

HYPERSENSPECTRAL REMOTE SENSING FOR SUSTAINABLE AGRICULTURE

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Bentham Books

Hyperspectral Remote Sensing for Sustainable Agriculture

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ISBN (Online): 979-8-89881-396-3

ISBN (Print): 979-8-89881-397-0

ISBN (Paperback): 979-8-89881-398-7

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First published in 2026.

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PREFACE

Over the past decades, the challenges facing global agriculture—climate change, soil degradation, water scarcity, and feeding an ever-growing population—have made it very clear that traditional agriculture alone will not be sufficient. The demand for sustainable, efficient, and data-driven farming practices has never been more pressing. Hyperspectral remote sensing has assumed its position as a significant part of innovation among the many technological innovations shaping the future of agriculture. With its ability to capture and quantify intricate spectral information across hundreds of adjacent bands, hyperspectral imaging enables researchers and practitioners to detect subtle differences in vegetation, soil health, water stress, and more—long before they are apparent to the human eye. Coupled with recent advances in artificial intelligence and geospatial analysis, the possible applications for this technology in agriculture are nothing less than revolutionary.

This book, “Hyperspectral Remote Sensing for Sustainable Agriculture”, brings together a broad range of research works encompassing not only the theoretical foundations of hyperspectral sensing but also its actual applications along the agricultural value chain—from crop monitoring and disease detection to nutrient management and irrigation planning.

What makes this book especially valuable is the balance it achieves between depth and accessibility. It speaks to students and early researchers without oversimplifying the complexity of the subject, and, simultaneously, it offers veteran scientists and practitioners a thoughtfully chosen overview of the contemporary trends, challenges, and future prospects. The fact that artificial intelligence is included in most of the chapters shows the forward-looking nature of this work and how interdisciplinary approaches hold the key to achieving true agricultural sustainability. I commend the vision and academic effort of the editors and contributors in compiling this important work. This book contains resources, references, and, most importantly, calls for responsible innovation. I am confident that “Hyperspectral Remote Sensing for Sustainable Agriculture” will serve as a useful guide for academic researchers, practitioners in the field, and policymakers as well, and will continue to inspire innovations in this important field.

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CHAPTER 1

Advancing Smart Irrigation Practices in Small-Scale Agriculture by Combining Hyperspectral Remote Sensing with IoT Solutions

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Abstract: Technology in agriculture has advanced significantly over the past few decades. However, small and medium-sized agricultural enterprises often face challenges in accessing and adopting these technological innovations. In India, the majority of farmers are marginal or smallholders cultivating up to 2 hectares of land. Because the productivity of these agricultural systems is typically lower than that of large-scale operations, it is essential to manage resource requirements precisely to maximize benefits. Irrigation remains one of the most critical needs in all types of agriculture. Appropriate and cost-effective irrigation methods can enable farmers to improve yields while conserving resources. This study presents an integrated approach combining hyperspectral remote sensing with an IoT-based manual irrigation system tailored for small-scale agriculture. Hyperspectral imagery is leveraged to assess spatial variability in crop health, soil moisture distribution, and stress indicators across fields, providing actionable insights to optimize water application. The designed system consists of an epicyclic gear train arrangement powered by solar energy and interfaced with IoT technology. An advanced circuit incorporating an ESP8266 microcontroller is implemented to monitor key environmental parameters, such as soil moisture content, relative humidity, and air dry bulb temperature. The integration of hyperspectral data

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with real-time sensor measurements enables more informed irrigation scheduling and targeted water delivery. The system offers programmable control to maintain ideal soil moisture content at 80% saturation, supporting sustainable water management and improved productivity for small and marginal farmers. This combined strategy demonstrates the potential of merging hyperspectral remote sensing and IoT solutions to advance precision irrigation practices in smallholder agriculture.

Keywords: Epicyclic gear train, External source, Farmer, Hand pump, IoT, Irrigation, Technology.

INTRODUCTION

Water scarcity and the rising demand for food production worldwide pose challenges for agriculture. Traditional irrigation methods lead to inefficient use of water and wastage. The need for sustainable farming practices and the presence of unfavourable climatic conditions are driving the adoption of advanced irrigation systems. Markom *et al.* demonstrated the digital technological farming process using IoT and artificial intelligence [1]. They concluded that farmers are satisfied with technology-based irrigation and other methods for agriculture. Technological growth is therefore a suitable pathway for farmers towards sustainability, as also indicated in their work.

Naim, A investigated how cutting-edge computing tools and artificial intelligence can be used to address urgent environmental issues [2]. The study demonstrated that processing large amounts of information on biodiversity, resource management, and climate change using High-Performance Computing (HPC) can result in more precise modelling and forecasts. The author reviewed several case examples where AI systems enhance resource efficiency, improve environmental monitoring, and promote sustainable practices across various industries. The study also emphasizes the necessity of multidisciplinary cooperation and policy guidelines for the successful incorporation of these developments into sustainability initiatives.

Peng *et al.* examined the application of artificial intelligence to optimize multi-energy systems for rural areas [3]. Their goal was to encourage a sustainable energy economy and a green transition in rural energy planning. The authors proposed a model integrating AI with multi-energy optimization, leading to efficient and environmentally friendly energy systems. This research contributed to a more sustainable and green rural energy landscape.

Uddin *et al.* examined the basic ideas that define autonomous systems, describing how AI-powered analytics and IoT connectivity could simplify resource management and operating procedures [4]. They provide examples in fields including smart cities, smart agriculture, and factory automation, showing how

these technologies can support instantaneous decisions and adaptive reactions to environmental change. The report highlights several implementation challenges, including scalability, compatibility, and data security, and makes recommendations for future research directions to address these issues.

S. Neethirajan demonstrated the possible application of AI with big data to achieve net-zero carbon dairy production [5]. By improving feed efficiency, waste management, and animal health tracking, among other aspects of dairy production, these developments can increase productivity and ultimately reduce greenhouse gas emissions.

Alazzai *et al.* studied the application of AI and IoT in agriculture to optimize crop management [6]. The research demonstrated the potential of these technologies to maximize resources, boost production, and enhance agricultural efficiency, highlighting their role in promoting sustainable and productive farming practices.

Hussein *et al.* discussed the use of AI and IoT in agriculture, emphasizing their ability to maximize resource utilization, enhance crop production, and encourage more efficient and sustainable agricultural practices [7].

Matar *et al.* investigated advancements in intelligent modular agricultural systems, demonstrating how technologies such as data analysis, automated processes, and the Internet of Things can improve farm operations [8]. The authors advocate a modular strategy because it allows farmers to scale and adapt to different conditions. Key advantages include improved crop yields, reduced environmental impact, and efficient resource management. The paper also addresses challenges, including the need for farmer training and the cost of initial investment, ultimately presenting intelligent modular farming as a viable approach for sustainable agriculture to meet global food demands.

The conference proceedings focused on advances in data-driven computing and intelligent systems, with major areas of focus including new approaches such as extreme gradient boosting for ship classification and deep learning techniques for seizure detection and skin disease diagnosis.

Other significant studies focus on open innovation in the Greek food sector, the fusion of multiple sensors for detecting mental stress, and real-time object detection in aerial images. Also discussed are problems of energy efficiency in telecommunications and anti-forensic image processing. The range of research demonstrates the increasing influence of data-driven strategies in different domains, showcasing the potential to maximize sustainability, efficiency, and innovation. Akavova *et al.* delve into the importance of machine learning and AI for the progress of sustainable development [9]. They discuss how resources can

CHAPTER 2

Land Cover Classification Using Hyperion EO-1 Data: A Case Study in Uttar Pradesh, India**Neelam Dahiya^{1,*}, Nitin Arora², Sartajvir Singh³ and Gurwinder Singh⁴**¹ *Department of Computer Applications, Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India*² *University Institute of Engineering, Chandigarh University, Mohali, Punjab, India*³ *Centre of Excellence, Socio-Environmental Sustainability for River Sand-Mining (SEnSRS), Indian Institute of Technology, Ropar, Punjab, India*⁴ *Department of Computer Application, Chandigarh Group of Colleges, Jhanjeri, India*

Abstract: Hyperspectral imaging (HSI) gathers spectral information across hundreds of narrow bands, offering a rich source of data that can accurately detect and distinguish materials. It is increasingly used by researchers to address challenges in agriculture, snow and object detection, and environmental monitoring. HSI provides critical insights about the Earth's surface in specific spectral bands that are often beyond the reach of traditional multispectral imaging. Remote sensing is a powerful tool for monitoring Earth's surface changes on a global scale using HSI. To support a wide range of applications, classification algorithms are essential for identifying and categorizing key surface features. Therefore, it is important to investigate the impact of emerging classifiers on hyperspectral datasets. In this chapter, the performance of several machine learning classifiers, including Random Forest (RF), Maximum Likelihood Classifier (MLC), and Minimum Distance Classifier (MDC), was evaluated using HSI over Uttar Pradesh State, India. The results confirmed the effectiveness of RF (accuracy 90.20%) over MLC (accuracy 88.80%) and MDC (accuracy 86.60%). This research is significant for exploring the potential of hyperspectral imaging with various classification algorithms in developing applications.

Keywords: Hyperspectral Image Sensing (HSI), Hyperion Earth Observing-1 (EO-1), Machine Learning (ML), Remote Sensing (RS).

INTRODUCTION

Hyperspectral imaging (HSI) represents a significant advancement in remote sensing in terms of data and information acquisition. Unlike multispectral imaging

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systems, which capture data over a few large spectral bands, HSI collects data across hundreds of narrow, adjacent spectral bands, enabling the distinction of materials based on their spectral signatures [1]. The primary goal of HSI is to obtain the spectrum for each pixel in the image. Additionally, it enables the identification of diverse processes and objects. It is widely used in agriculture mapping, environmental monitoring, and mineral mapping due to its numerous advantages. In addition to the applications, it can also be used to monitor plant diseases and accurately estimate and grade field crops [2, 3].

NASA launched a hyperspectral sensor (Hyperion EO-1) under the New Millennium Program, a remarkable development in spaceborne hyperspectral remote sensing. It covers a spectral range between visible (0.4 μm and shortwave infrared (2.5 μm) and records 242 bands with a detailed spatial resolution of 30 meters. Nonetheless, because of the noise and interference in some bands, it is conventional practice to use 196 operational bands for analytical purposes. Hyperspectral data is big and complex; therefore, Machine Learning (ML) analysis has proven to be particularly successful [4, 5]. Unlike previous approaches used for image classification, which rely on communicating data through statistical methods, ML algorithms learn directly from data and improve their performance as more data becomes available. This makes them particularly well-suited to dealing with hyperspectral data, which is high in dimensions and complexity [6, 7]. Hyperspectral imaging has various application areas, such as soil degradation [8], disease detection, climate monitoring [9, 10], drought, moisture level, and leaf detection [6, 11, 12].

A major challenge in HSI classification is managing data dimensionality due to the large number of spectral bands. Therefore, it is required to implement a simple yet effective model to process the dataset. Classification algorithms play an essential role in categorizing features or objects on Earth and, as a result, producing themed maps based on the detected classes [13, 14]. Various studies have developed classifiers based on machine learning or deep learning to extract distinct class categories from multispectral or hyperspectral datasets [15, 16]. Furthermore, as the number of spectral bands increases, so do the processing needs. As a result, the type of dataset to be classified typically determines how well various classifiers perform.

The main aim of this work is to compare numerous machine learning algorithms using HSI over an agricultural area, *i.e.*, Uttar Pradesh State, India. To implement the classification algorithms, ENVI 5.2 software is used. It contains data preprocessing features such as noise, atmospheric correction, and spectral feature extraction, essential for processing the hyperspectral data. After the data has been pre-processed, standard machine learning algorithms like Random Forest (RF),

Maximum Likelihood Classifier (MLC), Minimum Distance Classifier (MDC), and nearest neighbor have been implemented to categorize the hyperspectral dataset into classes such as Deciduous veg, Dense veg, and Buildup. There are several uses for this research in soil detection, vegetation monitoring, and forestry. In addition, it can be utilized for weather monitoring, crop stress monitoring, and many other purposes. The integration of Machine Learning (ML) with HSI is also shown below in Fig. (1). It depicts the main components required for the integration of ML with HSI.

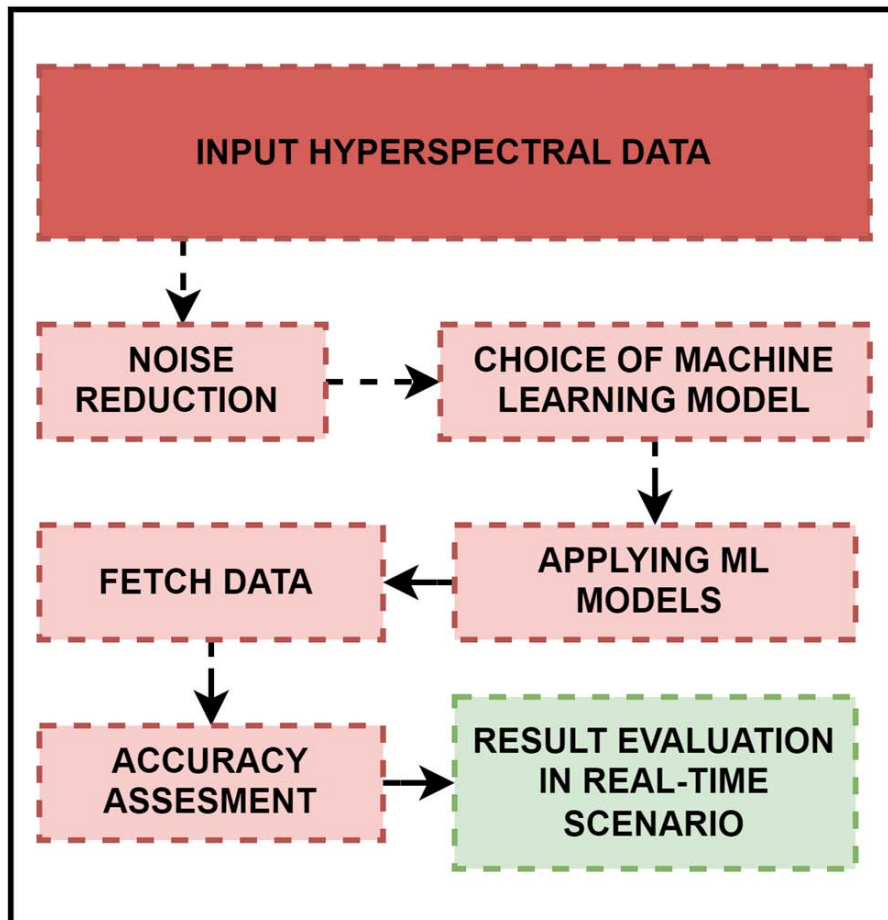


Fig. (1). Components involved in the integration of ML with HSI.

STUDY SITE AND DATASET

The current work has been accomplished over an agricultural area, *i.e.*, Agra (Uttar Pradesh State, India). The geographic location is marked on the map of India as shown in Fig. (2), on which the area of interest has been highlighted. The research

Emerging Trends and Challenges in Remote Sensing for Irrigation of Horticultural Crops

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Abstract: Remote sensing—using tools like satellites, drones, and ground sensors—has changed the way farmers manage irrigation for fruit and vegetable crops. These technologies let growers keep an eye on their fields in real time, tracking things like how much water the soil holds and how thirsty the plants are. Thanks to these advances, farmers can now use water much more efficiently—sometimes improving water use by 15–22%—by watering only where and when it is needed. Special imaging techniques, like hyperspectral cameras, help spot water stress in plants early, and Artificial Intelligence (AI) makes it easier to combine all this data and plan smarter irrigation schedules. Still, there are challenges, such as high costs for the best images and sensors, reliability issues in tough weather, and the difficulty of turning all this data into simple decisions. If we can make these tools cheaper and easier to use, they could help farmers everywhere save water and grow more, even as climate change makes things tougher.

Keywords: Drones, GIS, Horticultural crops, Hyperspectral imaging, Precision irrigation, Remote sensing.

INTRODUCTION

Getting water to fruit and vegetable crops is more important than ever, especially in places where droughts are common and the weather is unpredictable. Old irrigation methods—like just relying on rain or flooding fields—do not cut it anymore. They often waste water or fail to provide crops with what they need, which can result in yields up to 20% lower in dry areas.

That is where remote sensing comes in. With satellites, drones, ground sensors, and advanced cameras, farmers can now get detailed, up-to-date information about their fields. They can see which areas are dry, how much water is in the soil, and even how much water is evaporating from the plants. New tools, like hyperspectral cameras and AI-powered analysis, make it easier to spot water

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stress early—up to 30–40% more accurately than older methods. This means farmers can water more precisely, saving water and boosting yields.

This review examines the latest trends and challenges in the use of remote sensing for irrigation. It covers how different technologies—like satellites, drones with special cameras, and ground sensors—help monitor key things like soil moisture and plant stress. It also shares real-world examples, like how Australian vineyards used these tools to increase their yields by 10%. However, it does not overlook the tough parts: high costs, tricky weather, and the challenge of turning all this data into simple, helpful advice for farmers. The goal is to highlight what is working, what is not, and where research should go next to make these tools more accessible and sustainable, especially as water becomes scarcer.

LITERATURE REVIEW

Remote sensing has become a go-to tool for farmers who want to use water more wisely. Traditional irrigation methods, like surface or sprinkler systems, often waste 20–30% of water because they do not distribute it evenly. This section breaks down the latest advances in remote sensing—covering satellites, drones, ground sensors, hyperspectral imaging, and AI—and how they are helping farmers use water more efficiently, monitor plant health, and spot problems early. It also points out the main hurdles, like cost and weather.

Satellite-Based Remote Sensing

Satellites like Landsat, Sentinel-2, and PlanetScope give farmers a big-picture view of their fields. Sentinel-2, for example, can check in every five days and offers pretty detailed images (10–20 meters resolution). This helps track things like soil moisture and plant health using special indices. In India, for example, Sentinel-2 helped citrus farmers spot dry zones and cut water use by 15%. The catch? The best images can be pricey, and clouds can block the view. Plus, some satellites only pass over every couple of weeks, which is not always fast enough for changing field conditions.

UAV-Based Remote Sensing

Drones (UAVs) with regular, multispectral, or thermal cameras can fly low and capture super-detailed images (down to 5 centimeters). In Australia, drones helped vineyard owners spot water stress days before it was visible, letting them act quickly and boost yields by 10%. Drones with hyperspectral cameras can pick up even more detail, but they are expensive and need skilled operators. Battery life is also a limitation, with most drones only able to fly for 20–30 minutes at a time.

Ground-Based Sensors

Sensors stuck in the ground—like soil moisture probes and temperature monitors—give real-time, spot-specific data. For example, in Ethiopia, soil salinity sensors helped map out salty patches in sugarcane fields, improving irrigation by 15%. In Spain, soil moisture sensors confirmed what drones were seeing, making irrigation even more precise. The downside? These sensors only cover small areas, so they work best when combined with aerial data.

Hyperspectral Imaging in Irrigation Management

Hyperspectral cameras capture hundreds of colors, letting farmers spot early signs of water stress, nutrient problems, or disease. For example, in Brazil, using these cameras helped mango farmers cut water use by 14% without hurting yields. In California, they helped vineyard owners spot drought stress days before it showed up, saving 18% more water than older methods. The main problem is cost—these cameras can cost \$10,000 to \$50,000—and the data is complex, often needing cloud-based software to process Table 1.

Table 1. Comparison of hyperspectral and multispectral imaging.

Feature	Hyperspectral Imaging	Multispectral Imaging
Spectral Bands	Hundreds of very narrow bands (1–10 nm wide)	A handful of broad bands (50–100 nm wide)
Applications	Early stress detection, detailed plant health, and advanced indices (WBI, NDWI, PRI)	General crop monitoring, basic stress detection, common indices (NDVI, SAVI)
Spatial Resolution	Drones: 0.5–5 meters; Satellites: 10–30 meters	Drones: as sharp as 5 cm–1 meter; Satellites: 10–20 meters
Cost	Expensive: \$10,000–\$50,000	More affordable: \$1,000–\$10,000
Example	Helped California vineyards cut water use by 15%	Widely used for everyday crop monitoring

How AI and Machine Learning are Changing the Game

Artificial Intelligence (AI) and Machine Learning (ML) are making remote sensing even smarter. Instead of farmers or experts having to sift through mountains of data, AI can now do the heavy lifting—analyzing images, spotting patterns, and even predicting when and where to irrigate.

For example, in Australian apple orchards, a type of AI called Random Forest was used to analyze hyperspectral images and could spot water-stressed areas with 92% accuracy. This led to a 20% improvement in water use efficiency. In India,

Role of Remote Sensing and Geographic Information System (GIS) in Integrated Pest Management (IPM)

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Abstract: Insect pests are recognized as a significant global threat to agricultural productivity. Preventing and managing insect infestations is critical to minimizing these impacts. The recognition, categorization, and management of insect pests are crucial to prevent substantial losses. Employing manual ways to practice the process is laborious and not as efficient in accomplishing the objective. Traditional pest management techniques frequently struggle to adapt to the dynamic behaviors of pests, resulting in considerable crop damage and excessive reliance on chemical treatments. This ongoing global challenge can be effectively addressed through the integration of precision agriculture technologies, such as Remote Sensing (RS) and Geographic Information Systems (GIS), within the framework of Integrated Pest Management (IPM). RS and GIS technologies have demonstrated significant utility in monitoring pest occurrences, enabling timely and informed decision-making in pest control strategies. These tools offer rapid and large-scale access to real-time spatial data on insect populations, which enhances the effectiveness of IPM practices. The combined use of GIS, GPS (Global Positioning System), and RS provides valuable spatial insights into pest population dynamics, enabling surveillance across broad geographic areas and over time. Moreover, hyperspectral imaging—a cutting-edge form of remote sensing—further enhances pest detection and classification capabilities. By capturing data across hundreds of narrow spectral bands, hyperspectral sensors can detect subtle physiological changes in plants caused by pest stress before visible symptoms appear. This allows for early intervention, improved pest identification, and more precise application of control measures, thereby reducing unnecessary chemical usage and im-

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proving crop health outcomes. This chapter explores the application of RS and GIS in IPM, highlighting their role in pest surveillance, outbreak prediction, pest distribution mapping, and yield loss assessment due to pest attacks. In addition, it introduces the basic working principles behind these technologies and discusses the emerging role of hyperspectral imaging in advancing pest monitoring and management.

Keywords: Geographic information system, Integrated pest management, Pest monitoring, Pest mapping, Pest forecasting, Remote sensing, Sensors, Yield loss assessment.

INTRODUCTION

As reported [1], between 20 and 40 percent of global crop production is lost annually to insect pests and diseases, resulting in economic losses exceeding USD 220 billion worldwide. These insect pests damage the plants and thereby induce them physiologically to produce symptoms. Generally, plants respond to insect attack in numerous ways by developing symptoms including chlorosis, wilting, leaf curling, leaf crinkling, necrosis of photosynthetic tissues, stunting, or, in extreme instances, a decrease in leaf area due to substantial defoliation. Prompt identification and evaluation of these damage symptoms are highly important. Conventionally, the assessment of pests and diseases in crop plants is carried out through a visual method, relying on human observation and judgment to determine their presence. However, the drawback of this traditional approach is that it tends to be both time-consuming and labor-intensive. In this regard, precision agriculture involving Remote Sensing (RS) and Geographic Information System (GIS) paves the way for automated recognition, diagnosis, and quantification of pests and diseases, thereby easing pest management tactics. RS tools clearly quantify and monitor electromagnetic radiation changes in insect-infested plant canopies with high accuracy, speed, and reliability.

RS techniques primarily rely on the acquisition and decoding of sensory data around the surface of the Earth without having significant direct contact with it [2]. RS mostly relies on electromagnetic radiation, which determines data collection and interpretation. This method is employed to measure and keep track of the reflection and transmission of electromagnetic energy from the intended zone utilizing the sensor equipment. On the other hand, GIS provides resources for the archive, access, interpretation, and presentation of geographical information as well as images. Geospatial data pertains to all data regarding a specific geographical region of the Earth. Information can be gathered and presented by means of GPS-enabled portable devices and GIS software. In this scenario, pest and crop field data are gathered and represented in shapefiles. After data gathering, individual shape files are presented as vector forms inside a specified coordinate system to provide a geo-referenced map of the spatial data

and photographs. Significant RS applications documented across diverse domains encompass agriculture, meteorology, forest ecosystems, hydrology, pest control, and the marine environment (Fig. 1). Both GIS and RS, as precision agriculture technologies, empower farmers to assess the spatial-temporal heterogeneity of different key variables affecting plant health and yield. Data obtained from sensors are aggregated on digital devices for decision-making purposes [3].

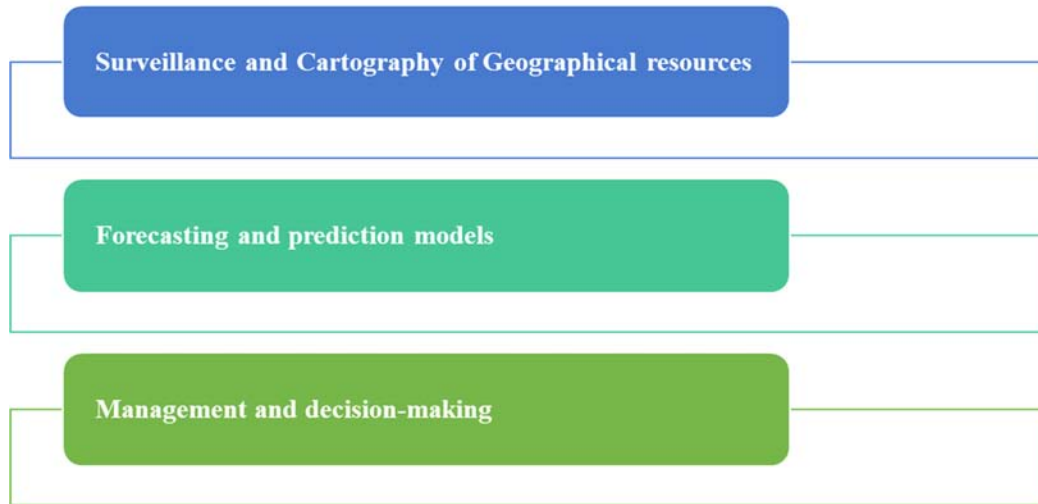


Fig. (1). Applications of remote sensing.

Currently, RS technologies are deployed on navigation satellites and utilize multi-spectral imaging technologies, which provide a comprehensive perspective, rapid assessment, high precision, and coverage of unreachable regions, in contrast to traditional surveillance and mapping approaches. Moreover, several studies in crop protection possess spatial dimensions, including the examination of the spatial ecology of insect pests, their host plants, and their entomophagous insects within and among crops. This information might be additionally connected across landscape elements to enhance knowledge of the pest's population dynamics. Spatial analysis facilitated by GIS tools can aid in managing insects at both local and regional scales, including forecasting the spatiotemporal pattern of insect pests [4], by employing GIS-based multi-spectral imagery to enhance pest monitoring for targeted pesticide implementation [5], and identifying insect infestation in crop agricultural fields [6]. In this view, this chapter examines the implications of RS and GIS in Integrated Pest Management (IPM), focusing on the implementation of these precise technologies for pest monitoring, mapping, outbreak prediction, and assessment of yield loss resulting from pest infestations. This chapter also encompasses the fundamental principles and practical concepts related to RS and GIS, along with their potential applications in IPM.

CHAPTER 5

A Smart IOT-Based Framework for Predictive Crop Health Monitoring and Precision Farming**Hashmat Fida^{1,*}, Jaspreet Kaur², Binod Kumar Mishra² and Vinod Kumar²**¹ *School of Computer Science and Engineering, Presidency University, Bangaluru, India*² *Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, India*

Abstract: This chapter focuses on a novel IoT-based framework designed to help improve precision farming by closely monitoring soil and crop health. The system aims to reduce physiological disorders in crops through real-time data gathering, analytical machine learning, and automated alerts. Continuous data gathering regarding the soil conditions and the crop health parameters is carried out through the network of field sensors, which are then processed *via* a centralized system using advanced algorithms. Insights derived from the framework are sent to farmers through an easy interface that empowers farmers to make data-based decisions and interventions in time. Connecting this with already established farm management systems enables integrated precision agriculture. This encompasses improving resource efficiency, preventing crop diseases, boosting crop yield, lowering costs, and enhancing sustainable farming. This research is a benchmark in agricultural technology that could transform crop management practices and usher in enhanced productivity and sustainability on the farm. The system's prediction and preventive measures of possible occasions, enabling a farmer to act before they occur, will revolutionize modern farming ways around sustainable food production.

Keywords: Application programming interface, Crop health, IoT, Precision agriculture, Soil moisture, XG-Boost.

INTRODUCTION

Agriculture is one of the oldest and most important of all industries, and it is facing unprecedented challenges posed by rapid population growth, environmental pressures, and increasing food production demand. Traditionally, farming had been dependent on human experience and intuition, complemented by periodic manual inspections in the farming field. Still, farming is promptly transforming into a more scientific, data- and tech-based industry, in which

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farmers continue to apply already-established knowledge and operational practices in managing their fields. The integration of smart technologies into the farming system has transformed the way farmers have historically managed their fields. One of the most promising transformational technologies is the Internet of Things (IoT), which is changing the way that precision agriculture is being implemented and practiced. The present research provides an IoT-driven precision agriculture framework in the form of an advanced technology that monitors based on the most complete soil and crop health indicators to proactively manage physiological stress that results in crop disorders.

The research is motivated by the increased need for farmers to register, track, and respond to soil and crop real-time health indicators to allow for data-based responses to achieve effective resource optimization and maximize crop yield. Using emerging IoT technologies, the system retrieves, processes, and analyzes the data collected from a variety of sensors within the field. This continuous flow of data provides farmers with real-time information on crop health, environmental status, and resource needs. The advancement emphasizes a need to mitigate the space between conventional traditional farming agricultural practices and future farming as a smart agriculture filled with technology, strongly rooted in agronomic knowledge, promoting efficiency, sustainability, and productivity.

The study integrates the principle of remote sensing using IoT-ground sensors, drone multispectral photography, and likely satellite integration. In comparison with traditional remote sensing methods utilizing the majority of information from satellites, this chapter is focused on obtaining high-accuracy real-time information using UAVs and sensor systems deployed on site to have accurate precision farming, accompanied by prompt detection of disease and predictive capabilities.

Precision Agriculture and its Importance

Precision agriculture is a farming management concept that relies on deliberate observation, measurement, and response to inter- and intra-field variability in crop growth. Its goal is to dial in the returns on inputs and irrigate sparingly so that more water can be preserved. To achieve this, precision agriculture considers the fact that no two parts of a field are the same. Soil fertility, moisture, and a dozen or so other aspects can change drastically within a single farm. By delivering the same amount of water, fertilizers, or pesticides throughout the field, a farmer might either not give enough to the parts that need it or give too much to others, potentially polluting the environment.

With modern farming growing increasingly complex with factors like climate change, soil degradation, water scarcity, and worms causing crop havoc, there is a need for more sophisticated ways of evaluating the conditions. The conventional

method of assessing soil and crop vitality – visually examining and laboratory testing the soil – consumes time, and much like checking a thermometer, the true condition of soil and crop may have already changed over time. Farmers are also frequently compelled to base their assumptions on their historic experiences, rules of thumb, and periodic tests, which can be too late or too early with the changing seasons.

This is where IoT comes into the picture. With IoT, an interconnected system of devices is able to talk to each other and exchange data. Smart sensors that assess temperature, acidity, and fertility could help farmers see in real-time about the moisture levels, when disease is appearing, or before the plant starts wilting. Due to the ability to capture data at a granular level, IoT can give a detailed picture of a farm that allows for informed decisions.

Remote sensing is important in precision agriculture since it helps farmers observe crop health, soil status, and the environment at various scales. Airborne drones with spectral sensing, which provide real-time measurements of plant health, are used in this study to combine remote sensing. As a high-resolution remote sensing system at the farm scale, IoT-based ground sensors also continuously consider significant agronomic aspects. In precision agriculture, several technologies work in tandem to facilitate data-driven decision-making.

The Role of IoT in Precision Agriculture

IoT technologies have fundamentally transformed the quality of precision agriculture with real-time monitoring of farm conditions. An IoT-based system can monitor, capture, and analyze data across various parameters, such as soil moisture, temperature, humidity, light exposure, nutrients, *etc.* Cloud computing and data science analytics are then utilized to derive recommendations for farmers based on the data. The data made available from an IoT system is vital to assist farmers in early decision-making regarding crop health, which affects early intervention in less than two to three days.

The proposed IoT ontology for precision agriculture is an IoT implementation that focuses on education that is precise for all aspects of soil health and crop health, providing farmers with continual feedback so they can modify farming practices in this critical time of crop development. For instance, when the soil sensors alert farmers that the soil moisture level is declining, the farmer can bear with the notification and irrigate their plot long before experiencing a soil moisture deficit that might stress crop water levels as a result of prolonged dry soil conditions. Similarly, when soil nitrogen levels show there is a deviation below the optimal level, the system may identify what level of nutrients should be fertilized based on the values that are stored in the application from prior periods.

CHAPTER 6**Precision Agriculture Practices for Crop Yield Management with AI Models****Rishikesh Ratan^{1,*}, Arshdeep Singh¹, Krishna Rawat², Danish Monga¹, Adarsh Tripathi¹, Sakshi Sinha³, Jyotsana Patel¹ and Amish Goyal¹**¹ *Department of Agricultural and Food Engineering, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal, India*² *School of Water Resources, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal, India*³ *Department of Dairy Sciences and Food Technology, Banaras Hindu University, Varanasi, 221005, Uttar Pradesh, India*

Abstract: Advanced computational techniques have revolutionized precision agriculture by enabling information-based strategies and forecasting algorithms for optimizing crop yield. This chapter discusses the integration of artificial intelligence models, such as machine learning and deep learning, with precision farming techniques to reduce ecological footprints and increase agricultural productivity. Some of the main topics are the use of Remote Sensing (RS), Geographic Information Systems (GIS), Global Positioning System (GPS), and Internet of Things (IoT) technologies to monitor agricultural productivity, weather patterns, and soil conditions on a continuous basis. AI applications under scrutiny include predictive modelling and optimisation methods for crop productivity forecasting. This chapter further discusses the issues of incorporating AI in agriculture, specifically with regard to data precision, computational power, and economics, while highlighting emerging solutions and future developments. The ultimate target is to exemplify AI's revolutionary capacity to be used in farming activities, aimed particularly at the rising necessity of environmentally responsible food production that would respond to global problems, including climate change and population growth.

Keywords: Artificial intelligence, IoT, Machine learning, Precision farming, Remote sensing.

INTRODUCTION

Agriculture, a prime economic growth driver of most nations, continues to satisfy humanity's most basic food and fibre needs. In the previous century, the greatest

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changes in the agricultural environment were made through technological breakthroughs, above all the Green Revolution [1 - 3]. Precision agriculture has emerged as a key technology, employing state-of-the-art sensors and analytics to help farmers maximize crop output and apply sophisticated field practices. The growing adoption of remote sensing technologies in farm productivity management and nitrogen application enhances yields while reducing operational costs and energy consumption. This concept highlights the importance of meeting immediate and long-term nutrient and crop production goals. Various factors, including water levels and temperature, significantly impact plant health [4]. PA permits a farmer to ascertain the exact characteristics required for optimal crop health, pinpointing specific locations and quantities of nutrients at any given time [5]. Hence, it is a viable method to guarantee global food security.

The increasing need for higher food production, driven by unsustainable agricultural methods, along with climate change and urban expansion, is rapidly reducing arable land availability and impacting the sustainability by affecting both productivity and the environment [6]. Crop growth and productivity need to be monitored in order to know how the crops react to environmental factors and agronomic practices. Monitoring crop growth and productivity is necessary in order to establish effective management measures for field operations and timely intervention [7]. Crop growth and health indicators, such as Leaf Area Index (LAI) and biomass, are integral parts of predictive models for predicting crop yield. Nonetheless, physical or optical *in-situ* methods of LAI estimation tend to be labour and time-intensive [8]. Similarly, conventional field measurements of biomass entail destructive sampling and are a matter of much effort and expense. RS measurements of some crop growth parameters like LAI and biomass are essential inputs; thus, they need some description of site-specific conditions (soil type and topography, *etc.*). This enables water and nutrient management optimisation and stress factors, such as disease and deficiencies [9].

AI-enhanced agriculture is the implementation of advanced technologies, including but not limited to Machine Learning (ML), data analytics, and automation, to optimise and maximise agricultural operations. This ability of AI is crucial for addressing global food challenges, including the effect of water scarcity and water quality issues on the growth of crops and food safety [10, 11]. AI combined with the power of the Internet of Things (IoT) has already changed the way farmers can conduct their operations, allowing them to monitor and make decisions based on real-time data [12]. Precision agriculture is arguably the most common example of this technological synergy in India, where agriculture accounts for more than 18% of GDP and provides a livelihood for well over 50% of the working population. The AI technologies are changing traditional methods of precision agriculture to data-driven and science-based approaches to manage

crop yields. This chapter covers an overview of precision agriculture and implementation aspects of the tools, including sensors, IoT, GPS, and satellite imaging. It briefly explains AI algorithms, highlighting their uses in soil analysis, crop health monitoring, and weather forecasting. It also presents the real-life case studies on the economic and environmental advantages of these technologies, and future developments with sustainable, efficient, and environmentally friendly farming solutions globally.

TECHNOLOGIES ENABLING PRECISION AGRICULTURE

In the last few years, precision agriculture has been part of renovating the systems used in the agricultural industry, which has allowed farmers to make location-specific and data-driven decisions. These technologies in agriculture have enhanced productivity, improved resource use efficiency, and reduced degradation. Precision agriculture relies on advanced technologies that enable precise monitoring, analysis, and management of agricultural conditions [13]. By using real-time information, these technologies enable farmers to easily detect problems in the initial stage and make sound decisions. PA integrates various technologies, including sensors and IoT devices, GPS and GIS systems, along with remotely sensed satellite imagery. Each of these technologies is important to the development of highly efficient agricultural systems, which is driven by data [14].

Precision Farming relies on the interdependent installation of sensors and IoT systems, which systematically amass critical data throughout a plethora of agriculture parameters, including moisture in soil, temperature, nutritional values, and crop fitness. The sensors allow real-time collection of information, giving farmers additional situational awareness and enabling them to solve emerging problems immediately and thus achieve optimal field health and output. Soil moisture sensors measure the volumetric water content of the soil so that farmers can use precision irrigation methods that dictate the time and location of irrigation [15]. Farmers are thus able to apply irrigation accurately where needed, saving water, reducing over-irrigation, and promoting good root growth, ultimately leading to higher yields. Traditionally, gardeners would check soil data, such as nitrogen, phosphorus, and potassium (NPK) levels, and the acidity of the soil, by checking nutrient and pH sensors. Such accurate diagnostics result in accurate fertiliser application, optimising nutrient use efficiency while minimising the environmental damage caused by excessive chemical application [16]. Climate sensors that track variables like temperature, humidity, and light intensity provide essential microclimatic data, allowing farmers to synchronise planting, irrigation, and harvesting with ideal environmental conditions. These sensors, integrated *via*

Land Cover Classification in Bhatinda and Comparative Analysis of Machine Learning Algorithms Using Google Earth Engine

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Abstract: Agriculture in Bhatinda, Punjab, a key part of India's grain belt, supports the economic base through crops like wheat and cotton. Hyperspectral image analysis using Hyperion imagery provides in-depth information about crops, soil, and water, aiding in sustainable cultivation. The hyperspectral image analysis makes it easy to identify some major problems in water supply management, urbanization, and wasteful resource usage in agriculture. This study classifies land cover (vegetation, urban areas, and water bodies) in Bhatinda using Google Earth Engine and compares the performance of four machine learning algorithms: Random Forest, Support Vector Machine (SVM), Gradient Boosting Trees (GBT), and Classification and Regression Trees (CART). Results show that CART with 97.01% accuracy and 95.51 Kappa works best in vegetation, while others work best in individual classes (e.g., RF with 95.52% in water bodies). This study contributes to the benefits of agriculture by providing precise land cover maps, aiding in resource planning, and guiding sustainable approaches in Bhatinda's dynamic environment.

Keywords: Agriculture, Google earth engine, Hyperspectral images, Land cover classification, Regression, Water bodies.

INTRODUCTION

Farming in the present era has several challenges, like growing more food with less water, land, and chemicals. Sustainable agriculture involves new ways of smart farming, so that nature can remain healthy for future generations [1]. This

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can be achieved by Hyperspectral remote sensing. It gives the farmers and scientists a way, which allows them to gain information about crops, soil, and water with the help of advanced technology like Hyperion. By sensing light in hundreds of narrow bands, it shows them just what's happening on the ground—whether crops are thriving, where water has collected, or how much land is covered by urban areas and not fields, *etc* [2, 3].

Land cover classification takes it a step further. It distinguishes between vegetation, urban land, and water bodies by analyzing fine details in light. In a place like Bhatinda, Punjab, where agriculture is a primary means of livelihood, these details are particularly important.

In this chapter, it is described how such a technology, in conjunction with software like Google Earth Engine and machine learning, can be utilized to understand Bhatinda's landscape better. It is about using science to make farming sustainable, and it starts with a different way of looking at land [4 - 6].

Hyperspectral remote sensing means looking at Earth from space using specialized cameras that capture hundreds of tiny slices of color, much more than our eyes can see or regular cameras can capture. Unlike earlier methods that use only a few broad colors—red, green, and blue—hyperspectral imaging slices light into very narrow bands, giving a close-up look at what is on the ground. It can be applied by scientists and farmers to analyse crops without ever entering a field. It can ascertain whether plants are stressed, water-stressed, or in perfect health by picking up subtle variations in color patterns that would be impossible to spot otherwise. It is also effective at identifying what is in a field—crops, weeds, or bare ground—and how much land it occupies. This aids in planning more productive farming techniques and water management, and in ensuring crops develop to their full potential without wasting resources. The hyperspectral remote sensing offers a clear, high-resolution view from overhead, making agriculture smart and sustainable [7, 8].

Importance of Land Cover Classification in Bhatinda, Punjab

Land cover classification, differentiating and mapping land as vegetation, urban land, or water bodies, plays an important role in landscape comprehension and management, particularly in agricultural regions like Bhatinda, Punjab. The region, which forms part of India's grain belt, relies heavily on agriculture, with wheat and cotton crops propelling the economy. Urbanization and inconsistent water supply, however, pose a challenge to sustainable land use. Vegetation classification indicates the health and extent of croplands, and farmers can use it to increase production and ensure soil health. Urban map monitoring indicates urban extent into cultivatable land, a concern in Punjab because it undermines

food security. Differentiating water bodies, such as canals and reservoirs, aids irrigation planning and keeps water resources essential to agriculture in this semi-arid region in perspective. Bhatinda offers a good case study because it represents these competing demands—agriculture, urbanization, and water management—such that it becomes imperative to have accurate land cover data to make effective choices and ensure sustainable growth [9, 10].

Google Earth Engine (GEE) as a Tool

Google Earth Engine (GEE) is a cloud platform for processing and analyzing huge amounts of geospatial data [11]. It provides access to a lot of satellite imagery, including hyperspectral imagery such as Hyperion, and high-performance computational tools to conduct analyses at a huge scale that would be impossible with regular computers. GEE simplifies tasks, such as image preprocessing, classification, and mapping for researchers with a simple interface and pre-existing algorithms. It is particularly useful for processing across huge areas and timeframes to study dynamic environments such as Bhatinda's, whose land cover change reflects human and environmental pressures. It enables rapid, scalable analysis that encourages studies to inform sustainable resource management with timely, accurate findings [12, 13].

Research Objectives

This chapter has two main objectives. First, the chapter aims to classify land cover in Bhatinda, Punjab, using Hyperion hyperspectral imagery, with emphasis on distinguishing vegetation, urban areas, and water bodies (*e.g.*, lakes, water storage). The high spectral resolution in Hyperion provides a rich source of information to capture unique features and enable high classification accuracy. Secondly, the chapter compares four machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Trees (GBT), and Classification and Regression Trees (CART)—implemented in GEE. By applying these algorithms to a common Hyperion dataset, the study compares them in terms of reliability and accuracy to map land cover. This comparison not only outlines each algorithm's merits and demerits but also provides real-world guidance for selecting appropriate tools in similar agricultural landscapes, encouraging the application of remote sensing in sustainable agriculture.

STUDY AREA

In this chapter, Bhatinda, Punjab, is taken as the study area, as shown in Fig. (1).

Bhatinda, in southwestern Punjab, India, lies at approximately 30.21°N latitude and 74.95°E longitude, covering a flat, alluvial plain typical of the Indo-Gangetic

Significance of Remote Sensing in Optimizing Fertilizer Use for Nutrient Mapping

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Abstract: With a drastic growth in the population of the world, the food demand has also increased substantially; to address this, current farming systems must be optimized for maximum yields. Given that it is not always feasible to expand agricultural land, we must find a solution to optimize crop growth in a feasible and environmentally safe way. The amount of fertilizer required for different crops in different environmental conditions varies significantly; using too much or too little fertilizer than required can be non-conductive. For this, fertilizer optimization and nutrient mapping using remote sensing are valuable tools in smart agricultural systems as they allow efficient use of fertilizers while reducing environmental impacts and, at the same time, providing better yields. The important key factors that play an important role in modern agriculture are efficient nutrient management, wastage of fertilizers, cost reduction, and decision-making. These methods improve the ways of optimizing fertilizers and nutrient management through remote sensing.

Keywords: Decision support systems, Fertilizer optimization, Precision farming, Remote sensing.

INTRODUCTION

Agriculture is one of the core sectors of the economy, providing food, fodder, and raw materials for various industries. It is also a source of income for millions and a strong deciding factor for the GDP of a country. It is therefore extremely important for a country to explore and improve agricultural methods in order to grow economically. To this end, researchers worldwide have implemented various technologies to optimise resource use and maximise crop yields. These technologies include the Internet of Things, Precision Agriculture, Remote Sensing, Artificial Intelligence, Big Data and Analytics, Cloud Computing, and Robotics. The primary focus of this study is to help understand and explore the

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capabilities and methodologies used for remote sensing in agriculture, with a primary focus on the use of remote sensing for fertilizer optimization.

Remote Sensing (RS) refers to the process of extracting useful information from physical entities without actual physical contact with them [1]. With advancements in fields like Satellite Technology, GIS (Geographic Information System), GPS (Global Positioning System) LiDar, Synthetic Aperture Rader (SAR), Hyperspectral and Multispectral Imaging along with other advancements in Artificial Intelligence and Data Processing, RS has become a very capable and powerful tool of great relevance in research, providing practical applications for real-life problems [2]. This task of RS is usually performed with the help of satellites, drones, aircraft, and even ground-based devices. Fig. (1) highlights the basic methodology for RS.

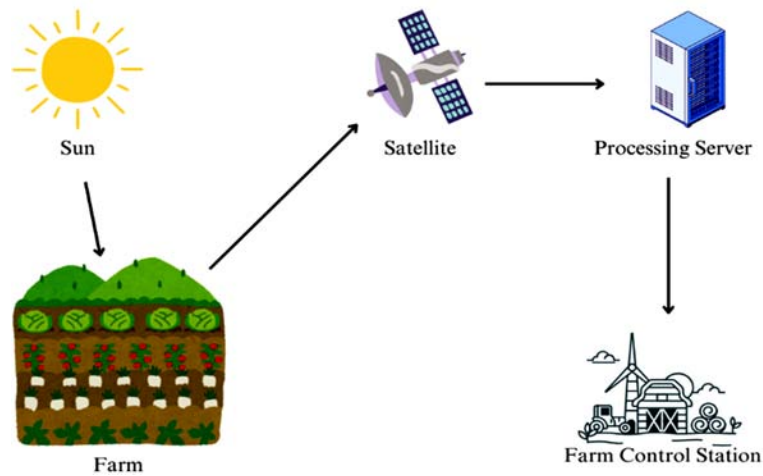


Fig. (1). Overview of hyperspectral remote sensing for agriculture.

In the twenty-first century, Precision Agriculture (PA) is an essential part of sustainable agricultural systems. Although there have been several definitions of PA, the fundamental idea has remained constant [3, 4]. When making decisions about the use of water, fertilizer, pesticides, seeds, fuel, labor, and other resources, PA involves a management approach that employs a variety of sophisticated information, communication, and data analysis techniques. This approach helps to improve crop productivity while lowering water and nutrient losses and adverse environmental effects. There are various applications of RS; the primary focus of this study is to describe its use in agriculture, with a particular focus on optimizing fertilizer use and nutrient mapping in precision agriculture.

Role of Hyperspectral Remote Sensing in Agriculture

The use of hyperspectral RS in agriculture can be of great significance, as it can be applied to solve several problems within the field. In India, 70% of the population depends on agriculture, while also accounting for 35% of the country's GDP [5]. Major challenges faced by current agricultural implementations include the lack of resources such as land and manpower, an increasing population resulting in higher demand for food, and an increasing scarcity of natural resources such as clean water, minerals, and energy. With little scope for agricultural land expansion and limited resources, it is crucial to use the resources at hand effectively. For this, it is essential to have accurate data on available resources, crops, wastelands, forests, soils, and natural calamities like floods and droughts. By traditional methods, gathering such information at a large scale can be tedious, time-consuming, and require significant manpower. With RS, the same task can be achieved much more quickly and with less manpower. RS, with its ability to provide consistent, multi-temporal, and multi-spectral data, is essential for providing thorough insights for efficient agricultural planning and management. Fig. (2) describes the basic implementation of hyperspectral RS in agriculture.

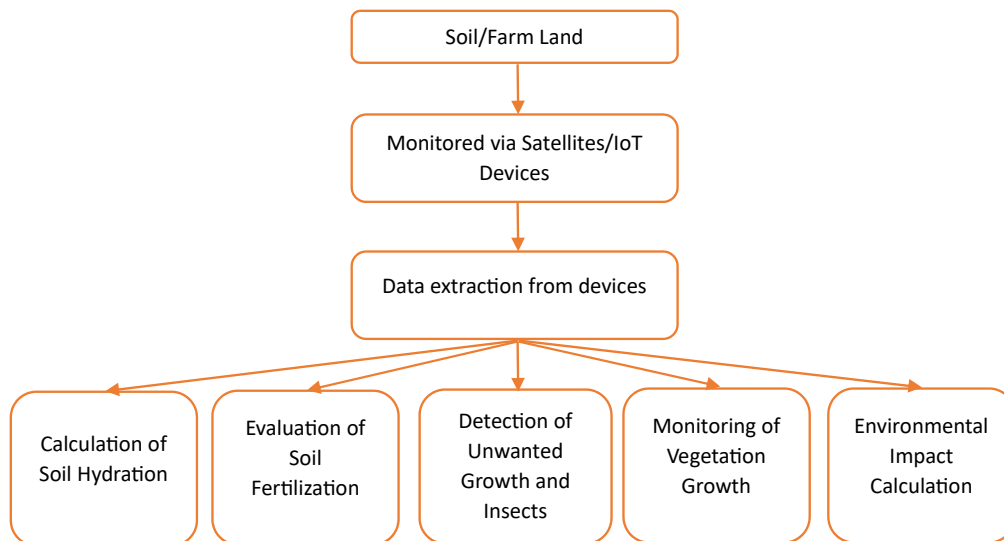


Fig. (2). Basic implementation methodology of hyperspectral RS in agriculture.

CHAPTER 9

Study on Harnessing Remote Sensing for Advanced Wildlife Monitoring and Conservation

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Abstract: Remote sensing is growing rapidly as a valuable and, at times, critical technology in monitoring the environment. This allows large-scale data acquisitions for ecological applications. The chapter describes the impact of integrating remote sensing into wildlife monitoring and conservation, particularly Hyperspectral Remote Sensing (HRS), on sustainable agriculture. Monitoring of wildlife changes with the ongoing advancements like satellite imagery, drone sensor-based techniques, and AI technologies. This helps to map habitats, estimate populations, and monitor biodiversity. On the other hand, HRS has a crucial role to play in agriculture through more detailed spectral data, enhancing productivity through crop health assessment and soil and water-resource management.

The chapter discusses some of the recent methodologies used in wildlife conservation, such as species tracking with GPS collars, vegetation mapping with multispectral imagery, and machine learning ecosystem classification. For sustainable agriculture in hyperspectral data, precision farming, disease detection, and yield have potential applications. This chapter compares how these two areas relate through comparative analysis to show that ecological and agricultural monitoring could evolve together using remote sensing technologies. A case study demonstrates the application of integrated remote sensing in an agro-ecological landscape in terms of how habitat conservation can be made to coincide with agricultural sustainability. Additionally, a thorough literature review synthesizes key research works, for presentation in tabular comparison, demonstrating methodologies and applications. Also, there is a flow chart that represents the different components and processes involved in wildlife monitoring and conservation through remote sensing technologies.

Keywords: Artificial Intelligence, Agriculture, Ecology, Hyperspectral remote sensing, Machine learning, Remote sensing, Sustainability, Wildlife monitoring.

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INTRODUCTION

Hyperspectral Remote Sensing (HRS) is a sophisticated technology that gathers data in hundreds of close spectral bands and enables detailed analysis of surface materials. These features allow farmers to make effective decisions and implement sustainability and precision agriculture. HRS facilitates monitoring crop health, early disease and nutrient deficiency detection, and measurement of soil quality parameters like moisture, salinity, and organic content. These features allow farmers to make effective decisions, minimize input waste, and increase productivity in a responsible, environmentally friendly way. The current developments in remote sensing technologies have expanded opportunities in wildlife monitoring and conservation efforts that will enable a whole series of applications, such as wildlife conservation and sustainable agriculture. These are used to unleash the benefits of biodiversity management through the unprecedented capabilities to acquire real-time information on the distribution of species, habitat conditions, and dynamics within ecosystems. Remote sensing technologies, for example, satellite imagery, aerial photography, and unmanned aerial vehicles, possess the extraordinary ability to monitor large and inaccessible regions [1]. Such an ability allows researchers and conservation managers to track and monitor the status of wildlife populations and their habitats across vast spatial and temporal scales. Most importantly, these technologies will inform and enable policymakers and decision-makers to provide the necessary information to define and implement appropriate strategies for sustainable development and effective biodiversity conservation. This chapter is primarily concerned with the technological and methodological foundations of remote sensing and also focuses on the likely transformative potential of the technology in responding to the global challenges posed by biodiversity loss and food security. They allow a variety of diverse applications, for example, wildlife conservation and sustainable agriculture, within these broad areas. This includes habitat monitoring, species tracking, and biodiversity assessment by wildlife conservation. Sustainable agriculture, on the other hand, generates profits from hyperspectral imaging for crop health, soil fertility, and water resource management [2].

The nexus of these two areas revolves around environmental sustainability as a common goal. Both of these require precise acquisition, processing, and analysis, with remote sensing technology playing a critical role in the chapter on AI and ML techniques for processing remote sensing data for predictive modelling, anomaly detection, and decision support. Through integration of remote sensing techniques, conservationists and agricultural planners can integrate ecological preservation with sustainable food production [2]. Computer-based simulation techniques, such as geographic information systems, active and passive RADAR,

and lidar systems, are being used with critical importance for real-time monitoring of biodiversity.

METHODOLOGIES

There are no limits to the types of data that can be acquired, processed, and analysed for AI/ML applications. Satellite-based sources such as Landsat and Sentinel-2 can be used to capture habitat data, while drone-mounted thermal imaging can be used to locate animal movements as part of remote sensing technologies for wildlife monitoring. Real-time species tracking is enabled by IoT devices such as GPS collars. The application of AI-powered models with neural networks includes CNN for species detection and Random Forest for habitat classification in data processing. NDVI and other spectral types assess vegetation health, and habitat-suitability assessments depend on them. GIS-based tools combine spatial data for habitat mapping and land-use monitoring. For instance, in India, Kaziranga National Park uses drones equipped with AI to detect illegal poaching, demonstrating how remote sensing technology is advancing conservation efforts.

Among these techniques is the mapping of the essential areas.

Remote sensing enables extensive use of techniques for acquiring information about the world's surface without physically touching the Earth's surface. Some of the key methodologies under wildlife monitoring are:

- **Satellite Imagery:** These satellites measure a number of different wavelengths of electromagnetic radiation through optical, infrared, and radar sensors [3]. They cover large areas and can thus detect habitat, vegetation patterns, and land-use changes that affect wildlife distribution and behaviour.
- **Aerial Imagery:** Aircraft and drones have comparatively higher resolution imagery and flexible data-acquisition modalities to provide detailed surveys of particular areas and record dynamic events, such as wildlife migrations or human-wildlife conflicts [4].
- **Acoustic Monitoring:** Passive acoustic sensors listen to animal vocalizations to provide information on species abundance and distribution, and, to some extent, behaviour.
- **Thermal Imaging:** With thermal sensors, heat signatures can be observed, enabling the identification and tracking of animals and the monitoring of their physiological processes under changing environmental conditions, especially for nocturnal species [5].

Key components of remote sensing are depicted in Fig. (1).

Advancement in Remote Sensing and GIS for Sustainable Groundwater Monitoring

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Abstract: This chapter discusses advanced approaches in remote sensing and Geographic Information Systems (GIS) technology for sustainable groundwater monitoring. The extraction and management of groundwater are fundamental to human survival, but aquifer depletion has emerged as a critical issue. Recent advancements in satellite platforms, such as Gravity Recovery and Climate Experiment (GRACE), Landsat, and hyperspectral remote sensing technologies, enable high-resolution, continuous monitoring of groundwater levels, recharge zones, and land use dynamics. Together with GIS, they can contribute to the spatial assessment of critical recharge zones, groundwater depletion, and agriculture-based water use. Artificial Intelligence (AI) and Machine Learning (ML), when embedded into the groundwater monitoring framework, allow automating the data analysis workflow and help in making better predictions that further assist in facilitating real-time decision-making. As case studies show, these tools have greatly enhanced the sustainability of groundwater across regions. Lastly, the chapter discusses the innovations in hyperspectral imaging, AI-driven analytics, and remote sensing, which are going to be the future of groundwater resource management.

Keywords: Geographic Information Systems (GIS), Groundwater Monitoring, Gravity Recovery and Climate Experiment (GRACE), Machine Learning (ML), Remote Sensing, Sustainability.

INTRODUCTION

Overview of Groundwater Importance and Global Water Crisis

Groundwater is a natural resource used for drinking water, irrigation, and industrial use. It comprises around one-third of global freshwater and is a key

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drought mitigation buffer [1]. Many rural and some urban populations rely on groundwater as a significant source of water supply [2]. Yet, for the past few decades, their underground reserves of freshwater have been drawn down at an unprecedented rate through unsustainable extraction and overexploitation of groundwater. The ongoing water crisis is being aggravated due to several factors, including the rapid rise in world population, escalating climate variability, and extreme weather events like extended droughts and flash floods. Several large areas in South Asia, the Middle East, and most of North America are experiencing a state of severe water inadequacy, with many reports showing a rapid decline in groundwater levels and a corresponding decrease in storage capacity [3]. These trends threaten the water security of millions around the world.

Need for Remote Sensing and GIS in Groundwater Monitoring

Traditional groundwater monitoring techniques are extensively used but are expensive, labour-intensive, and limited in the spatial context [4]. Due to these limitations, modern technologies have been adopted and developed, including remote sensing and Geographic Information Systems (GIS) for more efficient and accurate groundwater monitoring. These methods offer low-cost, high-resolution information on the water table and recharge area. Remote sensing facilitates large-scale groundwater monitoring by measuring gravity anomalies, soil moisture, and land cover changes [5]. These images are used to ascertain trends over time, which can tell us when aquifers are becoming less sustainable and whether they are still healthy. For example, Satellites like GRACE detect variations in Earth's gravitational field, which, through modeling, provide insights into global water storage changes, including groundwater.

In contrast, GIS is an integrative spatial analysis tool that combines multiple datasets such as topography, geology, and hydrology. GIS facilitates groundwater identification, recharge zone mapping, future prediction of water over time, and helps with informed decision-making to ensure sustainable groundwater overlaid with varied data layers [6]. The integration of remote sensing and GIS has transformed groundwater monitoring, allowing water managers to implement proactive water management strategies that reduce depletion risks, enhance water resource planning, and secure sustainable management in the long term [7]. These technologies are helping to overcome the various bottlenecks in the scarcity and depletion of water. Satellite technology, as adapted in capturing and analysing land surface data for groundwater assessment, is shown in Fig. (1).

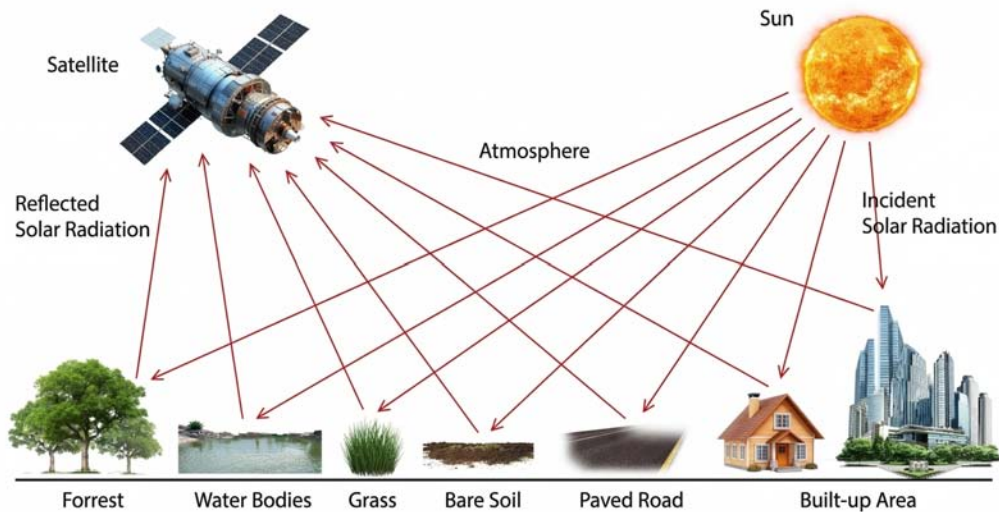


Fig. (1). Brief overview of the working of a satellite.

Objectives of the Chapter

In this chapter, the authors investigate the developments of remote sensing and GIS technologies that contribute to sustainable groundwater monitoring. The chapter will (a) emphasize that groundwater is a critical resource and has challenges in managing it worldwide, (b) understand the growth of remote sensing technologies and detect groundwater levels and quality, (c) explore how remote sensing and GIS systems are integrated to understand groundwater systems holistically, and (d) identify gaps in current groundwater monitoring capabilities and explore future trends, challenges, and technological advancements.

UNDERSTANDING GROUND WATER SYSTEMS

Basics of Ground Water Hydrology

Groundwater, stored in aquifers, is mapped using remote sensing to detect gravity anomalies and geophysical surveys to assess subsurface structures. Groundwater is the water that percolates into aquifers, which are rock formations in the Earth's geologic structure where water accumulates and is stored, providing a reliable source of fresh water for drinking or irrigation projects in villages [8]. Groundwater is integral to the Earth's available water reservoirs for ecosystems, agriculture, and human use. The groundwater cycle is interrelated with the hydrologic cycle, which includes precipitation, infiltration, percolation, and recharge [9]. Rainwater enters the ground and passes through soil layers to recharge aquifers. The time it takes for an aquifer to recharge depends on soil

Precision Agriculture, Irrigation Management, and Monitoring using Hyperspectral Remote Sensing and AI

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Abstract: Farming is changing rapidly, and new technology is making it easier to grow food in a way that is good for both people and the planet. Hyperspectral remote sensing is one of these game-changers—it lets us see details about crops and soil that we could never spot with the naked eye. When you add Artificial Intelligence (AI) into the mix, you get a powerful combination: hyperspectral cameras collect huge amounts of data, and AI helps make sense of it all. This paper looks at how these two technologies work together to help farmers spot problems early, use resources wisely, and grow healthier crops with less waste. The research work will focus on how this system works, why it is better than old-school methods, and what it could mean for the future of sustainable farming.

Keywords: Artificial Intelligence, Agriculture, Hyperspectral remote sensing, Irrigation management, Sustainable agriculture.

INTRODUCTION

Growing food sustainably is not easy. Farmers have to balance getting good yields with protecting the environment, and that is a tough job—especially when you cannot always see what is happening in your fields until it is too late. Hyperspectral remote sensing changes that by letting us “see” things like plant stress, disease, or soil problems before they become big issues. However, all that data can be overwhelming. That is where AI comes in. With machine learning, computers can sift through the data, spot patterns, and even predict what might happen next. By combining hyperspectral imaging and AI, farmers get a clearer picture of what is going on in their fields, so they can make smarter decisions, save money, and take better care of the land.

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The system can be integrated with artificial intelligence to predict future water requirements that will help adjust irrigation in the right manner because of the changing environmental conditions. It is this capacity that can help maintain crop production in the face of fluctuating climate factors. Incorporating AI and remote sensing has been observed to lead to efficient water use, resulting in up to 50% reduction in consumption for crops, higher yields, and lower environmental impacts [1, 2].

The collected works emphasize that, with the help of AI technologies, advanced irrigation systems save more water than the traditional method, contributing to the sustainable development of the agricultural sector in the future. The present research argues that technology, in particular AI, can play a crucial role in addressing solvable issues affecting food security and the environment by boosting PA and rebuilding a robust global food supply system.

LITERATURE REVIEW

Numerous studies have highlighted the need for hyperspectral remote sensing for effective water management in agriculture, especially in water-scarce regions. Table 1 showcases the work of researchers with key findings.

Table 1. Key finding by researchers.

Refs.	Year	Title	Key Findings
[3]	2025	High-precision inversion of vegetation parameters in the AI era: Integrating hyperspectral remote sensing and deep learning	The paper finds that combining hyperspectral remote sensing with deep learning significantly improves the accuracy and efficiency of vegetation parameter inversion, marking a major advancement in vegetation monitoring during the AI era.
[4]	2024	A Review on internet of things (IoT) and Machine Learning for Water Management in Agriculture	The application of IoT improves water management efficiency in agriculture while machine learning optimise the irrigation schedule in real time.
[5]	2024	IoT-Based Smart Irrigation System Using AI	IoT sensors and AI models reduce water wastage and, hence, increase the yield of different crops from irrigation systems.
[6]	2024	Water Use Efficiency in Precision Agriculture: Role of Remote Sensing and AI	AI applied to precision agriculture <i>via</i> remote sensing increases water use efficiency by between 25 and 30 per cent higher than conventional approaches.
[7]	2020	Artificial Intelligence Applications in Agriculture: Research Advances	Discusses the latest innovation in the process of using AI in agriculture, where the aspect of water usage and crop yield maximization improves through artificial intelligence.

(Table 1) cont....

Refs.	Year	Title	Key Findings
[8]	2024	Deep Learning Applications in Precision Irrigation	AI enables accurate forecasting of water demand and improved irrigation accuracy, thereby increasing water utilization efficiency by up to 20 percent.
[9]	2020	From Smart Farming towards Agriculture 5.0: A Review on Precision Agriculture	Explains the current innovations in smart farming, such as AI and Internet of Things (IoT), and their use in precision irrigation and crop management.
[10]	2024	Comparative Study of AI Methods in Crop Management	AI Scheme in irrigation Systems improves water use efficiency and labor productivity by 30% compared to conventional methods.
[11]	2021	Artificial Intelligence for Sustainable Agriculture and Water Management	Tackles the importance of AI in practices of making farming sustainable by optimally using water in irrigation practices.
[12]	2024	AI in Precision Agriculture: Recent Advances and Future Directions	Detects ML algorithms and the appropriate sensor to optimize water supply and increase tolerance to environmental factors.
[13]	2010	Precision Agriculture and Food Security	Discusses food security and precision agriculture, looking into notions such as sensor-controlled irrigation systems, as well as yield-enhancing advancements.
[14]	2023	Smart Irrigation Systems in Agriculture: A Systematic Review	Review and analysis of smart irrigation, with an emphasis on AI approaches used in both rural and urban agriculture, examining how smart irrigation has been implemented and how scarce resources, such as water, can be utilized optimally to achieve efficient irrigation.

Goriparthi (2022) examined the use of an AI decision support system in precision agriculture [15]. This chapter aims to investigate whether artificial intelligence, especially machine learning methodologies, can help enhance productivity in agriculture and, consequently, sustainability. These technologies promise to help farmers by processing data from numerous sources to provide insights that drive decisions on irrigation, fertilizer application, and pest control.

METHODOLOGY

We use drones or satellites equipped with hyperspectral cameras to scan the fields. These cameras pick up hundreds of tiny color bands, giving a detailed look at the crops and soil. The raw data is cleaned to remove any noise or errors. Then, AI is used. Using machine learning, the system looks for signs of stress, disease, or nutrient problems, such as changes in leaf color or moisture levels. The AI results are checked against real-world measurements from the field to make sure they are accurate. By combining hyperspectral data, AI analysis, and on-the-ground information, farmers are provided with practical advice on when to water, fertilize, or treat their crops.

Evaluation of Soil Fertility Using Deep Learning and Machine Learning Algorithms

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Abstract: The ability of the soil to supply nutrients in available form to the plants depends on its inherent fertility. Testing the fertility of soil is a long, laborious process, but it can yield substantial results. There are numerous soil factors responsible for plant growth development, which aggravate soil fertility evaluation by understanding those factors. This method requires costly equipment as well as solvents for soil analysis. There is greater precision and accuracy in the laboratory procedures, but they cannot perform soil analysis repeatedly. Artificial intelligence is involved in developing machine learning and deep learning algorithms that have the cognitive ability to carry out soil nutrient predictions. Both supervised and unsupervised training techniques are used in machine learning applications to improve data analysis and generate a large amount of data for statistical solutions. These algorithms utilize vast datasets of various soil and environmental factors to precisely estimate soil fertility levels. Hyperspectral remote sensing has also become a powerful tool for detailed, low-cost soil analysis. Hyperspectral remote sensing utilizes a revolutionary method for assessing soil fertility mapping, facilitating accurate and economical assessment of soil health. In contrast to multispectral sensors, which collect data in a restricted number of wide spectral bands, hyperspectral sensors obtain reflectance data across hundreds of narrow adjacent bands, enabling comprehensive evaluation of soil constituents. This chapter suggests different algorithms to predict soil nutrient levels and identifies new pathways for evaluating soil fertility.

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Keywords: Environmental factors, Hyperspectral sensors, Inherent fertility, Laborious process, Nutrient predictions, Precision and accuracy.

INTRODUCTION

Evaluating soil fertility requires assessing the soil's ability to supply the required nutrients, which determine the crop's growth, development, and overall yield. If a soil is to be healthy, it needs periodic soil testing alongside effective soil management. Recognizing the characteristics of soil that affect plant growth is vital for efficient management of soil fertility. Testing soil fertility is a challenging and tedious task, but it is crucial for accurate results. The obstacles stem from comprehending and incorporating soil variables, which are affecting plant growth [1]. Evaluating the fertility of the soil is an important part of sustainable farming since it has a direct impact on how well crops grow and how nutrients are managed. Plant tissue evaluation, microbiological testing, and chemical assessments are accurate, but expensive and not feasible to undertake on a wide scale or at frequent intervals. Soil fertility evaluation is performed by testing the nutritional deficiency in plants, testing plant and tissue samples, microbes and higher plants, isotopic dilution techniques, and chemical analysis to assess the nutrient content. This systematic approach assures sustainable and efficient management of soil fertility [2]. Traditional assessment of soil fertility uses random grid sampling to collect soil samples. The sample cores are meticulously wrapped and sent to the laboratory for further analysis.

analysis [3]. This method requires costly equipment as well as solvents for soil analysis. There is more precision and accuracy in laboratory procedures, but they cannot perform soil analysis repeatedly. [4].

Artificial Intelligence (AI) is a subfield of computer science focused on the development of algorithms and tools that can perform activities that typically require cognitive ability [5]. To enable robots to replicate neurological processes such as understanding, logical reasoning, and decision-making, artificial intelligence integrates several techniques to process, analyse, and interpret data. AI uses ML and DL calculus to replicate intellectual work like recognizing patterns and rendering decisions in new ways. These methods use big data to make soil fertility estimation flexible and automatic. Machine learning is an AI component that focuses on creating techniques that enable computers to learn from observations and progressively improve their performance without the need for custom programming. Using artificial neurons and deep neural networks, a subfield of machine learning, machine learning models intricate patterns in massive datasets [6]. These networks consist of multiple layers (hence the term “deep”) of neurons that process information in a manner similar to the

organization of the human brain. Applications involving computing natural language benefit greatly from deep learning picture and speech recognition, and even gaming. Hyperspectral remote sensing is also a high-resolution, non-invasive way to study how soil nutrients change over time. It collects data from numerous small spectral bands, which lets you look at the soil's makeup in detail.

Soil nutrient predictions are made using both machine learning and deep learning tools. Both supervised and unsupervised training techniques are used in ML applications to improve data analysis and generate a large amount of data for statistical solutions. For soil nutrient assessment, deep learning algorithms have been implemented for efficient understanding of large amounts of data [7]. These methods use large datasets that cover a variety of soil characteristics and environmental conditions to produce accurate predictions of soil nutrient levels. This prediction ability improves crop management techniques and maximizes fertilizer use.

DEEP LEARNING ALGORITHMS

Artificial Neural Network

Artificial neural networks comprise mathematical structures that mimic the structure and functionality of biological neural systems observed in the minds of humans. They serve as the cornerstone of machine learning and are extensively employed in a variety of applications, including pattern recognition, regression, and classification [8]. Artificial Neural Networks (ANNs) are ideal for evaluating soil fertility, as they can reflect complex, nonlinear correlations between different soil properties and fertility levels [9]. ANN operates through a network of layered neurons, in which each neuron transmits its output to the next layer upon stimulus activation (Fig. 1). The performance of the ANN has been optimized through forward and backward propagation. These procedures operate together to alter network judgments and weights, thereby reducing the discrepancy between anticipated and actual values [10].

Advanced Remote Sensing Techniques for Monitoring Agricultural Changes

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Abstract: Agricultural activity is of great importance for a sustainable future and economic growth. With limited resources and manpower, it is important to use them efficiently for optimum results. Smart agricultural systems incorporating remote sensing tools can help optimize and simplify agricultural systems. Ensuring food security, maximizing resource use, and tackling climate variability all depend on monitoring agricultural developments. Because they offer quick, precise, and scalable insights regarding crop development, soil health, and environmental effects, advanced methods of remote sensing have completely changed this process. Precision farming and sustainable land management are supported by these methods, which integrate high-resolution information with machine learning, artificial intelligence, and geospatial technologies. This chapter discusses the potential applications and methodology for applying remote sensing for improved yields of crops. A literature review of different implementations and solutions proposed by other researchers in the field of agriculture using remote sensing is also discussed.

Keywords: Precision agriculture, Remote sensing, Smart agricultural systems.

INTRODUCTION

The growing world population means a growing need for resources and food supply. This increased requirement, if not satisfied, is a great threat to the quality of life and a sustainable future. To circumvent this issue, given the limited availability of resources, more efficient and sustainable solutions need to be brought to life. A clear requirement for a growing population is food; this means an increased requirement for higher-quality and efficient crop production. To ensure better crop production on a large scale, the extent of crops also needs to be monitored efficiently. For this, remote sensing can be implemented to get insights about different parameters relating to crop growth on a wide range.

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Remote Sensing Evolution

With the advent of imaging and satellite technologies paired with Artificial Intelligence (AI), the capabilities of remote sensing have improved significantly. Remote sensing is the process of using recording equipment that is not in close proximity to the features being observed (usually from a certain distance), in order to gather and measure data on certain characteristics of materials, objects, or occurrences. RS employs two different types of sensors, namely active sensors and passive sensors. Natural radiations that are reflected or released from the earth are detected by passive sensors. On the other hand, active sensors (like LIDAR and RADAR) are those that emit electromagnetic radiation of their own. RS is extensively used in the fields of agriculture, geostatistics, disaster management, climate monitoring, biodiversity monitoring, *etc.* Remote sensing in the hyperspectral range records hundreds of continuous, narrow spectral bands, permits thorough examination of soil composition, crop health, and nutrient status, identifies crop disease, stress, and nutritional deficits early, and supports mapping soil health and applying fertilizer precisely. Employing RS-based solutions for various real-life problems tends to be more efficient compared to traditional approaches.

Methods and Techniques of Remote Sensing

As discussed above, RS is used to extract meaningful information about a physical entity or region without coming in physical contact with it. The same can be implemented with different methodologies, each with its own advantages and limitations. In this section, the different methodologies and the technologies they employ are presented.

Satellite-Based Remote Sensing

Satellite-based RS technologies typically depend on electromagnetic radiation for collecting information, which may use Synthetic Aperture Radar (SAR) or Multispectral Imaging (MI). An imaging radar installed on a moving platform is called a SAR [1]. The meaning behind “Synthetic Aperture” in SAR springs from the nature of the radar, which “simulates” a larger aperture by using the motion of a satellite platform. In SAR, Electromagnetic (EM) waves of varying wavelengths and intensities are successively broadcast, just as in a traditional radar. An energy pulse is released, reacts with physical structures, and is then backtracked to the SAR for imaging. Applications for SAR are numerous and include mapping wetlands [2], following oil spill routes [3], and researching icebergs [4]. MI in Satellite-based RS is implemented by detecting radiation across different bands or wavelengths reflected or emitted by the planet. The data from the sensors is then used to create images that resemble photographs captured by a camera high in

space. Multispectral (MS) imaging is the most popular technique for gathering data about vegetation. These MS photos are typically obtained from satellites or airplanes, although they are typically costly. Furthermore, cloud cover frequently affects satellite data, which presents a problem for image interpretation. Unmanned Aerial Vehicle (UAV)-based MS image acquisition is a flexible and useful method. Depending on the geographic area, medium-sized and big farms choose to use this strategy to varying degrees. The adoption rate for crop farms in the USA is 67%, which is significantly higher than the average of 25% for the EU [5].

Aerial Remote Sensing

Aerial Remote Sensing employs airborne platforms that are not necessarily satellite-based and are usually close to the observed area. For this, platforms like UAVs or aeroplanes are embedded with RS tools to gather data [6]. Compared to satellite-based solutions, Aerial RS tends to be cheaper and more accessible, given the high cost of implementation of satellites and other tools used for satellite-based RS [7]. Due to the limited number of satellites and their reliance on the weather, using satellite imagery is very expensive and not feasible for small farms [8]. These factors make satellite imagery impractical. Commercial flights were the most practical means of acquiring aerial photos until recently, but they are still very expensive and scarce because there are so few businesses that specialize in this activity. Numerous businesses devoted to the production of small UAVs have been bolstered by the development of compact integrated inertial sensors and the decline in the price of high-precision GPS receivers, making UAVs an efficient and practical solution for many farmers.

A cutting-edge imaging technique called hyperspectral remote sensing (HRS) gathers and analyzes data from all over the electromagnetic spectrum. Hyperspectral sensors measure reflectance in hundreds of small, contiguous bands, usually between 400 and 2500 nanometers (visible to shortwave infrared), in contrast to standard imaging systems that only record a few spectral bands (such as red, green, blue, or near-infrared). Hyperspectral sensors pick up on how an object transmits, reflects, or absorbs light. Each element has a distinct spectral signature, including water, plants, dirt, *etc.* HRS can precisely identify and measure particular materials or circumstances by examining these spectral characteristics.

Use of Hyperspectral Remote Sensing in Agriculture

In the field of agriculture, various parameters affect overall crop production and therefore need to be optimized for better yields and sustainability. However, manually measuring these parameters through traditional methods can be time-

CHAPTER 14**Remote Sensing for Precision Agriculture:
Optimizing Fertilizer Use through Nutrient
Mapping****Jaspreet Singh¹, Rupinder Singh^{2,*}, Amanpreet Singh² and Jaswinder Singh²**¹ *Department of Computer Science & Engineering, Chandigarh University, Mohali-140413, Punjab, India*² *Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India*

Abstract: Efficient use of fertilizers is of utmost importance in sustainable agriculture, as it leads to higher crop yields and limits environmental pollution. Fertilizer application in the traditional way usually overapplies or underspends, causing nutrient imbalances, soil degradation, and environmental pollution. A new application of remote sensing technology in precision agriculture is that of accurate and timely measurement of the levels of soil nutrient availability and crop health. Remote sensing combines satellite imagery, drone-based sensors, and spectral analysis to obtain the most accurate mapping, enabling site-specific fertilizer application. By focusing on this data-driven approach, not only is fertilizer use optimized, but crop productivity is increased, costs are reduced, and environmental risks are mitigated. This chapter examines under what conditions remote sensing is used in nutrient mapping, how it is used, and the comparative merits. It also touches on the integration of remote sensing with artificial intelligence, machine learning, and IoT-enabled smart agriculture for better decision-making. Finally, the chapter discusses the challenges of using remote sensing for fertilizer optimization, as well as current trends in digital agriculture, including government initiatives, policies, and frameworks that support e-governance in agricultural practices.

Keywords: Cost reduction, Crop health, Food security, Precision agriculture, Remote sensing, Satellite imagery.

INTRODUCTION

In the last few decades, agriculture has undergone significant technological changes to achieve greater efficiency while ensuring sustainability. That is why there is a need for innovative ways to optimize agricultural practice to meet the needs of an increasing population and food demand. Fertilizer application is one

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of the significant factors affecting agricultural output. However, the application of traditional fertilizer management techniques relies mainly on empirical practices, that is, they often use excessive or insufficient nutrient application. The contributing causes to this are such inefficiencies that lead to soil degradation, low crop yields, and environmental pollution. Precision agriculture can now be practiced despite the unavailability of real-time, accurate spatial data, with the help of remote sensing, which provides real-time, spatially accurate data for the optimal distribution of fertilizer, minimization of waste, and improved soil health.

The word remote sensing means the use of satellites, data, and drones to monitor various factors of agriculture. These technologies allow farmers to monitor nutrient deficiencies and predict crop health, among other things, and then apply fertilizers where needed. Geographic Information Systems (GIS) and Global Positioning Systems are further integrated to increase the accuracy of nutrient mapping and thus the efficacy of field (site-specific) fertilization [1]. The usefulness of GIS-based nutrient maps is especially in differentiating areas of variation in soil fertility within a given area and in making informed decisions about fertilizer application rates for these parcels. Fig. (1) depicts satellite-based nutrient monitoring, drone-based imaging, GIS mapping of soil, variable-rate fertilization, and field-based smart sensors.



Fig. (1). Role of remote sensing in precision agriculture [4].

Benefits of Remote Sensing in Nutrient Management

Multispectral and Hyperspectral imagery provide a means for fine-scale soil and crop analysis using remote sensing techniques. Data are collected at a few broad spectral bands for multispectral imaging and at hundreds of narrow bands for hyperspectral imaging, which are sufficient to obtain a more precise measurement of nutrient levels [1]. Also adding to the crop stress and soil properties that affect nutrient availability are thermal imaging and LiDAR. The use of these technologies improves nutrient management in the following ways:

- **Early Detection of Nutrient Deficiencies:** Remote sensing aids in the early identification of areas of fields that can be fertilized proactively before symptomology becomes visible.
- **Efficient Resource Allocation:** It aids in reducing waste, lowering costs, and minimizing environmental impacts. Inefficient fertilizer application can also increase resource use by having farmers apply fertilizers only where they are actually needed.
- **Time and Labor Savings:** Remote sensing saves time and costs, allowing for the substitution of labor and the time-intensive sampling of soil by hand.
- **Data-Driven Decision Making:** Advanced analytics and AI-powered models increase prediction accuracy to develop the best fertilizer application strategy.

A major advantage of remote sensing in fertilizer optimization is the ability to implement Variable Rate Technology (VRT). Such an approach enables differential fertilizer application depending on real-time nutrient assessments and hence reduces costs and environmental impact. FAO (2020) reports that studies show that precision fertilization using remote sensing data can lead to yield increases of 20 to 30 percent and reductions in fertilizer waste of 20 to 25 percent. Dynamic soil health monitoring provides a balance between sustainable agriculture and maintaining productivity.

The analysis of how remote sensing can optimize fertilizer use for nutrient mapping is provided at length in this chapter. It examines different remote sensing techniques, their applicability, and the use of AI-driven decision-making techniques for precision agriculture. This chapter will, through case studies and comparative analyses, present the future prospects of digital agriculture and sustainable nutrient management to the best of our knowledge.

REMOTE SENSING TECHNIQUES FOR NUTRIENT MAPPING

Data from soil and crops are collected remotely using satellites and UAV (drone) sensors, and analyzed for different soil and crop parameters that constitute remote

Smart Irrigation Systems: A Review of Current Trends and Future Prospects

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Abstract: Crop health monitoring is one of the most critical aspects of farming to ensure the desired output from the cultivated crop. Timely and accurate irrigations ensure healthy and maximum fruit from the crop. Recent advancements in technologies, such as the Internet of Things and machine learning, and their notable contribution in various areas of agriculture, have motivated the present study to explore their use in monitoring various aspects related to field irrigation. The present study provides an extensive review of various proposed models used in the field of smart irrigation.

Keywords: IoT, Machine learning, Smart irrigation, Sensors.

INTRODUCTION

Agriculture is one of the most important and widely followed occupations in India. The ever-growing population of the world necessitates researchers to adopt farm practices that can be beneficial to the farmers as well as to the environment. Adoption of sustainable agriculture practices ensures maximum production from the grown crop and also helps protect our natural resources from depletion. According to statistics, the total irrigated area of India amounts to 96 million hectares, which is only 50% of the total cultivated land. The agricultural sector is one of the largest users of water resources, accounting for approximately 80% of the country's total water resources. The irrigation needs of the country are heavily dependent on two sources: groundwater (60%) and canal irrigation (40%) [1]. The continuous decrease in groundwater levels due to over-extraction in various agriculture-based states of India is alarming. The major states of India, such as Punjab, Rajasthan, and Haryana, are already struggling to cope with severe groundwater level depletion. In some states, the rate of fall of the groundwater table level has gone from 1-3 meters/year. According to the National Water Policy, by 2030, India's 2 billion population might face continuous stress due to

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severe water scarcity [2]. The present erratic climatic conditions have led to protracted droughts and hefty rainfalls, giving a huge setback to both rainfed and irrigated fields. Some prominent and important Indian states like Karnataka, Maharashtra, and Andhra Pradesh faced consecutive droughts for multiple years, giving a huge blow to crop production in these states [3]. Many natural Irrigation structures (around 60%), like irrigation canals, are also not working optimally due to aging and poor maintenance. There is around 40-50% loss of water due to evaporation and seepage during flood irrigation. Thus, the farmers' dependence on groundwater and canal irrigation to fulfill their irrigation requirements has led them to huge yield losses. Also, continuous water pollution due to industrial discharge and agricultural waste in the form of fertilizer runoff has made much of the available irrigation water unfit for crops. The need of the hour is to discover ways of regulating irrigation practices on fields to ensure good health for the crop. Recent advancements in technology have proposed many promising solutions for sustainable agriculture practices.

ROLE OF TECHNOLOGY FOR SMART IRRIGATION

Traditional irrigation practices have proven to be inefficient in fulfilling the water needs of the crops. The unpredictable climatic variations have further compelled researchers worldwide to discover ways of coping with the changing climate and water scarcity problems. Advancements in the area of technology, in the form of IoT and machine learning, have shown promising results in the area of smart irrigation. Smart irrigation refers to the use of practices that can infer the water needs of the crop at the right time and provide the required amount of water without any wastage. Today, many sensors are available that can sense the needs of the crop based on the environment, which can be used by the farmer and researcher for optimum results. A network of sensors embedded in an automation system can provide the runtime data, which can be used for predictions and analysis using various data analytics tools and machine learning and deep learning algorithms. Various tools and technologies used in smart irrigation can be categorized as follows:

Sensors

One of the most crucial parts of any smart irrigation system is sensors that can sense and provide data on the condition of a crop. A wide range of sensors is provided to facilitate efficient use of water resources. These are as follows:

Soil Moisture Sensor

This type of sensor provides the state of moisture in the soil, which details whether there is any requirement for irrigation or not. Various types of soil moisture sensors are available. Figs. (1a, b, and c) show various types of soil moisture sensors. Different soil moisture sensors can be categorized as mentioned below.

- a. **Resistive** Sensor- This type of sensor works on the principle of electrical resistance. The resistance between electrodes is gauged in the soil, which shows an inverse proportion to the moisture present in the soil.
- b. **Tensiometric** Sensor- This type of soil sensor measures the suction or pull required by the roots of the plant to extract water from the soil. This suction is mapped with the soil moisture levels.
- c. **Capacitive** sensor-This sensor is based on the soil dielectric constant, which varies with changes in soil moisture level [4].

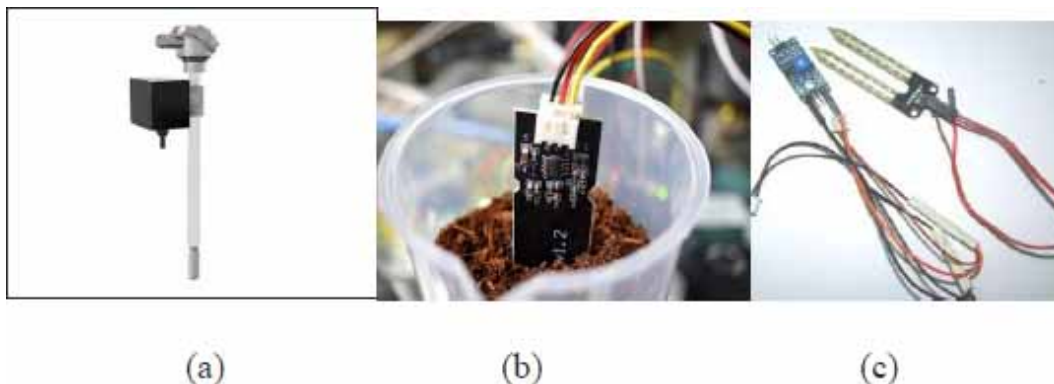


Fig. (1). Types of soil sensors (a) Tensiometric Sensor [4]. (b) Capacitive Sensor [5] (c) Resistive Sensor [6].

Rainfall Sensors

Rainfall sensors provide an accurate amount of rainfall in a region. The data can be used to halt irrigation at the time of rain and if sufficient water has already been provided to the crop [7]. Various types of rainfall sensors are available:

- a) **Tipping Bucket Rain Gauge**- This type of sensor collects rainwater in a bucket up to a specific level, and when water drips, a particular reading is saved. Fig. (2) shows the structure of a tipping bucket rain sensor.

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