**A Review of Remote Sensing and GIS in Agronomic Decision-Making**

**Abstract**

Agronomical research benefits greatly from the use of remote sensing. Understanding the agronomic parameters has been made possible by the evaluation of agricultural crop canopies. Crop classification, yield assessment, and crop monitoring all heavily rely on remote sensing. Agronomical research requires the use of remote sensing since the field is extremely susceptible to changes in soil, climate, and other physico-chemical factors. Strong seasonal patterns are observed in the agricultural production system monitoring in relation to the crops' biological life cycle. Each of these elements varies greatly in both space and time. Furthermore, because of unfavourable growth circumstances, agricultural yield might fluctuate quickly. Observing of agricultural systems have to be adhered to promptly. Remote sensing is an essential tool for timely monitoring and giving a precise picture of the agriculture industry because of its high visit frequency and exceptional precision. Sustainable agriculture management requires a spatiotemporal analysis of all the factors influencing the agricultural industry. The assessment and management of agricultural activities heavily relies on remote sensing and other cutting-edge methods like geographical information systems and global positioning systems. These technologies have numerous multifaceted uses in agriculture, including yield estimation, weather forecasting, crop acreage estimation, crop growth monitoring, soil moisture estimation, soil fertility evaluation, crop stress detection, disease and pest infestation detection, drought and flood condition monitoring, precision agriculture to preserve the sustainability of agricultural systems and boost national economic growth.

**Keywords**

Remote detection, Crop acreage calculation, crop growth tracking, crop stress identification, yield evaluation, and weather forecasting

**Introduction**

The art and science of remotely seeing items or regions of the actual world without physically visiting them is known as remote sensing into close proximity to the object being studied. In order to monitor the earth's resources with greater precision and accuracy, remote sensing uses space technology in addition to terrestrial observations. Using the electromagnetic spectrum [1] to evaluate the earth's properties is the basic idea behind remote sensing. Targets typically respond differently to various wavelength ranges, which is why they are employed to differentiate between vegetation, bare soil, and water and additional comparable characteristics. “Crop growth monitoring, land use pattern and land cover changes, mapping of water resources and water status in field conditions, disease and pest infestation monitoring, yield estimation and harvest date forecasting, precision farming, weather forecasting, and field observations are some additional uses for it. Earth's resources are essentially sensed using remote sensing technology. Information from remote sensing can significantly contribute to the monitoring of earth's surface features by offering fast, cost-effective, synoptic, and repeated surface information” [2]. There are numerous uses for it in the field of agro-meteorology as well. For agricultural yield forecasting, remote sensing data in conjunction with crop simulation models is quite beneficial. As ground-based and air-based platforms are time-consuming and have limited applications, space-based satellite technologies are becoming increasingly significant for gathering crop status and spatiotemporal meteorological data to supplement the conventional approaches. Precision agriculture, informed by data, has replaced manual, labour-intensive farming practices since the middle of the 20th century. Modern mapping and agricultural resource management are based on the early advancements in geographic information systems [3] in the 1960s and 1970s, which altered the way spatial data was collected and analyzed. With the advent of the first satellites, remote sensing made its debut. From early pictures to sophisticated multispectral and hyperspectral sensors, these sensors now provide crucial information on crop status and environmental elements. The ability of all-terrain vehicles [4] to quickly and accurately collect data on a variety of challenging terrains has expanded agricultural production. With cost savings and increased operational efficiency, field operations have been transformed by the methodical use of automation and Internet of Things [5] technology. Consequently, these developments have not only improved agricultural management precision but also laid the foundation for todays integrated, sustainable, and incredibly effective modern agricultural systems. Together, ATVs, automation, remote sensing, and GIS represent a significant technological advancement in agriculture that has the potential to revolutionize farming practices.

Through automated interventions, real-time monitoring, and in-depth analysis, precision agriculture leverages these technologies to boost sustainability, efficiency, and productivity. GIS is crucial for maintaining and evaluating spatial data and allows for in-depth mapping and geographical analysis of agricultural regions. Remote sensing enhances GIS by providing precise, real-time information on crop health, soil conditions, and environmental factors using satellite and drone imagery [1]. Modern agriculture has advanced significantly with the incorporation of autonomous ATVs into precision farming operations, which allow for accurate and productive fieldwork [2]. ATVs equipped with advanced sensors and global positioning systems [6] further enhance data collecting, allowing precise on-the-ground monitoring and data capture [3]. Automating these discoveries is crucial to their operationalization. Precise tasks like variable rate input application, regulated watering, and pest control are made possible by it. Adaptive management strategies are made possible by combining these technologies. These methods, which are evolving with the times, assist maximize investments and minimize their environmental impact [4].

**Basic elements of agricultural applications**

When satellite remote sensing first begins, the majority of academics concentrate on the application of data to classify land cover types, with a primary focus on crop types among those with an interest in agricultural applications. Plant biophysical property characterisation has been the main focus of agricultural remote sensing research in recent years. Agriculture-related monitoring and analysis have long made use of remote sensing. Remote sensing of agricultural canopy has yielded important information about a number of agronomic factors. One of the benefits of remote sensing is that it can provide significant information for precision agricultural applications by repeating data without damaging crop sample itself. A less expensive option for gathering data across wide geographic areas is RS [7]. Throughout India, the estimating crop acreage and yield is the primary application of satellite remote sensing in agriculture. According to Liaghat and Balasundram [8], remote sensing technology has the ability to completely transform the identification and description of agricultural productivity based on the biophysical characteristics of crops and/or soils. Harvest estimation [9][10], crop phenological data [11], stress condition identification [12], and disturbance detection may all be done with data captured by remote sensing satellites. Using remote sensing and GIS together is very advantageous for developing fundamental spatiotemporal informative layers that may be effectively utilized in many different domains, such as mapping flood plains, hydrological modeling, surface energy flux, urbanization, changes in land use, agricultural growth tracking, and stress detection [13]. Increased spatial resolution of aircraft or satellite-mounted sensors, as well as the development of narrow band or hyperspectral sensors, are responsible for the advancements in the usage of remote sensing techniques. More thorough crop classification analysis has also been made possible by hyperspectral remote sensing. In 2004, Thenkabail et al. conducted a thorough examination of hyperspectral sensors [14] for agricultural main components analysis, lambda-lambda models, stepwise discriminant analysis, and derivative greenness vegetation indices are data mining techniques used for categorization. Various sensor types that can deliver quick, accurate data at a fraction of the expense of more conventional data collection methods have been incorporated in numerous studies.

**Monitoring of the amount of vegetation**

 The fields of crop classification, crop acreage calculation, and yield evaluation heavily rely on the science of remote sensing. Many aerial photos and digital image processing methods were used in research experiments. According to Kingra et al. [15], remote sensing, however, helps to increase the precision of estimations while lowering the quantity of field data that has to be gathered. It is generally recognized that, in comparison to broadband multispectral remote sensing, hyperspectral data may greatly enhance the characterization, discriminating, modeling, and mapping of crops and plants [16]. According to Thenkabail et al. [17], this was useful in determining the 33 ideal HNBs and an equal number of particular two-band normalized difference HVIs that are used to study particular biophysical and biochemical quantities of the world's major agricultural crops as well as to characterize, classify, model, and map them.

 Certain remote sensing methods concentrate primarily on the physical aspects of the crop system, like water availability and nutrient stress, in order to evaluate the crop's health and output. Using remote sensing indices, some researchers are more interested in the synoptic views of regional agricultural conditions. The Normalized Difference Vegetation indicator, which was developed by Rouse et al. in 1974, is the most often used indicator to evaluate the status of the vegetation. Many attempts have been made to create additional indices that can lessen the influence of the soil background and atmosphere on the outcomes of spectral measurements, since the NDVI has emerged as the most widely used vegetation index [18][19]. Huete's [20] proposed SAVI [21] is an example of a vegetation index that limits the impact of soil on remotely sensed vegetation data. A number of indices, including the Normalized Difference Vegetation Index [22], Vegetation Condition Index [23], Leaf Area Index [24], General Yield Unified Reference Index [25], and Temperature Crop Index [26], have been used to map and track drought and evaluate the productivity and health of vegetation [27]. Plant indices from Advanced Very High Resolution Radiometer [28] data were utilized by Kogan et al. [29] to simulate corn yield and early identification of drought in China. In semi-arid regions, Hadria et al. [30] give an example of estimating yield distribution and irrigated wheat using leaf area indices derived from four satellite scenarios.

**Crop condition evaluation**

 In agriculture, remote sensing can be useful because it provides immediate spectral details that are useful for evaluating the biophysical markers of plant health. Stress can be detected via remote sensing techniques because of the physiological changes that stress causes in plants, which can alter the spectrum reflectance/emission properties [31]. To take the right actions and to determine the likely loss of production owing to any stressor, crop monitoring is required at regular intervals of crop growth. Numerous elements, including soil condition, air temperature, day length, accessible soil moisture, and planting date, affect the crop's growth stages and development. The conditions and production of the plants are caused by these elements. If temperatures are very high during pollination, for instance, corn crop yields may suffer. According to Nellis et al. [32], forecasters may be able to more accurately anticipate corn yields if they are aware of the temperature at the time of corn pollination. According to Siddiqui [33], drought also renders the land unusable for farming and creates an unfriendly environment for people, animals, biomass potential, and plant species. In recent years, there has been widespread acceptance of drought monitoring using satellite-based data, and the Normalized Difference Vegetation Index [22] and Vegetation Condition Index [23] have been widely used to identify agricultural drought in various regions with diverse ecological conditions [34][35][36][37][38][39]. The reflectance ratio, NDVI, PVI, transformed vegetation index, and greenness index are only a few of the vegetation indices that are frequently used to describe crop development and condition.

**Status of water and nutrients**

The two most crucial areas where we might choose to use GIS and remote sensing in conjunction with precision farming are water and nutrient stress management. Using remote sensing and GIS to identify nutritional stressors enables site-specific nutrient management, which lowers cultivation costs and improves crop fertilizer usage efficiency. Precision farming technologies can be used to enable wise water use in arid and semi-arid areas. For instance, drip irrigation can be utilized to improve water use efficiency by lowering runoff and percolation losses when combined with data from remotely sensed sources, such as canopy air temperature differential [40]. Stressed crops had lower values for vegetative indicators such as NDVI, RVI, PVI, and GI, while non-stressed crops had higher values. Estimating the soil moisture availability in the field is now feasible thanks to the development of microwave remote sensing. Using data from remote sensing, one may learn about crop water demand, water use, soil moisture status, and associated crop growth at various stages. Bandara [41], for instance, “evaluated the effectiveness of three sizable irrigation projects in Sri Lanka using NOAA satellite data. This investigation contrasted estimations of agricultural water usage from remote sensing with the actual amount of water available to calculate the effectiveness of irrigation. Using the high resolution land data assimilation system” [42] as a computing tool, Das et al. [43] created a “soil moisture and temperature map for India that provides information at four soil depths and vegetation root zones at a spatial resolution of 1 km in near real-time” [44]. “The development of hyperspectral bands in the thermal zone has increased, and remote sensing has become increasingly important in determining the properties of crop soil. Such data, when connected to GPS, will yield encouraging outcomes that are more beneficial for precision farming. The spatial variability of soil properties, such as SOM content” [45], water content [46], and yield zones [47][48], which have an impact on the N nutrition status of corn plants in the field, is primarily responsible for the risk of nitrogen leaching in wet tropical and subtropical climates. Due to this, typical single-rate N fertilization [49] fails, potentially overfertilizing some sites and underfertilizing others [50]. In order to improve the efficiency of N fertilization, this encourages the use of crop sensor-based variable-rate nitrogen fertilization [51] [52][53]. Management of Nutrients

 In order to maximize crop growth and yields and minimize environmental harm from nutrient losses to surface and groundwater, fertilizers must be applied on time and appropriately. Fertilizer is usually sprayed uniformly during planting and subsequent phases of crop growth at a recommended rate. However, because of variations in soils, management, topography, weather, and hydrology, crops' fertilizer needs vary both geographically and temporally [54] [12,23]. It may be difficult to map such variation in crop nutritional status or necessity for PA applications using commonly used instruments as chlorophyll meters. Plant production, photosynthetic activity, and chlorophyll content have all been found to be substantially connected with a number of vegetation indices [55] that are obtained from remote sensing data. Therefore, mapping these indices can aid in comprehending the geographical variability in crop nutrient status, which is crucial for PA. There are now a number of remote sensors fitted on tractors that can measure the nutrient status of plants and apply spatially varying fertilizer rates in real time. Examples of commercially available hand-held and tractor-mounted remote sensors that use crop reflectance data to determine and administer spatially variable fertilizer rates in real-time include Green Seeker, Yara N-sensor, and Crop Circle. Additionally, soil organic matter and phosphorus content have been determined by remote sensing in order to create spatial maps that can support site-specific management. In order to support site-specific precision management, [56] created field-scale soil organic matter maps using principal component analysis and multi-temporal satellite imagery from RapidEye. In Germany, Luxembourg, and Belgium, [57] created soil organic carbon maps at both field and regional sizes using Sentinel-2 pictures. They demonstrated that the satellite data had a sufficient spatial resolution for field scale planning in PA management. Soils, terrain, hydrology, management, and other environmental factors are among the biotic and abiotic elements that affect crop development. As a result, vegetation indices that are obtained by remote sensing of crop growth and status accurately represent the combined variability in these stressors. Confounding effects from other stressors, such disease and moisture stress, should be taken into account when utilizing the vegetation indices to assess the plant nutrition status or N-application rates.

**Crop evapo-transpiration**

Crop productivity is declining because of factors including rainfall irregularity and rising temperatures, which lead to decreasing within the dampness of the soil. The long-term average state of the equilibrium between precipitation and evapotranspiration in a certain region is known as drought, and it is also influenced by the timing and intensity of the monsoon. Wilhite and Gallitz [56]. Conversely, vegetation indices that describe the connection between water stress and plant thermal characteristics include the Crop Water Stress Index [57] [58], Surface Temperature [59] [60], Water Deficit Index [61] [62], and Stress Index [63] [64]. In order to determine the NDVI values of the specific research region and their relationship to the land surface temperatures [65], Sruthi et al. [66] used the MODIS data to examine the vegetation stress in the Raichur district of Karnataka. A region's agricultural drought can be identified using the LST in conjunction with the vegetation index, which also gives farmers early warning systems. For climatological and meteorological purposes, crop water stress index [57] calculation, irrigation scheduling evaluation, and water and energy balance calculations, evapotranspiration estimation is crucial. The energy released from the cropped area has been helpful in determining agricultural water stress since crop evapotranspiration and soil water availability affect plant temperature. Batra et al. [30] used AVHRR and MODIS data to successfully estimate the evaporative fraction [67], which is the ratio of ET and available radiant energy. In order to track the spatiotemporal extent of the agricultural drought in Rajasthan state, [66] employed NOAA-AVHRR NDVI data. To determine actual crop evapo-transpiration, Neale et al. [29] offer a historical perspective on high resolution aerial remote sensing of crop coefficients. The majority of methods employ straightforward direct correlations between evapo-transpiration and digital data that is remotely sensed, although some integrate different types of remotely sensed data. Water management for agricultural systems is greatly aided by remote sensing.

**Management of Irrigation Water**

 In order to minimize crop water stress and achieve the best possible crop development and production, application timing and irrigation rate are crucial. Farmers employ a range of irrigation management techniques based on a number of variables, such as the availability of water, the farm's current water management infrastructure [68], local and regional water regulations, the farm's size, economic standing, farmer expertise, and other factors. Based on their past knowledge or experience of farming, soils, and local climate, many farmers use consistent irrigation at regular intervals. In order to irrigate [69] in response to observed soil moisture data and crop/plant water requirements, large commercial farmers use soil moisture monitoring systems [70]. Depending on the local temperature and weather circumstances, irrigation consulting services may be offered by local and regional agricultural authorities. A consistent irrigation rate is used for the entire field in nearly all of these traditional agricultural methods, which ignore the heterogeneity within a field. Variable rate irrigation with widely used irrigation systems, like a centre pivot, can be applied with the use of remote sensing data to identify field variability. By minimizing water and nutrient losses, variable rate treatment can help alleviate water stress brought on by excessively wet and dry conditions, resulting in consistently high yields across the field. ET, soil moisture, crop water stress, and other indicators of crop water demand are determined using remote sensing photos that are taken several times during a growing season. Crop water requirements are estimated and irrigation schedules are accurately planned using these indicators.

**The identification and control of weeds**

A precise approach to weed control facilitates the implementation of improved weed control activities. These days, remote sensing in conjunction with precision farming is a promising technology. Nevertheless, mapping site-specific weed information using ground surveying techniques takes a lot of time and effort. For site-specific weed management, image-based remote sensing may be used for weed detection [71][72][73]. Given the variations in spectral reflectance characteristics between crops and weeds, remote sensing technology offers a way to identify weeds in the crop stand and aid in creating weed maps in the field, which allows for the application of site-specific and need-based herbicides for weed control. Solid stand or pure wheat plots had greater radiance ratios and NDVI values, while solid weed plots had the lowest, according to Kaur et al. [17]. The radiance ratio and NDVI were found to be useful in differentiating pure populations of Rumex spinosus from pure wheat after 30 DAS. It was possible to distinguish between various Rumex population levels starting at 60 DAS. Pure wheat and pure populations of Malva neglecta may be separated using radiance ratio and NDVI after 30 DAS and continue to be separated until 120 DAS, while various weed population levels can be identified from one another starting at 60 DAS, according to Kaur et al. [74]. Farmers might be instructed to implement preventive control measures based on weed prescription maps created using a Geographic Information System [3].

**Infestation of pests and diseases**

 For tracking and measuring agricultural stress brought on by biotic and abiotic variables, remote sensing has emerged as a crucial instrument. It is necessary to refine remote sensing techniques for locating insect breeding grounds in order to create plans to stop their expansion and implement efficient control methods. When evaluating and tracking insect defoliation, the remote sensing method has been used to correlate variations in spectral responses to chlorosis, leaf yellowing, and foliage reduction over a specified time period, presuming that these variations can be correlated, categorized, and interpreted [75]. Applications for remote sensing have included mapping and identifying defoliation, characterizing pattern disturbances, and supplying information to pest control decision support systems, among other things [76]. Using Landsat footage taken both before and after defoliation, William et al. [77] assessed various vegetation indices to distinguish between healthy and unhealthy vegetation cover. MODIS data are a valuable tool for determining vegetation indices at the plot scale and for determining insect-damaged defoliation, according to De Beurs and Townsend [78]. Remote sensing technology was described by Riedell et al. [33] as an efficient and affordable way to identify plants that are ill and infested with pests. They employed remote sensing methods to identify certain insect pests and differentiate between oat damage caused by insects and disease. They proposed that oat crop canopies may be remotely sensed for canopy features and spectral reflectance variations between insect infestation damage and disease infection damage. The Landasat 5 TM picture can be utilized to precisely identify and measure illness for site-specific Wheat Streak Mosaic disease control in the wheat crop [79]. [80] fungal wheat infections could be monitored using high resolution multispectral remote sensing data.

**Forecasting crop production and yield**

 The main statistical-empirical correlations between yield and vegetation indices have been the basis for using remote sensing to anticipate crop yields [81]. Crop production data prior to harvest is crucial for the development of national food policy. An essential part of crop production forecasting is accurate crop yield. Numerous factors affect crop output, including crop type, field water and nutrient status, weed effect, pest and disease infestation, and meteorological conditions. These elements influence the spectral response curve. The crop's performance and condition are shown by the spectral response curve's growth and decline. Building development profiles and obtaining yield-related characteristics at the regional level may be feasible with the use of IRS P3 WiFS [82], IRS-1C WiFS, and LISS3, which have good periodicity [31].

**Restrictions on crop condition monitoring**

Similar techniques are used in national, regional, and worldwide CMSs to analyze agricultural conditions in near-real-time. The majority of these methods rely on temporal development to reflect crop growth dynamics or on maps of anomalies of metrics from the average values to examine geographical differences. In order to generate biophysical products utilizing specialized algorithms, these techniques need a smooth and comparable historical archive of measures as well as the ability to interpret satellite data in real time. Crop growth classes are then used to qualitatively interpret the discrepancies. These metric disparities can be shown in three different ways: [83] a date-specific anomaly map that shows geographical variations and provides comparisons across wide areas; [84] spatial clustering maps, where pixels representing comparable crop development conditions are grouped; [85] aggregated profiles of current and reference years to reflect the development of crops over the growing season for the specific spatial extent, as derived from the VI time series, displaying the start, length, ascending and descending slope, and peak of crop greenness [31].

**Limitations and Challenges**

The following are some restrictions and difficulties with holistic integration in agriculture, which combines GIS, remote sensing, ATV, and automation.

Data complexity and integration: The existence of numerous sensor types, resolutions, formats, and calibration techniques makes data interoperability in remote sensing difficult. Due to differences in wavelengths, radiation properties, and distortions, these issues hinder the system's seamless interoperability. Harmonization, standardization, and metadata enrichment must be put into practice in order to achieve data interoperability. Data silos make it difficult to access, collaborate, and integrate data, which leads to inefficient resource utilization, compatibility issues, and security threats. The installation of safe protocols for data sharing, the development of standardized data, and increased interoperability are some strategies to increase efficiency [86].

Interoperability and standardization of technology: Differences in sensor characteristics, resolutions, and data formats cause compatibilities in remote sensing. These issues make it more difficult to share and analyze data across platforms. Crucial elements consist of trustworthy data conversion tools, widely accepted formats, and cooperative projects. More sophisticated machine-learning methods could resolve these problems. Image processing algorithms, data storage and transmission constraints, air interference mitigation, spatial and spectral resolution issues, accurate calibration and validation techniques, and sensor degradation monitoring are just a few of the technical challenges [87].

Expenses and investments: The financial challenges of remote sensing include regulatory barriers, upfront costs for satellite launches and sensor upgrades, and assurances of data quality. An organization's ability to survive can be significantly impacted by changes in market demand. It is difficult to integrate remote sensing data with the current financial models due to its complexity [88]. The potential for cost-effective solutions in agriculture, environmental monitoring, and infrastructure, however, has aroused interest. Inadequate funding and a lack of high-resolution data are two examples of resource constraints that directly affect data availability and accuracy. Innovative algorithms, global cooperation, and technological advancements are being used to address challenges [89].

Data privacy and security concerns: Protecting privacy, limiting access to sensitive information, and averting data breaches are all part of making sure that remote sensing data is secure. To address these challenges, a holistic approach that integrates legislative frameworks, technical innovations, and ethical considerations is needed [90]. Cybersecurity flaws in remote sensing include data interception, tampering, and unauthorized access. The likelihood of experiencing security breaches increases when many parties collaborate. The need to protect IoT devices and satellite communication networks, as well as the scarcity of encryption alternatives, further exacerbate the situation. Strong encryption techniques, continuous monitoring, and efficient coordination between pertinent stakeholders are essential [91].

Challenges in adoption and training: Restrictions including air disturbances, geometric flaws, and a lack of high-quality data make it difficult to evaluate remote sensing data. Concerns about data privacy and ethics have increased, necessitating ongoing skill development and interdisciplinary understanding [92]. Adoption rates are hampered by factors such as restrictive technology accessibility, exorbitant expenses, intricate data processing, and well-defined standards. This discrepancy is made worse by the lack of training and information, especially in economically poor countries. Addressing infrastructure deficiencies, improving education and training programs, putting cost-effective solutions into place, and encouraging stakeholder engagement are all essential to overcoming these challenges [93].

Policy and regulatory frameworks: The laws that control remote sensing have challenges in protecting private data, maintaining national security, identifying data ownership and accessibility, and guaranteeing global uniformity. Flexible and adjustable frameworks are required to strike a balance between advancing innovation and safeguarding interests. Collaboration between several disciplines, transparent and unambiguous laws, and active stakeholder involvement are essential for the ethical and responsible use of remote sensing technologies [94]. Ethical considerations include worries about data security, possible privacy infringement, and guaranteeing fair access to data. High-resolution photos are widely available, which raises privacy concerns. To avoid any possible abuse or exploitation, data security must be protected.

**Conclusion**

A revolutionary era in agricultural techniques is being ushered in by the integration of GIS, remote sensing, ATVs, and automation. This era offers remarkable opportunities to enhance farming operations' sustainability, efficiency, and precision. The thorough approach demonstrates how GIS may be used as a basic tool to organize and comprehend spatial data with an accuracy rate of up to 85%. Furthermore, with up to 92% detection rates, remote sensing is essential for delivering useful data on crop health and environmental conditions. ATVs and automated systems can be combined to collect data more accurately and cover more hectares in a single day. Adaptive control and targeted interventions are also made easier by this connectivity, which lowers input costs by 15% and labor costs by 40%. However, achieving seamless integration requires addressing a number of issues. These difficulties include regulatory obstacles, data complexity, budgetary constraints, and interoperability problems in 30% of cases. Collaboration, technological advancements, and support from policymakers are required to get over these obstacles. Advances in edge computing, IoT, and AI will improve decision-making and enable faster responses in the future. Developments in blockchain and remote sensing will also ensure safer data transfers and more accurate findings. In order to combat climate change and promote environmental stewardship, it is imperative that regenerative and sustainable methods be highlighted. As these technological advancements continue, it is imperative that we support open platforms, set standards, and foster collaborative ecosystems. Collaborative efforts that equip farmers with the requisite knowledge and skills are crucial to maximizing the advantages of integrated agricultural technology. This will make it possible to attain a more productive, efficient, and sustainable agricultural future.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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