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REVIEW ARTICLE

Harnessing remote sensing for smart agriculture

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Abstract

Remote sensing technologies are transforming smart agriculture by delivering real-time data for decision-making in several spheres of crop health monitoring, precision irrigation, soil analysis and pest control. Crop growth stage monitoring, disease diagnosis and measurement of soil moisture are all made possible through these technologies which rely on advanced image processing algorithms and machine learning techniques. With this integration, farmers can implement precision agriculture practices, which in turn reduces resource waste and maximizes crop yields. Geographic information system (GIS) is also used to create detailed maps of agricultural areas, enabling the implementation of location-specific management practices. However, there are significant barriers that need to be addressed, including the requirement for high -resolution data, weather dependency and the need for technical capability. Despite these challenges, remote sensing technology has the potential to significantly improve agricultural productivity and sustainability. It is expected that further developments in remote sensing technology will lead to extensive application of the technology as well as tremendous impact on the agriculture sector.

Keywords: crop monitoring; GIS; remote sensing; smart agriculture

Introduction

Remote sensing is the science of obtaining information about objects or areas from a distance, typically from aircraft or satellites. In 1840, the early stage of remote sensing began with the invention of the photographic camera by balloonist (1). Remote sensing technology evolved from the interpretation of aerial photographs to the analysis of satellite imagery, enabling both local and global scale analysis. Nowadays, remote sensing is widely used in agriculture, monitoring, disaster management, climate, land use mapping, urban planning, weather forecasting, forest mapping, water management, mining and so on (2). Advances in technology, especially in the field of remote sensing, have brought about a notable revolution in agriculture in recent times. The application of remote sensing in agriculture began with the Landsat MSS satellite in 1972. This analysis explores the cutting edge of smart agriculture, highlighting remote sensing as a central technology and examining its various applications in agriculture. Agricultural operations are being revolutionized by remote sensing, includes satellite imaging, unmanned aerial vehicles (UAVs) and ground-based sensors. It provides real-time data on crop health, soil conditions and environmental factors (3). Farmers may maximize resource allocation, maximize output and minimize environmental effect by integrating this technology and making well-informed decisions.

The way farmers monitor and manage their crops has been completely transformed by remote sensing technologies. In the past, farmers evaluated crop health and made management decisions by hand sampling and visual inspection. These techniques, however, are labour and time intensive and frequently yield incomplete and subjective data. On the other hand, farmers can swiftly and correctly gather data over wide areas through remote sensing, which enables them to make decisions more rapidly and intelligently (4). Large-scale agricultural activities can be effectively monitored through the frequent revisits and worldwide coverage provided by satellite based remote sensing. Farmers can monitor changes in crop growth, spot abnormalities and pinpoint problem areas like pest infestations, nutrient shortages or water stress by examining satellite imagery (5). Farmers can use this knowledge to take preventative action and deal with problems before they escalate, ultimately improving crop yields and profitability.

Additionally, UAVs are valuable tools for collecting data and doing high-resolution imaging in agriculture. UAVs that fly at low altitudes are able to obtain extremely sharp and detailed images of crop fields. This allows growers to keep a closer eye on their crops and spot minute changes in growth patterns or stress levels. UAVs are very helpful in precision agriculture applications where exact data on crop health and soil conditions is necessary to maximize input use, like variable rate fertilization (6).

In order to provide more precise and localized information regarding crop and soil conditions, ground-based remote sensing techniques are used in conjunction with satellite and UAV-based approaches (7). Real-time monitoring of variables including temperature, vegetation indexes and soil moisture content is done using sensors that are placed right in the field. With the help of this data integration, farmers can better understand their crops and adjust their fertilization, irrigation and pest control techniques (8).

The intricacy of data processing and interpretation, as well as financial obstacles for small-scale farmers, are some of the obstacles that remote sensing in agriculture faces despite its potentially revolutionary potential (9). In order to overcome these obstacles, more research, infrastructure development and capacity-building programs are needed. Through the provision of easily obtainable and navigable remote sensing solutions and the development of technical expertise among farmers, the agricultural industry may fully leverage the potential of remote sensing technology to augment sustainability, productivity and efficiency (10).

To sum up, remote sensing technology is essential to smart agriculture since it gives farmers access to real-time information and insights that help them maximize crop management techniques. Remote sensing, which includes satellite images, UAV-based imaging and ground-based sensing, provides a range of instruments to tackle the problems that modern agriculture faces (11). Farmers can improve food security, reduce the effects of climate change on agriculture, preserve natural resources, make well-informed decisions and pave the road for a more resilient and sustainable future by utilizing remote sensing technologies.

Fundamentals of remote sensing in agriculture

Remote sensing involves methods and strategies for gathering, processing and evaluating data from sensors installed on airplanes, drones or satellites. By capturing electromagnetic radiation that the Earth's surface emits or reflects, these sensors can provide important insights into agricultural landscapes (12). A fundamental concept in remote sensing is the electromagnetic spectrum, which comprises various energy wavelengths. Various agricultural elements, including water, soil and vegetation, interact differently with different wavelengths, making it possible to identify and characterize them. One important concept used in remote sensing is spectral reflectance, which describes how things reflect or absorb light at various wavelengths.

Spectral data are the source of vegetation indices, such as the normalized difference vegetation index (NDVI), which are commonly used to evaluate the biomass, growth stages and overall health of plants (13). Monitoring agricultural phenomena at different scales and frequencies is made possible by the varying spatial and temporal resolutions offered by remote sensing platforms. To extract useful information for crop management activities including crop type identification, yield estimation, disease diagnosis and irrigation scheduling, remote sensing data is processed using image processing techniques like classification, change detection and spatial analysis. Comprehending these foundational concepts endows agricultural professionals with the aptitude to proficiently employ remote sensing technologies to maximize crop yield, resource administration and ecological sustainability in contemporary agriculture (14).

Role of remote sensing in optimizing crop management

Through the provision of vital information on numerous facets of agricultural activities, remote sensing plays a critical role in enhancing crop management. In the use of advanced sensors on satellites, drones and other aerial platforms, remote sensing assists farmers and agricultural experts in assessing field conditions and tracking crops at different stages of growth. Also, it helps detect abnormalities like pests, diseases or dietary inadequacies (15). With the use of this data, accurate decision-making is made easier. Timely interventions, such as targeted fertilization, irrigation or insect control, can maximize production while minimizing resource inputs and environmental effect. Furthermore, remote sensing helps in mapping land uses, estimating crop yields and tracking changes in agricultural landscapes over time. These tasks provide important insights for policy-making and sustainable land management (9).

Smart agriculture

Smart agriculture optimizes farming practices by leveraging advanced technologies such as IoT, AI, drones and remote sensing. Drones equipped with high-resolution cameras, can scan fields for early indications of pest infestations. IoT-connected sprayers deliver targeted fertilizer or pesticide just where needed after AI analyzes the imagery to identify the affected zones, lowering chemical use and enhancing crop health (15). It enhances agricultural monitoring, irrigation, soil management and pest control, enhancing efficiency, yields and sustainability. This data-driven strategy facilitates precision decision-making, promotes resource conservation and resistance to climate change. The process of the smart farming loop is explained in Fig. 1.

Satellite-based remote sensing for crop monitoring

Satellite remote sensing systems for earth observation consist of satellite platform systems, satellite operation control systems, data transmission processing systems and image data application systems. Sensors gather image data, which is sent to the ground from satellite earth observation equipment. At the same time, terrestrial sensors including flux towers, meteorological stations and soil moisture probes employ visible light, infrared or microwave technologies to monitor and document ground-level conditions in real time, therefore enhancing compared to airborne platforms, which are restricted to shorter-term observations and smaller areas, spaceborne platforms provide more reliable long-term monitoring and wider coverage (16). Processing and connectivity are managed by the spacecraft, which carries various observation instruments satellite observations with precise on-site data (17, 18).

Integrating the satellite data of every station in the system, the satellite control system manages the satellite. For the purpose of correcting the satellite's operating route, controlling its operation status and carrying out satellite operation and other operations, satellite platform is furnished with detecting equipment, attitude and orbit operation through the ground command station. Part of the satellite data

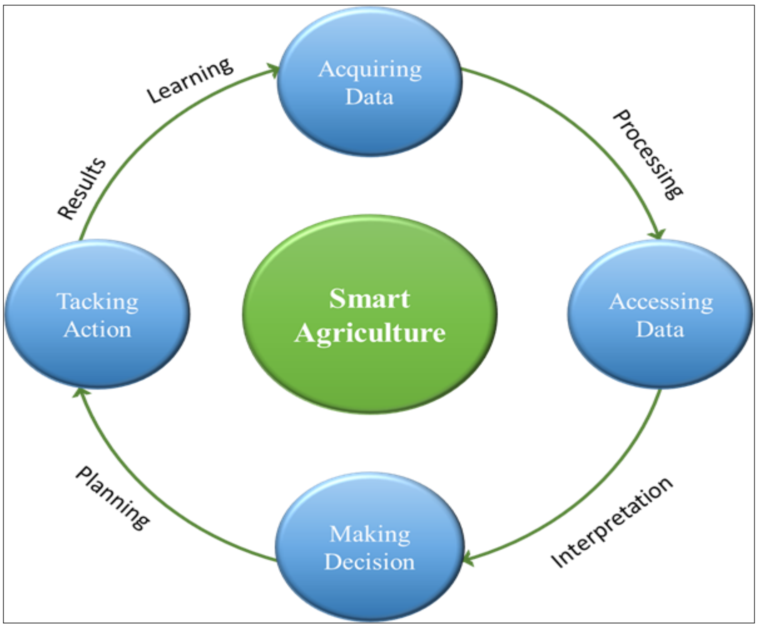

Fig. 1. Process of smart farming loop.

transmission processing system are ground receipt and transmission, communication data calibration, compression, conversion, data inversion and other operations, access to data processing center for backup, data control and other operations (18).

Received from satellite observation image data, image data application system sends remote sensing image data to the ground processing system. Positioning control, standard product manufacture, advanced image processing, typical industry applications and other products are among the many industries for which ground processing systems offer control. Finally, processed data are delivered to end users through a dedicated user service interface (19). Three-mirror anastigmat (TMA) system for remote sensing optical satellites through the system being examined in our country and it comprises of several tiny optical satellites and covers a huge number of space satellite ground networks (20). Shoot the Earth whole day to accomplish the re-examination objective quickly. Presently, there are satellites for technology verification, video and earth observation. European space agency (ESA) aiming to construction of a massive Earth observation network with 137 satellites and additional orbiting satellites will allow for every 10-minute visits to Earth's surface targets.

Estimation of crop acreage and yield has been instrumentalized by satellite remote sensing, particularly through the utilization of multispectral scanner (MSS) and thematic mapper (TM) sensors (21). Additionally, the monitoring of plant and soil conditions, detection of drought stress and estimation of water balance evapotranspiration have been undertaken utilizing this technology (9). The precision of these applications has been further enhanced by high-resolution satellite sensors, enabling crop identification, yield variability mapping and pest management (22).

Optical domain: Recent developments in geoscience technology, including Sentinel-2, have greatly increased optical domain satellites' ability to capture minute details in precision farming (23). These satellites are particularly useful for monitoring plant and soil conditions and can assist farmers in decision-making (9). The integration of optical and radar remote sensing has been explored as a means to extract information about plants and soil, overcoming the limitations of cloud-free quality imaging (24). Furthermore, to support agricultural management throughout the growing season. The Earth oobservation data particularly optical remotely sensed data is increasingly being incorporated into smart farming methods (25).

Thermal domain: Many uses of thermal satellite remote sensing exist in agriculture, such as production calculation, irrigation scheduling, disease detection and monitoring of nurseries and greenhouses (23). High-resolution thermal datasets are utilized to compute latent heat flux, enabling satellites outfitted with thermal infrared sensors to offer significant information on crop water stress levels and irrigation requirements. This facilitates the optimization of irrigation schedule using real-time data. Furthermore, thermal satellite pictures are employed to detect water scarcity conditions, enhance irrigation techniques and evaluate evapotranspiration rates in agricultural regions. The angular variability of land surface emissivity, which is essential for precise predictions of land surface temperature, impacts the calculation of surface upwelling longwave radiation and improves the accuracy of split-window approaches across various surfaces. Thermal satellite remote sensing improves agricultural output and water management strategies.

Microwave domain: Microwave remote sensing is efficient for assessing soil moisture, aiding in crop development, irrigation scheduling optimization and monitoring crop yields. It can penetrate clouds, providing reliable vegetation health, distribution and water requirements, especially in overcast conditions where conventional VIS/IR hyperspectral data may be limited (26). Microwave remote sensing provides publicly accessible data on soil moisture (SM) and vegetation data at regional and global levels, making it vital for drought monitoring by providing daily updates. A case study in Senegal demonstrates the effectiveness of combining satellite-derived SM, vegetation and rainfall data for assessing droughts, though challenges still exist in integrating microwave data with other climate variables (27).

Unmanned aerial vehicles (UAVs) in precision agriculture

In remote sensing, UAVs (drones) are used to gather high-resolution data for uses such as disaster relief, environmental monitoring and agriculture. Application of the obtained UAV data or information in real time is more advantage in nowadays (28). Ongoing agricultural activities would benefit much from having real-time information available. However, UAV applications that monitor crops and give imaging data are subsequently processed to extract certain suitable information and vegetation indices, identifying problematic areas in a crop suffering from various diseases and pest infestations. The data obtained by sensors of UAV can be spectral, spatial and temporal. The selection of the suitable sensor and data depends on the application nature. For instance, temperature data is appropriate for determining the water status, while the spectrum information constitutes a good alternative for diagnosing any plant diseases (29).

Due to their low operating costs, UAVs can be deployed in limited regions for site-specific precision agriculture. Enhancing the framework of digital platforms is crucial to assisting farmers in obtaining dependable and practical results. Platform developers and agricultural experts suggest that farmers participate in the collection, interpretation and analysis of photos. This aids farmers in making better decisions for the proper management of their fields. Data analysis must be able to provide a set an explanation for agricultural output differences, not only a list of variations. Currently, the industry's best course of action is to make sure that UAVs can do more for the agriculture sector than just gather data (30).

Crop spraying is usually a tough and onerous task for farmers and agricultural production companies. It involves covering extremely large expanses of land comprehensively to ensure proper growth of crops. Agricultural UAVs have simplified crop spraying for farmers, as they can cover large expanse of land within a very short time interval. Spraying of agricultural input using a drone in onion crop is illustrated in Fig. 2, which serves as a reference for UAV application. Using sensors, UAVs can automatically adjust their height when spraying across uneven fields. This improves the spraying accuracy and conserves resources.

Ground-based remote sensing techniques

Agricultural remote sensing has been utilized to monitor various aspects of farming, including soil conditions, crop development, weed presence, insect infestation, disease outbreaks and water levels (31). This technology provides valuable data and information to assist in making informed decisions regarding agricultural management techniques. Precision agriculture has been achieved by creating prescription maps of crop fields using data collected from space-based, aerial and ground-based platforms (32). Ground-based remote sensing tools are useful in precision farming because they are easy to move, can be used in many ways and are easy to control. Two significant concerns in weed management are crop damage caused by pesticide spray drift and the development of herbicide resistance in weeds. Ground-caused by dicamba and distinguish between glyphosate resistant and sensitive weeds (33).

An important obstacle highlighted in the preceding sections regarding the utilization of remotely sensed data for precise soil property mapping is the multitude of elements that can influence the spectral signal of the soil or crop. Advancements in terrestrial sensors exhibit potential to offer data sources. Water has a crucial role in crop productivity, making it essential to evaluate how crops respond to water availability under real-world situations. This is particularly significant because water is expected to become scarce in the future. Sensing devices operated from airborne systems or satellites may make possible a fast examination of huge areas. For the development of remote sensing technology in India, it is essential to have a comprehensive understanding of how plants respond to water scarcity, which can be detected by remote sensing devices (34).

Hand-held radiometers can be deployed to acquire data and create correlations between spectral data and crop growth parameters for this aim (35). Assessment of crop water stress in the field with remotely sensed data has mainly proceeded along two lines. The first is based upon leaf temperatures measured with hand-held infrared thermometers. The second relates alterations at reflective wavelengths to crop factors that are responsive to the development of water stress. Leaf temperature measures, regardless of how they are obtained, are sensitive to changes in plant water status and correlate well with data describing water stress by more established measuring techniques.

Application of remote sensing in smart agriculture

Remote sensing has several uses in agriculture, helping to increase output and make better use of available resources. It is essential for assessing the texture, fertility and moisture

Fig. 2. Spraying of agriculture input using drone in onion crop.

content of soil. Effective weed control methods are supported by the early detection of weed infestations made possible by spectral photography. By detecting stress indicators, remote sensing aids in the management of pests and diseases by locating impacted crop areas. By identifying inadequacies, it also aids with nutrient management by enabling targeted fertilizer application. Accurate agricultural yield estimates are made using vegetation indices obtained from remote sensing. Also, it helps with irrigation optimization by offering data-driven insights for the location and timing of water applications. Fig. 3 shows the application of remote sensing in agriculture.

Soil property evaluation using sensor measurements

Assessing soil properties through sensor measurements entails utilizing contemporary sensors to track significant soil conditions and provide precise, current information to aid in improved soil management. IoT-enabled sensors, for instance, may assess temperature, nutrient levels and soil moisture to help farmers make informed decisions (36). Using techniques like capacitance or time domain reflectometry (TDR), soil moisture sensors, for instance, track the volumetric water content in the soil and help to optimize irrigation schedules to prevent over- or underwatering (37). Understanding seed germination and root development conditions requires an assessment of soil heat properties, which temperature sensors provide. By providing information on the acidity or alkalinity of the soil, pH sensors help to direct the application of sulphur or lime to maintain the right pH levels for crop growth. By detecting particular nutrient amounts, nutrient sensors which frequently use ion-selective electrodes allow for accurate fertilizer applications that increase agricultural yields while minimizing environmental impact. Sensors for soil compaction measure soil density and structure and recommend tillage techniques to encourage water and root penetration (38). Decisions driven by data can be made by continuously monitoring and analysing soil health when these sensor measurements are included into smart agriculture systems (39). Important soil parameters monitored include pH, moisture content, temperature, nutrient levels (NPK) and compaction, all of which are measured by the sensors listed in Table 1. Higher agricultural productivity, efficient resource management and sustainable farming methods follow from this, which eventually makes better food security and environmental protection possible.

Weed management

Weed management in smart agriculture makes use of cutting-edge technology and data-driven methods to efficiently stop unwanted plant development while reducing environmental damage and making best use of available resources. This is accomplished by integrated weed management (IWM), which integrates several approaches to fight weeds holistically. Using precision agriculture methods, such GPS-guided machinery and drones fitted with sensors and cameras, is one component of smart weed control (56). With these techniques, farmers can precisely map weed-infested areas, identify weed species and apply herbicide just where needed, therefore lowering chemical use and environmental damage. Moreover, examples of solutions included into smart agriculture are autonomous machines employing machine learning algorithms and robotic weeders. The process of automated weed detection and classification using remote sensing and machine learning techniques is illustrated in Fig. 4. The ability of these technologies to detect and remove weeds in real time reduces the need for manual labour and increases operational efficiency (57). Furthermore, important to effective weed control are predictive modelling and data analytics. Farmers may make educated decisions about weed management strategies, timing of interventions and choice of suitable herbicides or alternative approaches by examining historical data on weed prevalence, weather trends and crop growth stages (58). Overall, smart weed management in agriculture uses technology, data analytics and ecological principles to accomplish efficient, long-lasting and ecologically friendly weed management that guarantees maximum crop yields and farm productivity (59).

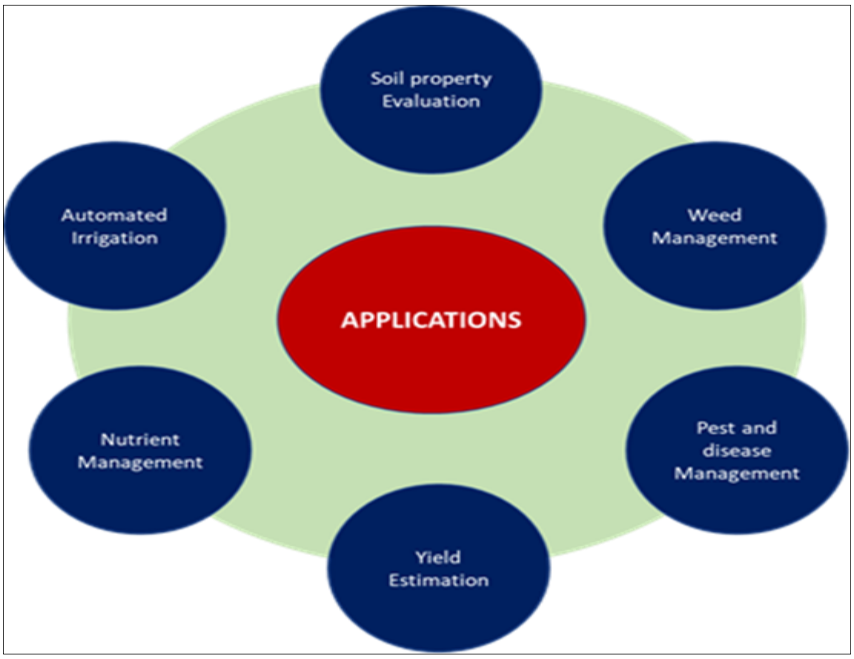

Fig. 3. Application of remote sensing.

Table 1. Types of sensors employed in the evaluation of soil properties

Soil properties	Sensor types	Measurement principles	Platforms	Applications	References
Soil moisture	Time-domain reflectometry (TDR)	Dielectric constant of soil	Ground based	Irrigation management, drought assessment	(40)
	Frequency domain reflectometry (FDR)	Capacitance-based measurement	Ground based	Precision agriculture	(41)
	Passive microwave radiometer	SMAP, AMSR2	Microwave emission variations	Large-scale soil moisture monitoring	(42)
	Active radar (SAR)	Sentinel-1, RISAT-1	Backscatter response	Soil moisture retrieval in all-weather conditions	(43)
	Thermal infrared sensor	Landsat, MODIS	Temperature-based soil moisture estimation	Drought assessment	(44)
Soil temperature	Thermal infrared sensor	MODIS, Landsat, ECOSTRESS	Radiant energy emission	Crop stress and land surface temperature studies	(45)
Soil pH	Hyperspectral sensor	PRISMA, EnMAP	Spectral reflectance in visible and NIR regions	Soil pH mapping based on spectral response	(46)
Soil electrical conductivity (EC)	Multi-spectral and hyperspectral sensor	Sentinel-2, Hyperion	Correlation between reflectance and salinity	Soil salinity assessment	(47)
	SAR (synthetic c aperture radar)	Sentinel-1, ALOS PALSAR	Dielectric pro perties of soil	Salinity detection in coastal and arid regions	(48)
Soil organic matter (SOM)	Hyperspectral sensor	PRISMA, AVIRIS	Absorption features of organic compounds	Soil carbon and organic matter estimation	(49)
	Multi-spectral sensors	Sentinel-2, Landsat	Indirect estimation via vegetation indices	Soil fertility assessment	(50)
Soil nutrient (N, P, K)	Hyperspectral sensors	EnMAP, HyspIRI	Absorption in VIS-NIR-SWIR regions	Nutrient content mapping	(51)
	UAV-based optical sensors	UAV	Reflectance-based estimation	Precision nutrient management	(52)
Soil textures (sand, silt, clay)	Multi-spectral sensors	Sentinel-2, Landsat	Reflectance variations in different bands	Soil classification, land suitability analysis	(53)
	Hyperspectral sensors	AVIRIS, PRISMA	Spectral signatures of soil minerals	Clay and sand fraction mapping	(54)
Soil compaction	LiDAR	Airborne, UAV	Surface ro ughness and elevation	Terrain analysis for compaction detection	(55)
	Radar (SAR)	Sentinel-1, ALOS	Penetration and backscatter response	Subsurface compaction assessment	(44)

Management of diseases and pests by remote sensing

With its rapid, precise and all-encompassing data provided by satellite, aerial and drone-mounted sensors, remote sensing technology has become a revolutionary tool in agricultural pest and disease management (60). Through the collection of data in visible, near-infrared, thermal and microwave spectral bands, these sensors allow for the comprehensive monitoring of crop health, environmental factors and the dynamics of pests and diseases (60). The use of remote sensing for early pest and disease detection is depicted in Fig. 5.

Recognition and monitoring early: One of the key advantages of remote sensing is ability to detect pest infestations and disease outbreaks early. Hyperspectral and multispectral imaging can identify subtle changes in plant physiology, such as variations in chlorophyll content or leaf structure, that often indicate stress or infection before symptoms are visible to the naked eye (61). For instance, an increase in reflectance in the near-infrared band can signal a reduction in chlorophyll due to disease (62). Early detection allows farmers to intervene promptly, reducing crop damage and economic losses significantly (63).

Spatial distribution mapping: The production of high-resolution maps illustrating the spatial distribution of diseases and pests in agricultural fields is made possible by remote sensing data. Application of focused management techniques depends on this spatial information. This information can be used, for instance, by precision agriculture methods to apply pesticides just to the afflicted areas, therefore reducing chemical consumption and environmental effect (64). Reduced indiscriminate use of pesticides is one way that targeted actions not only save money but also contribute to ecological balance.

Environmental monitoring: Dynamics of pests and diseases are greatly influenced by environmental variables like temperature, humidity and soil moisture (65). Through the useful information remote sensing offers on these circumstances, possible epidemics can be predicted. For example, remote sensing allows one to detect the high

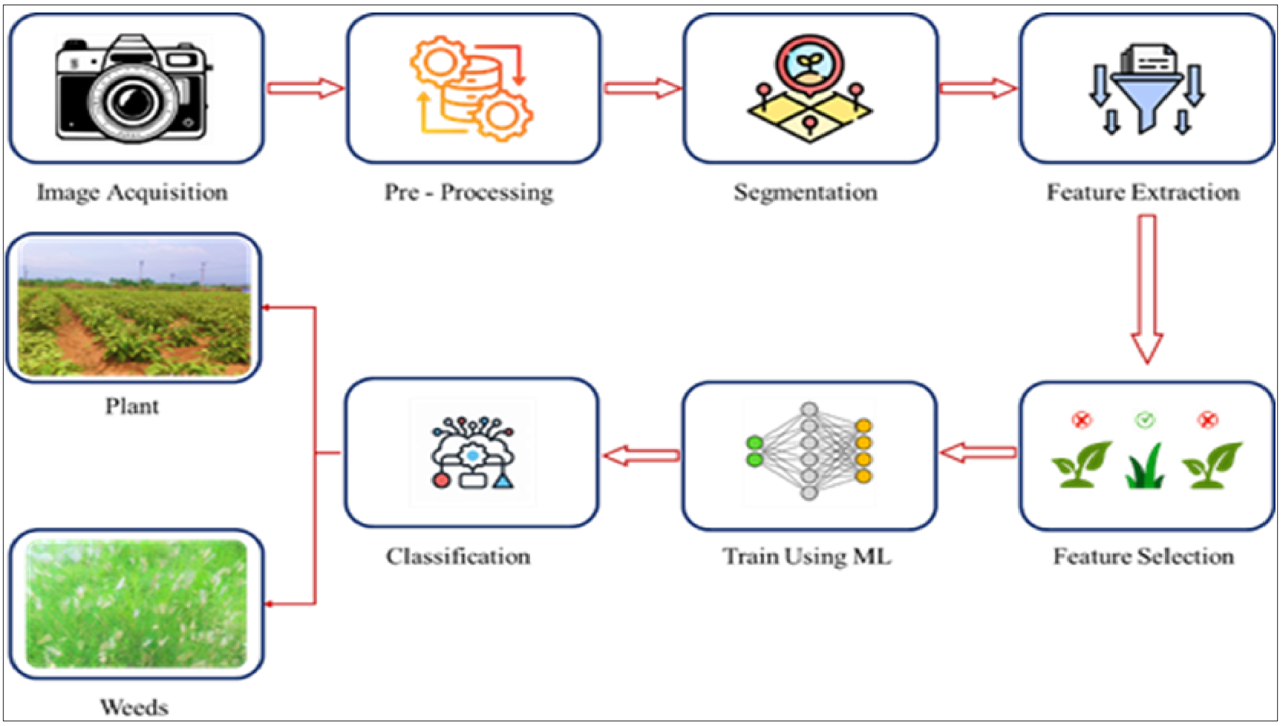

Fig. 4. Weed management using remote sensing and machine learning.

humidity and warm temperatures that certain fungal diseases prefer. By keeping an eye on these environmental factors, farmers can predict disease outbreaks and take preventative action, such changing watering schedules or using fungicides.

Assessing crop stress and damage: Technology for remote sensing thermal imaging can detect temperature variations in plant canopy, which are often linked to pest or water stress (66). Higher temperatures in specific field areas may indicate isolated infestations, directing targeted scouting and treatment operations. Decisions about crop salvage or replanting are made easier when satellite images show the extent of damage caused during an epidemic (67). Particularly large-scale assessments gain from this capability, which provides a comprehensive picture of affected areas that could be challenging to manually survey.

Integration with other technologies: Machine learning algorithms, geographic information systems (GIS) and internet of things (IoT) devices can all be used with remote sensing data to improve pest and disease control. Spatial data analysis with GIS allows one to trace the evolution of diseases and pests over time and pinpoint hotspots (68). By offering ground-truth data, IoT sensors raise the precision of remote sensing analysis. Proactive management alternatives are provided by machine learning models, which can forecast future outbreaks based on previous data and present conditions. This integration develops a strong decision-support system that improves the accuracy and efficacy of methods for controlling diseases and pests.

Yield estimation

Satellite data have been used to track a variety of elements of vegetation monitoring, including but not limited to assessment of crop acreage, estimation of primary productivity, crop yield production, monitoring the effect of vegetation cover conditions on biodiversity and assessment of vegetation

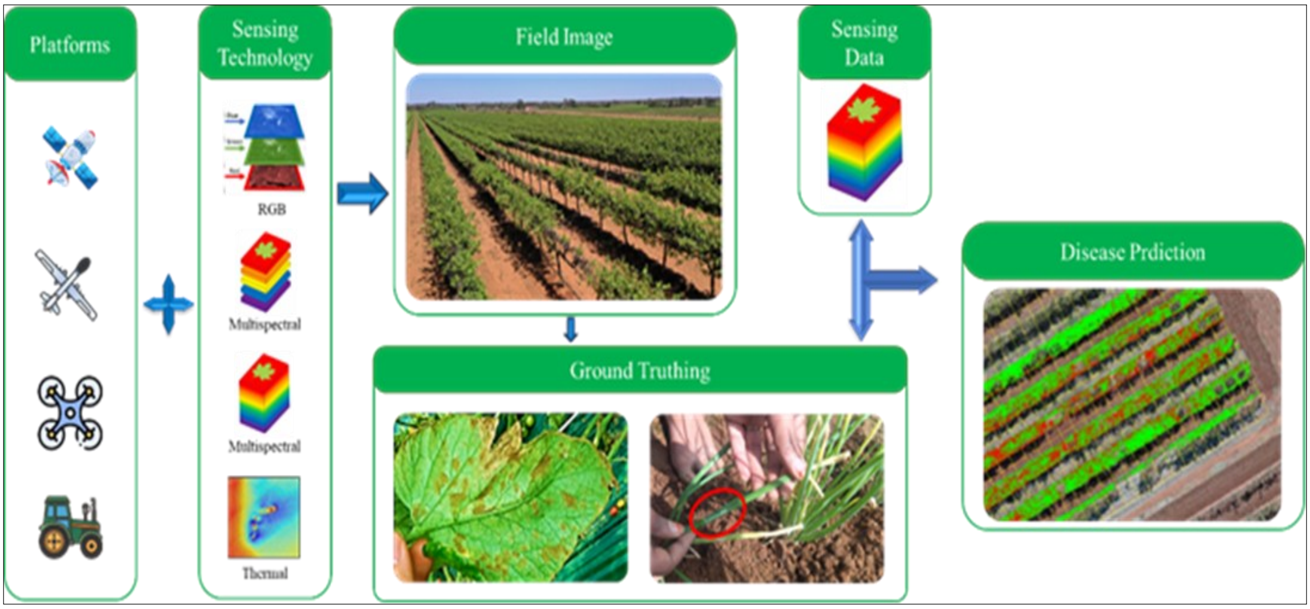

Fig. 5. Application of remote sensing in early pest and disease detection.

phonological conditions (44). Utilizing UAV-based multi-sensor imaging to measure a combination of plant height and cotton fibre index proved to be a successful method for assessing cotton yield (69). The application of remote sensing indicators and statistical models to estimate yield in durum wheat (70). The study successfully achieved excellent results by utilizing indicators that are biologically accurate. They emphasized the potential of high-resolution UAV photography in accurately estimating crop production, especially when considering vegetation indices (71). These studies jointly emphasize the importance of remote sensing in enhancing the precision and effectiveness of yield estimation in agriculture. The major advantages of satellite imaging are the huge regions covered that may be observed in a single image and the potential to update information temporally to monitor changes. Landsat, SPOT, World View and Sentinal-2 satellite data with a medium spatial resolution of 10–100 m was applied to analyses and estimate agricultural productivity at regional and local scales. Landsat 5 TM and SPOT 4 photos have been used to estimate agricultural yield and biomass. A strong association between yield and vegetation index values at 90 days after sowing. As showed by Quick bird, SPOT 5 and Landsat satellite photos with overcome the challenge of small areas and demonstrated remarkable crop yield accuracy. Further comparison between observed and predicted rice yield showed a strong connection in a study region in Egypt. Crop yield utilizing enhanced vegetation index acquired from MODIS data on a regional scale and they produced crop yield maps (72). Multiple studies have shown that remote sensing has the capability to estimate crop production in different types of crops using various models, as presented in Table 2.

Nutrient management

For precise growth and development of crop, sufficient amount of nutrients is required at right stage. Nutrient deficit like the case of nitrogen, it diminishes leaf chlorophyll content that results in low light absorption. Nutrient needs of crop plant can be evaluated by investigating leaf optic properties such as fluorescence, reflectance and transmittance. Chlorophyll fluorescence gives quick and precise information relating to stress based on the fluorescence emission pattern of leaves, tissues and even the whole plant. This emission is collected when some of light energy received by chlorophyll for photosynthesis is re-emitted when activated with UV- a near 340- 360 nm or blue-green light. The fluorescence emission at varying level of plant stress was successfully detected and imaged on different crops for lack of nitrogen and zinc on maize (*Zea mays)*, as well as heat and water stress on Azalea (*Rhododendron* spp.) (75). Plant dry matter accumulation and grain yield were observed to be significantly influenced by the absorption of photosynthetically active radiation. It was favourably associated to yield production at tillering and panicle initiation stage (76). They emphasize the relevance of remote sensing in crop nitrogen management and crop health monitoring (77, 78). Further research extends this application to the prediction of regional forest soil nutrients, demonstrating the value of remote sensing in mapping forest soil nutrients. These studies also underline the importance of incorporating nitrogen indices in soil quality evaluation, with remote sensing data playing a significant part in this process. These studies collectively underline the great potential of remote sensing in nutrient management, particularly in the context of sustainable agriculture and soil quality improvement. Reflectance in the red and near-infrared regions of the electromagnetic spectrum has been used to estimate crop nitrogen demand through early-season predictions of nitrogen uptake and potential yield (79). It was reported that the linkage between the NDVI inflection point and nitrogen content was found to be strongest at the maximum tillering stage, followed by the flowering, milky and tillering commencement stages. The results provide nitrogen estimation through hyperspectral instrument simply with little time consuming (80). The NDVI increases with increasing leaf greenness and green leaf area and can be used as a guide for in season nitrogen application (81). Soil moisture, vegetation and soil crusts can contribute to the retention of soil total nitrogen (81). Various indices employed for nutrient management are described in Table 3.

Table 2. Types of models used in yield estimation

Yield estimation model	Applied research	References
Regression model	Regression models utilize past data and identify pertinent variables to forecast yields depending on various aspects such as weather conditions, input utilization or economic indicators. It is crucial to select the appropriate regression methodology and thoroughly validate the model to guarantee precise predictions.	(73)
Deep learning	The researchers used a recurrent neural network with long short-term memory (LSTM) cells to transform a three-dimensional pixel histogram into a two-dimensional matrix. They used this model for transfer learning from Argentina to Brazil, initializing it with parameters from Argentine soybean harvests and then recalibrating the model and fine-tuning the remaining parameters.	(14)
Semi-physical model	This approach integrates mechanistic models of plant growth and environmental interactions with statistical correlations derived from historical yield data. By calibrating the model with historical yield data and validating it with separate datasets, we can assure its correctness. This makes it a reliable tool for predicting crop yields in different situations and with different management approaches.	(74)
DSSAT (decision support system for agrotechnology transfer)	The system is calibrated using past data and verified using other datasets, providing a reliable tool for evaluating management techniques, estimating the effects of climate change, optimizing resources and assisting in agricultural decision-making.	(74)

Table 3. Vegetation Indices used for nutrient management

Vegetation index	Formula	Nutrient indicators	Use in nutrition management	References
NDVI (normalized difference vegetation index)	$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}$	General plant health, plant nitrogen content	Detects nutrient deficiencies and biomass estimation	(82)
NDRE (normalized difference red edge)	$NDRE = \frac{\rho NIR - \rho RedEdge}{\rho NIR + \rho RedEdge}$	Nitrogen (N)	Helps in nitrogen stress detection in mid-to-late stages	(83)
CVI (chlorophyll vegetation index)	$CVI = \frac{\frac{\rho NIR}{\rho GREEN} * \rho RED}{\rho GREEN}$	Photosynthetic pigments, nitrogen (N)	Strongly correlated with leaf nitrogen content	(84)
GNDVI (green normalized difference vegetation index)	$GNDVI = \frac{\rho NIR - \rho GREEN}{\rho NIR + \rho GREEN}$	Photosynthetic pigments, nitrogen (N)	More sensitive to leaf chlorophyll variations than NDVI	(85)
PRI (photochemical reflectance index)	$PRI = \frac{R531 - R570}{R531 + R570}$	Nitrogen (N), photosynthetic efficiency	Detects stress from nutrient deficiency and drought	(86)
Chlorophyll red-edge (red edge chlorophyll index)	$Clred - edge = \frac{\rho NIR}{\rho RED} - 1$	Nitrogen (N)	Used for precision nitrogen management	(87)
SIPI (structure insensitive pigment index)	$SIPI = \frac{\rho NIR - \rho BLUE}{\rho NIR + \rho RED}$	Photosynthetic pigments, carotenoids	Indicates photosynthetic pigment variations	(88)
MCARI (modified chlorophyll absorption in reflectance index)	$MCARI = [(\rho RedEdge - \rho Red) - 0.2 * (\rho RedEdge - \rho Green)] * (\rho RedEdge / \rho Red)$	Photosynthetic pigments, nitrogen (N)	Detects chlorophyll content and stress	(89)

Automated irrigation

Irrigation is one of the key areas where water efficiency can be improved through automation. Using IoT, water conservation may be accomplished successfully without wasting any wate. The process of automated irrigation using remote sensing technologies is illustrated in Fig. 6. Data mining, artificial intelligence, machine learning, deep learning and fuzzy logic are just a few of the technologies that can be utilized to forecast water needs (90). The most sophisticated artificial intelligence approach for quick decision-making is deep reinforcement. A cloud computing, optimization and IoT based automated irrigation system was shown to lower agricultural water use. The automatic watering system is built using inexpensive sensors to identify characteristics of relevance including pH, temperature, humidity, kind of soil and weather. The data is kept for monitoring and archiving by Thing Speak cloud services (91). Limitations representing the physical circumstances were then included into an optimisation model to reduce water consumption. The optimal flow rate was discovered by solving the optimization model and solenoid valves were shown to be capable of automating it.

Conclusion

Remote sensing is a cornerstone of smart agriculture, providing critical data that supports the adoption of sustainable and efficient farming practices. The continuous growth of these technologies will be vital in tackling the global concerns of food security and environmental sustainability. As remote sensing becomes more ingrained in agricultural systems, its role will be important in ensuring a resilient and productive agricultural future. The synergy between technological breakthroughs and agricultural methods offers a new era of smart farming that is both commercially viable and environmentally sound.

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Authors' contributions

DSB conceptualized the review framework and led the overall coordination of the manuscript. DSB also prepared all the figures and tables and contributed to data compilation. KR conducted an extensive literature review and was responsible for drafting the sections related to remote sensing applications in agriculture. MD contributed to the review of recent advancements, assisted in synthesizing key findings and helped in refining the manuscript's analytical depth. CN was involved in technical content development, critically revised the manuscript and ensured the logical flow of ideas. KS supported data collection from secondary sources, contributed to writing the introduction and conclusion and assisted with citation formatting. All authors reviewed and approved the final version of the manuscript.

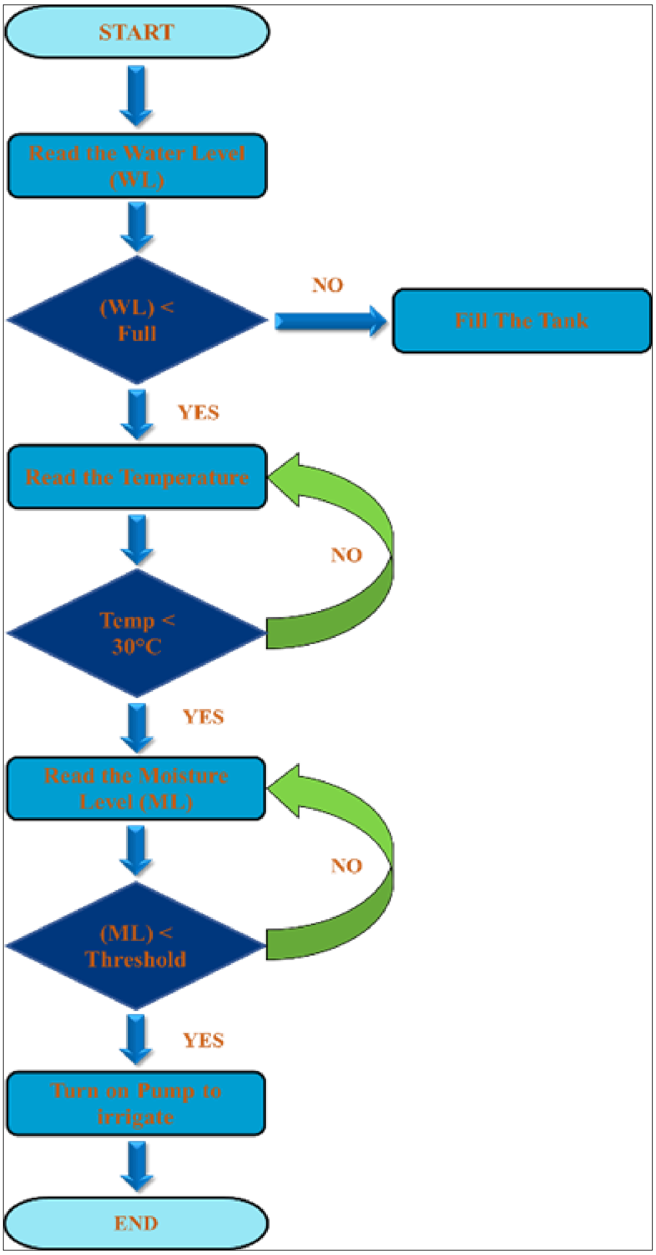

Fig. 6. Flow chart of automated irrigation using remote sensing.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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