frac{N_{\mathrm{IR}} - R}{N_{\mathrm{IR}} + R} \tag{1}$$

$$\mathrm{GNDVI} = \frac{N_{\mathrm{IR}} - G}{N_{IR} + G} \tag{2}$$

$$\mathrm{EVI2} = 2.5 \times \frac{N_{\mathrm{IR}} - R}{N_{\mathrm{IR}} + 2.4 \cdot R + 1} \tag{3}$$

where each variable stands for a different spectral component of the surface reflectance.

We examined the linear association between each index and the spectral bands for the times of year when the crop covers the entire area. This was done by taking into consideration the spectral features of the vegetation in each wavelength. According to a significant body of literature on spectral remote sensing of vegetation canopies, spectral indices associated to chlorophyll content are very sensitive to moisture stress in vegetation. The Green Index (GI) is one such metric that can be utilized with the MODIS sensor.

$$\mathrm{GI} = \frac{p_n}{p_g} \tag{4}$$

where p_g is the reflectivity in the green spectral range.

Irrigated plants with little to no soil moisture pressure will have higher chlorophyll concentration than non-irrigated cultivars that could experience water stress, which is the theoretical basis for employing the GI for irrigation evaluation.

$$\textit{Relative Sensitivity Index}\ (\mathrm{RSI}) = \frac{I_i - I_n}{I_n\,(\max) - I_n\,(\min)} \tag{5}$$

The irrigated and non-irrigated values of each index, I, at each time period are represented by I_i and I_n, respectively, in Equation (5), with I_i normalised by the annual amplitude (maximum-minimum) of I_n. The relative size of the differential between the watered and non-irrigated values of an index relative to the non-irrigated value's seasonal maximum change is represented by the relative size of the RSI is shown in Fig. 7. The GI is the most sensitive of the four indexes to the presence of irrigation when crop growth is at its peak.

Research on Internet of Things (IoT) and smart sensors for agricultural claims is summarized in Table 3, along with an overview and critical evaluation of related literature. Smart farming systems that regulate and monitor environmental parameters have been built on the basis of Remote Sensing data and other agricultural data acquired with the help of sensors, and these systems can be implemented on low-cost platforms. Internet-of-Things (IoT) and UAVs (unmanned aerial vehicles) that run on low to medium cost platforms are essential for this kind of development. As mentioned in, state-of-the-art technology like Arduino-based controllers; machine learning and deep learning-based techniques, and so on, can help make agriculture smarter and therefore improve it. The Flying IoT stands out as an innovative smart agricultural platform because it has been put through its paces in a real-world setting and its performance has been assessed in the context of smart farming practices employed in various nations. The low-cost IoT-based solutions are used to evaluate crop quality, control drought, and calculate drought-related losses. Smart farming makes use of remote sensing techniques to improve crop control by, for example, keeping an eye on how much water is being pumped out of the ground and determining what that number should be. Using

TABLE 3. Result analysis of existing with proposed imlea-stlf method on dataset.

Paper/Research	Methodology	Challenges
Agriculture data management	Remote sensing, precision agriculture	No specific sensor or IoT
Cropland agriculture	Crop classification	Not applicable for large areas
Sensors in agriculture	Digital Farming and sensors	Wide range of temperature and humidity
Soil moisture sensors and IoT	Disposable sensor and IoT	Long term stability
Multisensory data and analysis	Deep learning for UAV	Security and surveillance
Sensor network for rural agriculture	WSN, IoT, ZigBee	To be extended to large areas
Smart farming	Sensors and IoT	To be extended to large areas

the IoT and sensor systems can be helpful in smart agriculture because of certain indices utilized in this field.

These are some examples of major indices:

- Index for Evaporative Stress (ESI).
- Vegetation health index (VHI)
- Vegetation Index Enhanced (EVI).
- Standardized Anomaly Index (SAI).

In order to calculate the aforementioned indices or metrics, satellite-based Remote Sensing data is used. As an indicator of agricultural drought, the value of ESI is predicted to remain high, giving some indication of their significance. EVI demonstrates the improvement in the VHI, which measures the health of the vegetation. SAI is determined by combining the results of the other indices.

V. CONCLUSION

Precision agriculture has both financial and environmental benefits. That will eventually become the norm. Forecasting precisely when that day occurs is tricky. How quickly producer cadres learn and apply geospatial techniques will be a deciding element. The Upper Midwest Aerospace Consortium developed a novel learning community strategy in response to the challenges that have prevented agricultural producers from "catching on" to the technology's potential benefits. The manufacturers and scientists collaborate to develop the appropriate geospatial goods and make them available in near real-time, share expertise through structured training programs, and help each other find new applications, laying the groundwork for the technology's continued use and adoption. The number of companies that use these technologies has expanded substantially throughout the years. By their triumphs, the early adopters and inventors are now inspiring and guiding the rest.

This methodical review aims to bridge the gap between research and practice by focusing on precision irrigation, identifying significant obstacles and possibilities in areas that can be considered future research instructions of precision irrigation decision support systems. Our ideal precision irrigation decision-support system would use the most up-to-date technologies to irrigate every field in every region at a reasonable cost, and greater study in these areas would help get us there. New low-cost sensor networks and satellite fusion products with high spatial and temporal resolution offer great potential for expanding the usage of decision support systems for precision irrigation. Mechanically quantifying 'plant water stress' is proposed as a trigger to enhance irrigation conclusion by considering the interplay between soil water availability, atmospheric water demand, and plant physiological regulation. Observations and database design fusion methods should be used to analyze plant water connections for scaled fertigation systems. Adoption rates of new irrigation technology can be increased by the creation of adaptable tools and the rise of monetary incentives and support from governments.

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REFERENCES

[1] T. Ahamed, L. Tian, Y. Zhang, and K. C. Ting, "A review of remote sensing methods for biomass feedstock production," *Biomass Bioenergy*, vol. 35, no. 7, pp. 2455–2469, Jul. 2011.

[2] P. Defourny et al., "Near real-time agriculture monitoring at national scale at parcel resolution: Performance assessment of the Sen2-Agri automated system in various cropping systems around the world," *Remote Sens. Environ.*, vol. 221, pp. 551–568, Feb. 2019.

[3] E. Svotwa, A. J. Masuka, B. Maasdorp, A. Murwira, and M. Shamudzarira, "Remote sensing applications in tobacco yield estimation and the recommended research in Zimbabwe," *Int. Scholarly Res. Notices*, vol. 2013, Dec. 2013, Art. no. 941873, doi: 10.1155/2013/941873.

[4] X. Zhou, H. B. Zheng, X. Q. Xu, J. Y. He, X. K. Ge, X. Yao, T. Cheng, Y. Zhu, W. X. Cao, and Y. C. Tian, "Predicting grain yield in Rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery," *ISPRS J. Photogramm. Remote Sens.*, vol. 130, pp. 246–255, Aug. 2017.

[5] F. Tack, A. Merlaud, A. C. Meier, T. Vlemmix, T. Ruhtz, M. D. Iordache, and M. Van Roozendael, "Intercomparison of four airborne imaging DOAS systems for tropospheric NO_2 mapping—The AROMAPEX campaign," *Atmos. Meas. Techn.*, vol. 12, no. 1, pp. 211–236, 2019, doi: 10.5194/amt-12-211-2019.

[6] S. Esch, T. G. Reichenau, W. Korres, and K. Schneider, "Soil moisture index from ERS-SAR and its application to the analysis of spatial patterns in agricultural areas the analysis of spatial patterns in agricultural areas," *J. Appl. Remote Sens.*, vol. 12, no. 2, 2018, Art. no. 022206, doi: 10.1117/1.JRS.12.022206.

[7] B. Buchholz, B. Kühnreich, H. G. J. Smit, and V. Ebert, "Validation of an extractive, airborne, compact TDL spectrometer for atmospheric humidity sensing by blind intercomparison," *Appl. Phys. B*, vol. 110, no. 2, pp. 249–262, Feb. 2013.

[8] A. A. G. Hassan, I. Ngah, and S. D. Applanaidu, "Agricultural transformation in Malaysia: The role of smallholders and area development," *World Bank Agricult. Transformation Inclusive Growth*, vol. 15, no. 2, pp. 1–32, 2018.

[9] M. A. Khan, K. B. Marwat, H. Z. Umm-e-Kalsoom, Z. Hussain, S. Hashim, A. Rab, and K. Nawab, "Weed control effects on the wheat-pea intercropping," *Pak. J. Bot.*, vol. 45, no. 5, pp. 1743–1748, 2013.

[10] H. H. Ali, A. M. Peerzada, Z. Hanif, S. Hashim, and B. S. Chauhan, "Weed management using crop competition in Pakistan: A review," *Crop Protection*, vol. 95, pp. 22–30, May 2017.

[11] D. Prabakaran and K. Sheela, "A strong authentication for fortifying wireless healthcare sensor network using elliptical curve cryptography," in *Proc. IEEE Mysore Sub Sect. Int. Conf. (MysuruCon)*, Hassan, India, Oct. 2021, pp. 249–254.

[12] J. Delgado, N. M. Short, D. P. Roberts, and B. Vandenberg, "Big data analysis for sustainable agriculture on a geospatial cloud framework," *Front. Sustain. Food Syst.*, vol. 3, p. 54, Jul. 2019.

[13] J. K. Berry, J. A. Delgado, R. Khosla, and F. J. Pierce, "Precision conservation for environmental sustainability," *J. Soil Water Conserv.*, vol. 58, no. 6, pp. 332–339, 2003.

[14] A. Srinivasan, *Handbook of Precision Agriculture: Principles and Applications*. New York, NY, USA: Haworth Press, 2006.

[15] B. A. Aubert, A. Schroeder, and J. Grimaudo, "IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology," *Decis. Support Syst.*, vol. 54, no. 1, pp. 510–520, Dec. 2012.

[16] E. Pierpaoli, G. Carli, E. Pignatti, and M. Canavari, "Drivers of precision agriculture technologies adoption: A literature review," *Proc. Technol.*, vol. 8, pp. 61–69, Jan. 2013.

[17] C. Hedley, "The role of precision agriculture for improved nutrient management on farms," *J. Sci. Food Agricult.*, vol. 95, no. 1, pp. 12–19, Jan. 2015.

[18] R. Arridha, S. Sukaridhoto, D. Pramadihanto, and N. Funabiki, "Classification extension based on IoT-big data analytic for smart environment monitoring and analytic in real-time system," *Int. J. Space-Based Situated Comput.*, vol. 7, no. 2, pp. 82–93, 2017.

[19] G. R. Sinha, *Advances in Modern Sensors-Physics, Design, Simulation and Applications*. Bristol, U.K.: IOP Publishing, 2020.

[20] D. D. Koo, J. J. Lee, A. Sebastiani, and J. Kim, "An Internet-of-Things (IoT) system development and implementation for bathroom safety enhancement," *Proc. Eng.*, vol. 145, pp. 396–403, Jan. 2016.

[21] R. Hassan, F. Qamar, M. K. Hasan, A. H. M. Aman, and A. S. Ahmed, "Internet of Things and its applications: A comprehensive survey," *Symmetry*, vol. 12, no. 10, p. 1674, Oct. 2020.

[22] C. Ji, H. Lu, C. Ji, and J. Yan, "An IoT and mobile cloud-based architecture for smart planting," in *Proc. 3rd Int. Conf. Machinery, Mater. Inf. Technol. Appl.*, Qingdao, China, Nov. 2015, pp. 1001–1005.

[23] L. Tawalbeh, F. Muheidat, M. Tawalbeh, and M. Quwaider, "IoT privacy and security: Challenges and solutions," *Appl. Sci.*, vol. 10, no. 12, p. 4102, Jun. 2020.

[24] C. Brewster, I. Roussaki, N. Kalatzis, K. Doolin, and K. Ellis, "IoT in agriculture: Designing a Europe-wide large-scale pilot," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 26–33, Sep. 2017.

[25] S. Hadzovic, S. Mrdovic, and M. Radonjic, "Identification of IoT actors," *Sensors*, vol. 21, no. 6, p. 2093, Mar. 2021.

[26] E. Cordelli, G. Pennazza, M. Sabatini, M. Santonico, and L. Vollero, "An open-source smart sensor architecture for edge computing in IoT applications," *Proceedings*, vol. 2, no. 13, p. 955, 2018.

[27] T. Syrový, R. Vik, S. Pretl, L. Syrová, J. Čengery, A. Hamáček, L. Kubáč, and L. Menšík, "Fully printed disposable IoT soil moisture sensors for precision agriculture," *Chemosensors*, vol. 8, no. 4, p. 125, Dec. 2020.

[28] J. Rodríguez-Robles, Á. Martin, S. Martin, J. A. Ruipérez-Valiente, and M. Castro, "Autonomous sensor network for rural agriculture environments, low cost, and energy self-charge," *Sustainability*, vol. 12, no. 15, p. 5913, Jul. 2020.

[29] C. Koulamas and M. T. Lazarescu, "Real-time sensor networks and systems for the industrial IoT: What next?" *Sensors*, vol. 20, no. 18, p. 5023, Sep. 2020.

[30] M. Carminati, G. R. Sinha, S. Mohdiwale, and S. L. Ullo, "Miniaturized pervasive sensors for indoor health monitoring in smart cities," *Smart Cities*, vol. 4, no. 1, pp. 146–155, Jan. 2021.

[31] K. Makantasis, K. Karantzalos, A. Doulamis, and N. Doulamis, "Deep supervised learning for hyperspectral data classification through convolutional neural networks," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Milan, Italy, Jul. 2015, pp. 4959–4962.

[32] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 9, pp. 1904–1916, Sep. 2015.

[33] L. S. Galvão, A. R. Formaggio, and D. A. Tisot, "Discrimination of sugarcane varieties in Southeastern Brazil with EO-1 Hyperion data," *Remote Sens. Environ.*, vol. 94, no. 4, pp. 523–534, Feb. 2005.

[34] D. Li, S. Chen, and X. Chen, "Research on method for extracting vegetation information based on hyperspectral remote sensing data," *Trans. Chin. Soc. Agric. Eng.*, vol. 26, no. 7, pp. 181–185, 2010.

[35] B. E. Bhojaraja and G. Hegde, "Mapping agewise discrimination of arecanut crop water requirement using hyperspectral remote sensing," in *Proc. Int. Conf. Water Resour., Coastal Ocean Eng.*, Mangalore, India, Mar. 2015, pp. 1437–1444.

[36] P. Pereira, E. Brevik, M. Muñoz-Rojas, and B. Miller, *Soil Mapping and Process Modeling for Sustainable Land Use Management*. Amsterdam, The Netherlands: Elsevier, 2017.

[37] G. Metternicht, *Land Use and Spatial Planning: Enabling Sustainable Management of Land Resources*. New York, NY, USA: Springer, 2018.

[38] M. D. Nellis, K. P. Price, and D. Rundquist, "Remote sensing of cropland agriculture," in *The SAGE Handbook of Remote Sensing*. London, U.K.: Sage, 2009.

[39] J. Bell, E. Gebremichael, A. Molthan, L. Schultz, F. Meyer, and S. Shrestha, "Synthetic aperture radar and optical remote sensing of crop damage attributed to severe weather in the Central United States," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, United States, Jul. 2019, pp. 9938–9941.

[40] S. Najem, N. Baghdadi, H. Bazzi, N. Lalande, and L. Bouchet, "Detection and mapping of cover crops using Sentinel-1 SAR remote sensing data," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 17, pp. 1446–1461, 2024.

[41] C. Occhiuzzi, F. Camera, M. D'Orazio, N. D'Uva, S. Amendola, G. M. Bianco, C. Miozzi, L. Garavaglia, E. Martinelli, and G. Marrocco, "Automatic monitoring of fruit ripening rooms by UHF RFID sensor network and machine learning," *IEEE J. Radio Freq. Identificat.*, vol. 6, pp. 649–659, 2022.

[42] J. Daniel, R. Shyamala, R. Pugalenthi, and P. M. Kumar, "RANC-CROP recommendation attributed to soil nutrients and stock analysis using machine learning," *IETE J. Res.*, vol. 69, no. 11, pp. 8077–8089, Nov. 2023.

[43] D. Prabakaran and H. Sathyapriya, "A review on methodologies and performance analysis of device identity masking techniques," *Int. J. Sci. Technol. Res.*, vol. 8, no. 12, pp. 2018–2022, 2019.

[44] Y. Liu, N. Zhang, H. Guo, S. Huang, M. Huang, and S. Liu, "Spectral properties analysis of wastewater in oil field and its remote sensing detection with GF-2," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Waikoloa, HI, USA, Sep. 2020, pp. 1287–1290.

[45] Y. Xie, D. Feng, H. Chen, Z. Liu, W. Mao, J. Zhu, Y. Hu, and S. W. Baik, "Damaged building detection from post-earthquake remote sensing imagery considering heterogeneity characteristics," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 4708417.

[46] M. Leccisi, M. Cagnetti, F. Leccese, and G. S. Spagnolo, "Comparing routing protocols for WSN in agricultural scenario," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry (MetroAgriFor)*, Nov. 2021, pp. 80–85.

[47] M. Cagnetti, M. Leccisi, and F. Leccese, "A modified MPRR protocol for WSN in agricultural scenario," in *Proc. 10th Int. Conf. Sensor Netw.*, 2021, pp. 143–150.

[48] M. Maesano, F. V. Moresi, M. Greco, F. Leccese, M. Leccisi, E. D. Francesco, E. Brunori, R. Biasi, and G. S. Mugnozza, "Smart monitoring technologies for defining variability in vineyard microclimate, and vinegrape performances," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry (MetroAgriFor)*, Trento-Bolzano, France, Nov. 2021, pp. 17–21.

[49] M. Greco, F. Leccese, S. Giarnetti, and E. De Francesco, "A multiporpouse amphibious rover (MAR) as platform in archaeological field," in *Proc. TC4 Int. Conf. Metrol. Archaeol. Cultural Heritage (IMEKO)*, 2023, pp. 252–256.

[50] E. Petritoli, F. Leccese, and M. Leccisi, "Inertial navigation systems for UAV: Uncertainty and error measurements," in *Proc. IEEE 5th Int. Workshop Metrol. Aerosp. (MetroAeroSpace)*, Jun. 2019, pp. 1–5.
[51] E. Petritoli and F. Leccese, "Beamriding homing systems for UAV: New approaches and applications," in *Proc. IEEE 9th Int. Workshop Metrol. Aerosp. (MetroAeroSpace)*, Jun. 2022, pp. 560–565.

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