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Artificial Intelligence for Sustainable Agriculture and Food Security

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Preface

Artificial Intelligence (AI) applications offer unprecedented opportunities for sustainable agricultural production with superior precision and speed. This policy paper presents an analysis of the current status of AI applications in agricultural production systems. AI has been effectively utilized to achieve significant advancements in the yield and quality of major crops. These applications encompass field-specific soil condition assessment, plant phenotyping, precision application of agrochemicals, pest and disease detection, maintenance of optimal plant populations, crop health monitoring, stress mitigation, and improved prediction of biomass and quality. In spite of these developments, quite a lot of technical challenges must be addressed for AI to comprehend its full potential.

Recognizing the importance of AI tools in agriculture, the National Academy of Biological Sciences (NABS), the National Academy of Agricultural Sciences (NAAS), Coimbatore Chapter, and the ICAR–Sugarcane Breeding Institute (ICAR–SBI), Coimbatore, Tamil Nadu, jointly organized a brainstorming session on "Trends in the Application of Artificial Intelligence for Sustainable Agriculture" on September 18, 2020. The primary objective of the brainstorming workshop was to provide a common platform for scientists, industrialists, and policymakers to deliberate on emerging issues associated to the application of Artificial Intelligence for sustainable agriculture in India. The brainstorming workshop received an overwhelming response, with about 180 participants representing ICAR institutes, State Agricultural Universities, private research organizations, industries, and government departments. Sincere acknowledgment is extended to Dr. G. Hemaprabha, Ex-Director, ICAR–SBI, for chairing the session, and to Dr. R. Gomathi, Principal Scientist & Head (Plant Physiology), and her team for their effective coordination. The session featured five scientific presentations

delivered by eminent experts in the field. Special thanks are due to Dr. Karun Kumar Choudhary (NRSC, Hyderabad), Dr. P. V. Vara Prasad (Kansas State University, USA), Dr. R. Viswanathan (Director, ICAR–ISRI, Lucknow), Mr. Mandar Gadage (Precision Farming, Kandivali East, Mumbai), and Dr. Jagadish Rane (Director, ICAR–CIAH, Rajasthan) for their insightful contributions. This policy paper is an outcome of the valuable deliberations from this brainstorming session and intended to support researchers, policymakers, development agencies and technology providers in identifying priority areas for AI adoption in agriculture.

(D. J. Bagyaraj)
President, NABS

Artificial Intelligence for Sustainable Agriculture and Food Security

1. Introduction

Agriculture is the primary occupation worldwide for food, raw materials, and employment, contributing to economic growth. However, limited cultivable land, decreasing productivity factors, yield stagnation, pests and diseases, along with climate change and uncertainties, threaten food security for the burgeoning population. Recent advancements in genomics, phenomics, nanotechnology, and artificial intelligence (AI) enable the scientific community to maintain crop productivity while preserving the environment. Over the last decade, work on IoT, big data, and AI has been recognized as a paramount topic of interest globally (Misra *et al*.2020). Scientific advancements in recent years have facilitated the use of artificial intelligence (AI) to ease human tasks in various sectors, including agriculture. Particularly in agriculture, AI plays a substantial role in performing tasks efficiently and accurately, reducing the cost of cultivation. AI is one of the utmost prominent fields of computer science engineering, assisting humans in their daily tasks with superior results and maximum accuracy. Artificial Intelligence solutions can achieve tasks such as analysing field-specific soil conditions, implementing precise irrigation based on sensors, predicting and forecasting weather, managing weeds, monitoring pests and diseases, applying agrochemicals, harvesting crops, and processing post-harvest, all for forecasting, planning and decision support in agriculture. This results in enhanced assistance to farmers through improved farming techniques backed by accurate data as per requirements (Eli-Chukwu, 2019; Pathak *et al.* 2020; Singh *et al.*2021; Gomathi *et al.* 2023; Vinayaka and Prasad, 2024; Vinayaka *et al.* 2025).

Plant phenotyping is a vital part of modern, intelligent, and precise agricultural production. Various physiological (tissue water content, plant pigments, canopy temperature, leaf area, biomass) and

morphological parameters (crop volume, plant architecture) of plants are acquired by various sensors such as RGB cameras, lidar, and multispectral and hyperspectral cameras to serve as a decision-making basis for real-time and future plant management (Su *et al.*2021; Rivera *et al*.2023a & 2023b). Several spectra of light, namely RGB, infrared rays (IR), near-infrared rays (NIR), multispectral, and hyperspectral images, play a vital role in the rapid phenotyping of a great number of genotypes for traits such as plant height, biomass estimation, canopy temperature depression, relative water content, vegetation indices, and other traits relevant to biotic and abiotic stress tolerance, as well as yield estimation. Sensors mounted on UAVs collect data for estimating leaf colour, plant height, lodging, canopy cover, stand count, flower count, and fruit count. Additionally, spectral sensors may be employed to determine the nitrogen content of leaves, yield, leaf area index, chlorophyll content, and plant biomass. Approximately 31% of research and publications are devoted to yield estimation within the sugarcane industry. In agriculture, AI is being utilised for screening large sets of genotypes for biotic and abiotic stress tolerance through drone-based imaging, processing, and the accurate identification of tolerant genotypes in a rapid manner.

Pests and diseases occur erratically and are detrimental to plant growth and production. For timely control/management of biotic stress, the recent advancement in computer vision makes it a popular approach for successful accomplishment (Guo *et al*. 2023; Su *et al.*2021). Aiming at these biotic stress problems of rapid detection of field crop pests and diseases, the AI significantly leads to practical solutions in detection, forewarning and early management, lastly leading to the realisation of harvest yield with minimum losses. Conventional methods of monitoring crop fields, including sugarcane, take a significant amount of human effort and time to complete successfully. At the same time, UAVs with advanced sensors enable a farmer to assess crop health within a short time with less labour. UAVs can be furnished with different sensors that detect the wavelengths of light absorbed and reflected by plants, resulting in

the production of colour images and maps to identify various crops, including sugarcane health. According to the map produced by image processing, a farmer can easily identify and investigate an unhealthy area in the field and propose a suitable solution using a GPS-enabled smartphone or other computer.

The chief advantages of AI are **yield and quality mapping**, which allows the farmer to understand spatial variety over the field remarking zone for future activities and outcomes of the past sessions, and management. Accurate yield mapping is essential for timely and effective decision-making, which maximises the efficiency of soil and water usage, intending to minimise loss and waste, besides reducing variability and input cost (Su *et al*. 2021).

With swift implementation and continuous innovations, AI technology will become more and more accessible to the common farmer, and adequate scientific information is essential for different crops regarding field-based screening, applications of AI for crop monitoring, yield prediction, and finally leading to the enhancement of crop productivity. The present policy paper allows the scientific community to think critically about ideas of AI and solutions, form connections, share ideas with peers, and help to bring a road map for the real utilisation of AI in improving crop productivity to encounter the needs of the growing population. A distinctive focus on the strengths, limitations and ways of utilizing AI in practical applications for enhancing higher crop productivity is highly imperative, and the present policy paper discusses in detail the (i) Crop Monitoring and Yield Estimation Using Earth Observation Data, (ii) Usage of drones in two important commercial crops *viz*., sugarcane and cotton (iii) Smart Harvesting Technology through modern technological developments such as satellite-based remote sensing, artificial intelligence and machine learning, and cloud computing to provide important insights to sugar mills that can help crop growth monitoring, yield improvement, and boosting recovery by harvesting based on maturity. (iv) Artificial intelligence in plant phenomics.

Section-1
(1-a) Crop Monitoring and Yield Estimation Using Earth Observation Data
(1-b) Earth Observation Data: An Overview

Table 1. Summarises different satellites with their sensors, spatial resolution, temporal resolution, and applications in Agriculture

Table 1: Current EO sensors for Agricultural applications

Satellites	Sensors	Spatial Resolution	Temporal Resolution	Applications in Agriculture
Cartosat-2S /3	PAN, Multispectral	PAN 0.65 m; Multi spectral: < 2 m	Scene-specific acquisition; revisit depends on tasking	Very high-resolution mapping of field boundaries, cadastral-level crop assessment
Resourcesat-2/2A	LISS-IV LISS-III AWiFS	5.8 m 23 m 56 m	24 Days 24 Days 5 Days	Crop Mapping, Monitoring, Drought Assessment
Landsat 8	OLI, TIRS	30m, 100m (TIRS)	16 days	Crop mapping, monitoring health, and water management
Sentinel-2	MSI	10m - 60m	5 days	High-resolution crop monitoring, land cover changes
MODIS (Terra/Aqua)	MODIS	250m - 1km	1-2 days	Vegetation health, drought assessment

Satellites	Sensors	Spatial Resolution	Temporal Resolution	Applications in Agriculture
NOAA-20 (JPSS)	VIIRS	375m - 750m	Daily	Crop condition, soil moisture, fire detection
Gaofen-1	Various Cameras	2m - 16m	Daily to monthly	Precision agriculture, crop yield estimation
Sentinel-1	C-SAR	5m - 25m	6 days	Soil moisture, crop type classification
EOS-4 (RISAT-1A)	C-SAR	3m-50m	17 days	Soil moisture, crop type classification

The spatial resolution capabilities of the sensors on Indian Remote Sensing satellites vary from very fine resolution multi-spectral data of 2 meters to moderate resolution data of up to 56 meters, covering different sensors and their applications. It mentions the varied revisit periods, ranging from 5 to 24 days, and swath widths from 70 km to approximately 800 km, illustrating the satellites' ability to provide district-level information through LISS-III data and regional-level information through both AWiFS and WiFS data. This demonstrates the versatility and depth of remote sensing technology in delivering detailed, actionable data for natural resource management at multiple scales.

(1-c) Remote Sensing of Vegetation

Spectral reflectance from leaves is governed by traits like pigment concentration, nutrient status, and water content, and manifests as a combination of diffuse and specular components; the former results from internal scattering, while the latter depends on surface

characteristics like cuticular waxes. In the spectrum, green plants reflect differently compared to other objects, showing low reflection in the visible range (400-700 nm) due to chlorophyll absorption, especially in the blue (400-500 nm) and red (600-700 nm) regions, while reflecting more in the green region (500-600 nm), making them appear green to the human eye.

In the infrared spectrum (700-900 nm), healthy plants reflect more energy than most objects, with high reflectance continuing up to 1300 nm owing to the leaf's internal structure. Water content significantly influences reflectance in the 1300-2300 nm range, with main absorption zones at 1450 nm, 1950 nm, and 2600 nm. Healthier plants, with more chlorophyll, absorb more in the blue and red regions, while a decrease in infrared reflectance can indicate reduced vigour, affected by drought, disease, pest damage, or senescence, leading to changes in leaf structure and reflectance. The green crop plant has spectral reflectance features as shown in **Fig. 1** as the green curve, which is quite different from other objects such as dry/ wet soil in pink/black colour and turbid/ clear water in cyan/blue curves (Swain and Davis, 1978).

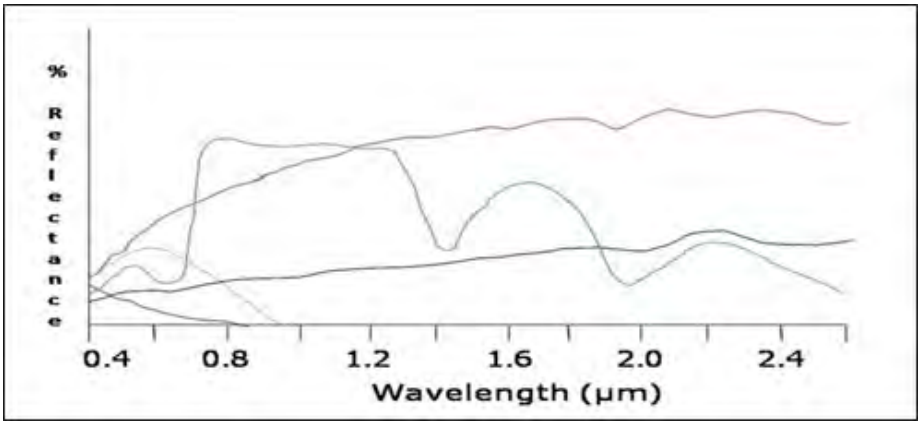


Fig 1: Typical spectral reflectance curves of various land features

(1-d) Satellite-Based Crop Mapping & Monitoring

Medium-resolution multispectral satellite data, such as that provided by Resourcesat-2, Sentinel-2, and Landsat-8/9, offers a valuable resource for this purpose. These satellites equip researchers and agricultural analysts with the ability to capture detailed images of the Earth's surface, including agricultural lands, with sufficient resolution to classify crop types accurately and monitor changes over time (Murthy *et al.* 2018; Murthy, 2018). This data is chiefly beneficial for creating detailed crop maps that can track the extent and health of different crops across multiple growing seasons **(Fig. 2)** as illustrated below in the crop maps compiled over several years.

These maps utilise temporal data from Sentinel-2 to provide a dynamic view of agricultural practices and changes, enabling the analysis of trends in crop coverage and the assessment of insurance units. This level of detail supports more informed decision-making in agricultural management and insurance, offering a technological avenue for improving the resilience of farming practices to environmental and market challenges. Non-linear relationships between crop types and bands can be captured through machine learning models to generate crop maps at local scales (Pandey *et al.* 2019). Availability of cloud-free satellite data during rainy seasons is a limitation which can be overcome by mixing data from multiple satellites and microwave data. Rice and Jute crop mapping using microwave radar (SAR) data is already operational in India (Parihar and Ozha, 2006; Sesha Sai *et al.* 2010; Zaho *et al*. 2016). Transplanted rice with its water background at the time of transplantation can be delineated with higher accuracy (>90%) than upland rice. SAR-based mapping for other crops like soybean, cotton, jowar, pear-millet, etc, are also reported in the recent literature, providing accuracies of 80-85% (Kumari *et al*. 2022).

The following set of indices, derived from satellite datasets, has proven to be crucial for assessing crop conditions and is commonly utilised in crop monitoring within an administrative boundary:

(a) Normalised Difference Vegetation Index (NDVI) is based on chlorophyll content, calculated from the reflectance values in the red and Near Infra-Red (NIR) bands. NDVI is renowned for its ability to quantify the impact of seasonal crop stress events, assess crop health, and map phenological patterns. However, the correlation between NDVI and yield can significantly vary, indicating that NDVI alone may not fully enhance crop insurance product design. **Fig. 3** illustrates the variability of wheat crop condition assessed through NDVI within an insurance unit.

(b) Land Surface Wetness Index (LSWI) measures soil and crop canopy moisture levels by analysing the reflectance values in Shortwave Infrared (SWIR) bands. LSWI is widely utilized to detect crop stress. When used alongside NDVI, it enhances the detection of anomalies and becomes more sensitive to ground agricultural conditions.

© RADAR backscatter is sensitive to soil and vegetation water content, laterally with additional factors like soil roughness and vegetation structure, which affect backscatter. The distinct sensitivity of microwave scattering to crop structure has prompted numerous studies to employ Synthetic Aperture Radar (SAR) backscatter for crop monitoring.

(d) Fraction of Photosynthetically Active Radiation (FAPAR) denotes the fraction of Photosynthetically Active Radiation absorbed by chlorophyll pigments in the crop canopy. It provides critical insights into canopy structure, illumination conditions, carbon dioxide assimilation, and biomass production. FAPAR offers a more accurate gauge of vegetation status than Vegetation Indices. The Copernicus Global Land Service (CGLS) provides global FAPAR time series data at a 300-meter resolution and a 10-day frequency.

Fig. 3: Wheat Crop Condition Monitoring using Season Maximum Greenness derived from NDVI (Murthy *et al.* 2018)

(1-e) Technology for Crop Yield Estimation

Satellite Composite Crop Yield Proxy: The satellite-derived crop health index (**Fig. 4)** has emerged as an alternative to yield data in insurance schemes. This ground-breaking approach was executed in West Bengal in 2020, covering a vast area of 3.5 million acres dedicated to paddy crops across 3200 insurance units. To generate a comprehensive crop map and assess crop health, a combination of Sentinel satellite data, gridded weather data, and mobile app-based field data can be utilised. A composite index known as the Crop Health Factor (CHF), which ranges from 0 to 1, integrates multiple indicators of crop health, such as the Normalised Difference Vegetation Index (NDVI), Land Surface Water Index, backscatter, and the Fraction of Absorbed Photosynthetically Active Radiation. The CHF is derived using data from these indicators combined through an entropy approach. In modern area yield insurance schemes, insurers have shifted to employing CHF over traditional yield data. This shift is grounded in the observed strong correlation between CHF and yield fluctuations across different years. By leveraging CHF, insurance providers can more accurately evaluate and manage the risks tied to crop performance (Murthy, 2018; Murthy *et al.* 2018; Murthy *et al.* 2022).

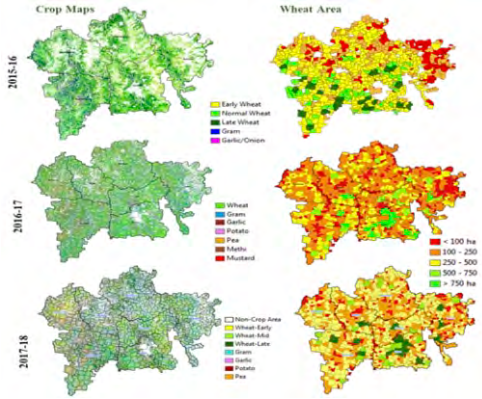


Fig. 2: Satellite-based crop maps and wheat area estimation in insurance units of Ujjain, MP (Murthy *et al.* 2018)

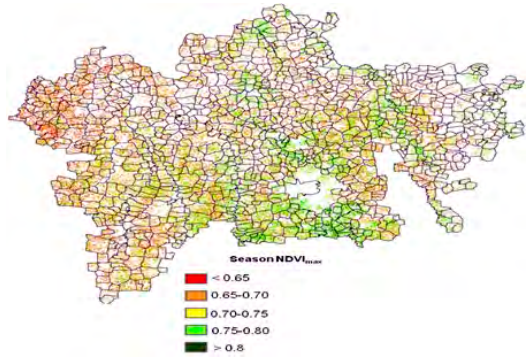


Fig. 3: Wheat Crop Condition Monitoring using Season Maximum Greenness derived from NDVI (Murthy *et al.* 2018)

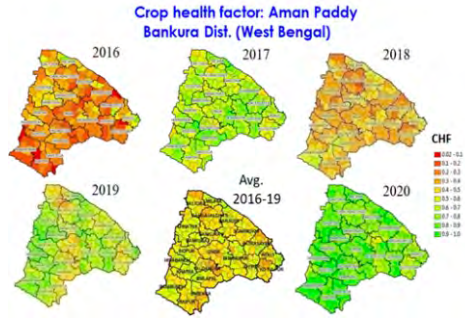


Fig. 4. Crop health index (CHF) of Aman Paddy over 5 years in Bankura, West Bengal *(CHF ranges from 0: No yield to 1: highest yield) (Murthy et al. 2022)*

(1-f) Models for Crop Yield Estimation

RUE models, which are production efficiency models, are widely employed for quantifying Gross Primary Productivity (GPP) and Net Primary Productivity (NPP) using remotely sensed data. These models are based on the radiation use efficiency concept originally proposed by Monteith (1972). According to this concept, when croplands are adequately watered and fertilised, their productivity demonstrates a linear relationship with the amount of absorbed

photosynthetically active radiation (FAPAR) by the canopies. Remote sensing data plays a critical role in the RUE model by providing valuable information regarding vegetation type, growth status, and environmental conditions. FAPAR is derived either through spectral vegetation index relationships, as demonstrated by studies like Goward and Huemmrich (1992), or using FAPAR products derived from radiative transfer models such as MODIS FAPAR, Sentinel-3 FAPAR, as discussed by Zhao *et al*. (2005).

Machine learning, a subset of artificial intelligence, empowers computers to learn from data without explicit programming. Machine learning models are non-parametric, enabling them to capture the complex and non-linear relationships between yield and the influencing features. By detecting patterns and correlations in the data, machine learning models can develop predictive models. During the training phase, historical data is utilised to determine the parameters of the predictive model, which incorporates multiple features. Machine learning has seen increasing use in research to enhance crop yield accuracy by incorporating satellite-derived vegetation indices, meteorological data, hydrological variables, edaphic factors, and more.

In the literature, two prominent machine learning approaches are commonly followed: decision tree-based models like random forest and deep neural network-based models. Random forest (RF) is a supervised ensemble learning model that combines the outputs of multiple decision trees to generate the final prediction. Each decision tree is trained independently and grows in random subspaces of the data using the Classification and Regression Tree (CART) methodology. Deep Neural Networks (DNN) leverage the universal approximation theorem, which states that a fully connected feed-forward neural network with a finite number of layers and neurons can approximate any relationship between input and output variables. This principle enables DNNs to model complex relationships between variables and make accurate predictions. Choudhary *et al.* 2019 showed the importance of a machine learning algorithm, i.e., Random

Forest regression, in the estimation of wheat grain yield using multi-temporal vegetation indices derived from medium-resolution data. Adding vegetation indices from different parts of the electromagnetic spectrum improved the wheat yield prediction accuracies.

Crop growth simulation models simulate the growth and developmental progress of crops based on input variables such as weather conditions, soil types, and crop management practices, offering insights into the potential yield under varying environmental conditions. When integrated with EO data, such as satellite imagery, these models are significantly enhanced. EO data provides real-time, spatially explicit information on crop health, soil moisture, and other critical parameters that affect crop growth. By assimilating this data, crop growth models can adjust their predictions to reflect actual field conditions, resulting to more accurate yield forecasts. This integration permits for the optimisation of agricultural practices, such as irrigation scheduling and nutrient management, ultimately contributing to more efficient and sustainable farming operations through digital land records progress by GOI (Parker *et al.* 2020; Lyu *et al*. 2026).

(1-g) YES-TECH Initiative Under PMFBY

The YES-TECH (Yield Estimation System based on Technologies) initiative under the Pradhan Mantri Fasal Bima Yojana (PMFBY) represents a significant technological advancement in agricultural insurance in India. Launched by the Indian government, this initiative aims to integrate satellite technology and remote sensing data into the crop insurance scheme to enhance the accurateness and efficiency of crop yield estimation and loss assessment processes. YES-TECH leverages satellite imagery and advanced remote sensing technology to monitor crop growth, assess crop health, and estimate yields at an insurance unit scale. The approach facilitates a timely and objective assessment of crop damage, ensuring that insurance claims can be processed quickly and accurately. It addresses the challenges of traditional crop yield estimation methods, which are often time-consuming, labour-intensive, and subject to errors. By incorporating

satellite technology, the PMFBY aims to make crop insurance more reliable and transparent, reducing the scope for disputes and improving trust among farmers.

Under YES-TECH states select an implementing agency called "Technology Implementation Partner (TIP)" and a mentor agency called "Mentoring Institute for Technology and Review MITR". TIP estimates the crop yield using the models explained above under the technical guidance of the MITR organisation. A complete SOP and operating guidelines are available at
https://www.pmfby.gov.in/pdf/YES_TECH_Manual_2023.pdf.

Applying remote sensing technology for crop yield estimation presents several challenges. The accuracy of remote sensing data can be affected by atmospheric conditions, such as cloud cover, which obscures the satellite's view of the Earth's surface. The spatial and temporal resolution of satellite imagery may not always align with the specific requirements for detailed crop monitoring, potentially leading to less precise yield predictions. The average land parcel sizes in India are quite small, i.e., less than 1 acre, which requires high spatial resolution datasets for accurately assessing and monitoring crops at the local scale. Capturing the crop damages due to natural disasters requires high temporal resolution data to capture timely and relevant information. Remote sensing data needs to be calibrated and validated using ground truth data to ensure reliable yield estimates. This involves collecting accurate and representative information from the actual crop fields, which can be time-consuming and resource-intensive. Remote sensing data can be affected by various sources of noise, including atmospheric interference, cloud cover, and sensor limitations. These factors can introduce inaccuracies in the analysis and interpretation of the data, potentially impacting the reliability of crop insurance assessments. Higher-resolution satellite data, which is often necessary for accurately delineating individual crop plots, can be expensive to acquire. Further, timely and continuous data delivery is crucial for effective crop insurance monitoring and assessment. Further, different crops and their stages of growth exhibit varied

spectral signatures, necessitating sophisticated algorithms to accurately interpret and classify this information. Another significant challenge lies in mixing remote sensing data with ground-truth observations and other agronomic data, which is indispensable for calibrating and validating yield estimation models. Lastly, there is the issue of accessibility and the technical expertise required to analyse and interpret remote sensing data, which can be a barrier for many stakeholders in the agricultural sector. Despite these challenges, advancements in satellite technology, data processing, and machine learning are continuously improving the reliability and applicability of remote sensing for crop yield estimation.

Various models can be integrated with the satellite-derived information to predict the crop yield at the local scale. Non-parametric models like machine learning and AI are gaining popularity in predicting crop yield through proper feature selection and optimisation. Furthermore, the YES-TECH initiative under PMFBY underscores a significant technological leap in agricultural insurance, enhancing the accuracy and efficiency of crop yield estimations and risk assessments. Despite the potential of EO data and remote sensing technologies, challenges such as data accuracy, resolution constraints, and the need for technical expertise remain. However, ongoing advancements and the integration of machine learning and crop simulation models are paving the way for overcoming these hurdles. As we move forward, the continued refinement and adaptation of these technologies hold the promise of revolutionising agricultural practices, ensuring sustainability, and bolstering food security in India.

Section-II

Using drones in sugarcane farming

By 2050, global requirements for food and fibre are forecast to grow substantially, driven by a UN-estimated world population of roughly 9.7 billion (UN, 2020). Meeting this demand while simultaneously conserving soil health, water resources, and biodiversity requires a

significant increase in crop production efficiency per unit area rather than extensification into new land (FAO, 2017). In India specifically, stagnating yields in sugarcane and cotton in rain-fed regions, combined with shrinking farm sizes and a diminishing agricultural workforce, make the case for precision crop management technologies particularly urgent. Agricultural research has greatly enhanced crop yields over the past century. Restoring yield advances to necessary levels while protecting our natural resources is achievable, but new methods must be brought to bear. One of the newest developments is the rise in the use of small, unmanned aerial vehicles (UAVs), generally known as drones, for farming. Drones are remote-controlled aircraft with no human pilot on board (**Fig. 5**). UAVs offer a range of better prospects for enlightening the management of crops, livestock, fisheries, forests and additional natural possessions. UAVs armed with distinct sensors can gather multispectral images that are stitched to create spectral reflectance bands. These bands allow operators to calculate indices such as a Normalised Difference Vegetation Index (NDVI), allowing farmers to view crop changes or stress conditions that are otherwise indiscernible to the human eye. Despite certain inherent constraints, these tools and technologies yield valuable data that can shape policies and decisions. Farmers, agricultural consultants and researchers have taken a great interest in drones over the past few years, and agriculture continues to be one of the chief growth sectors, fuelling the development and release of drone systems tailored specifically to agricultural applications. The drone itself is simply a platform that offers particular advantages over other overhead imagery and sensing options, such as satellites and manned aircraft.

Drones offer key benefits such as affordable acquisition and operation, plus the flexibility to fly under clouds and as frequently as needed. Fundamentally, UAVs provide farmers with an aerial perspective of their fields, revealing subtle crop variations often undetectable to scouts working at ground level. Their possible uses in agriculture, including in sugarcane cultivation, are discussed here.

(II-a) The platform

There are two drone platforms commercially available currently, each with specific properties and uses in agriculture are 1. Single rotor or Multi-rotor (**Fig. 5**); 2. Fixed wing



Fig. 5. Quadcopter drone

(II-b) Payloads

In addition to RGB camera or standard camera (**Fig. 6**), drones can carry one or two payloads and many allow the operator to swap payloads, meaning the platform can potentially carry out numerous different tasks using: – multi-spectral sensor (**Fig. 7**) for crop monitoring (eg NDVI) – 3D photogrammetry cameras – thermal imagery cameras (**Fig. 8**) (e.g. insect hot spots) – dry material spreader (e.g. pellets, seed, fertilizer) – water sampling – bird scarer – sprayer (liquid pesticide, fertilizer or herbicide). When deciding which drone platform to purchase, be sure to research the practicality and costs involved in retrofitting additional sensors. A clear understanding of current drone objectives, coupled with foresight into future uses, is crucial for effective deployment.



Fig.6. RGB camera



Fig. 7. Multispectral camera



Fig. 8. Thermal camera

(II-c) RGB Sensors and software for interpreting drone data

Flying a drone to make crop, livestock, and infrastructure inspections is quite easy and relatively inexpensive. If we want to use the drone to carry data-collecting sensors to create maps and make management decisions, we need to confirm that the drone platform is physically capable of carrying the necessary equipment, have access to data and image processing software (either purchasing the software or subscribing to a service) and have the ability to transfer the maps to a variable rate applicator. The software identifies and matches reference points in each photo and 'stitches' the images together to produce one seamless image of the field of interest, viewed from directly overhead. If a flight takes 20 minutes and the camera is pre-set to take an image every 5 seconds of flight time, this will result in 240 photos to process. Further analysis of the recorded data may be possible to extract specific information required for decision making. With agriculture seen as a growth sector for drone technology, there is an increasing number of drone systems coming onto the market that offer a range of applications suited to agricultural management and decision making. Prominent brands currently offering agricultural drone systems include AgEagle, DJI and Precision Hawk. In some situations, it may be more cost-effective to engage the services of a specialist drone service to collect and understand the data required.

(II-d) Application of drones in the agriculture sector

Currently, most of the drones come with standard cameras capable of capturing still images (digital photographs) and video footage in the visible light range. These drones can collect visually appealing footage for a range of uses such as routine inspections, checking for damage after floods, frosts or fire events and real estate. They can also be utilized in determining the irrigation, harvest and managing livestock. There are also opportunities to use these standard images to assess germination and determine plant density to assist with decisions such as whether to replant parts or a whole field. Crop

scouting without entering the field can assist with several key decisions that a farmer or agronomist might make based on visual assessments of a crop. These activities are potentially very informative and time-saving, and can overcome constraints such as gaining access to fields immediately after rain or other weather events. These images can also be used similarly to handheld digital cameras to monitor and evaluate trials or seasonal effects on different varieties.

UAVs' application in agriculture unlocks the doorway to accessing real-time data on the farm. It can be used at diverse stages throughout the cropping cycle. To use a drone to collect data that has additional value in terms of decision-making and precision agriculture, the user may need to add other sensors to the drone platform. With the appropriate sensors on board, drones can be utilized for a wide variety of following applications such as:

- **Precision farming:** Precision farming leverages sensor data, imaging, and real-time analytics to boost productivity by characterizing field-level spatial variability. Drone sorties generate the dense, high-quality raw data required to drive agricultural analytics. Within precision farming frameworks, drones enable soil health mapping, crop health monitoring, irrigation planning, fertiliser application, yield estimation, and weather-related data collection (Maldaner et al., 2021; Rivera et al., 2023a,b; Modi et al., 2023). Integrating these drone data with complementary datasets and analytical tools produces decision-ready information.
- **Assessment of greenness of the crop / photosynthetic active biomass** (which might correlate to nitrogen content). Drone-borne sensors that capture visible and NIR reflectance enable identification of plants according to their distinct green and NIR light signatures (Goward et al., 1992; Shendryk et al., 2020). The resulting multispectral images monitor crop dynamics and provide indicators of greenness and photosynthetic biomass that relate to important biometric traits (de Oliveira et al., 2022).

- **Crop health assessment** – The most recognized application based on drone-acquired image data is to evaluate the health of crop vegetation. An unmanned airborne platform equipped with infrared cameras can enable the development of a Normalised Difference Vegetation Index (NDVI). The NDVI view of the field permits the analysis of the intensity of solar radiation absorption and, therefore, the condition of the supervised plants (Narmilan *et al.* 2022). NDVI mapping using satellite and aerial imagery has long been established, but its relatively low resolution has limited precise field-scale applications. Drones have transformed NDVI mapping by delivering much higher spatial accuracy, allowing continuous monitoring of crop health and early identification of biotic stresses. This granularity enables precise, location-specific management through targeted fertiliser, pesticide, and herbicide applications (Sofonia et al., 2019; Castilho et al., 2024).
- **Crop monitoring** – Repeated imaging over time reveals detailed crop development patterns and pinpoints areas of suboptimal performance, guiding more effective management. Drones carrying infrared, multispectral, and hyperspectral sensors provide precise and accurate assessments of both crop condition and soil status. Integrating NDVI with indices like CWSI and CCCI in agricultural mapping systems delivers deeper insights into crop health (Fiorio et al., 2024). NDVI is grounded in the high NIR reflectance of foliage; when plants experience water stress or other stresses, NIR reflectance declines while visible reflectance stays largely constant, and the mathematical combination of these two bands enables separation of vegetation from background and healthy from unhealthy plants.
- **Crop stress** (for irrigation or drought management), UAVs mounted with Thermal infrared cameras show great potential in phenotyping as thermal images contain spatially distributed information about the energy emitted from plant leaves, and the captured thermal images can be used to notice the state of stress due to drought conditions**.** This would ultimately be beneficial to

screen the varieties for identifying and developing drought-tolerant varieties, and irrigation can be managed in the fields based on the thermal map (De Melo, *et al.*2022).

- **Weed stress**
- **Variable Rate Application (VRA)** – Additional application of drone technology in agriculture is crop spraying. Drones can scan the ground and spray the precise amount of liquid, controlling distance from the ground and spraying in real time for even coverage **(Fig. 9).** Drones such as the DJI Agras MG-1 are intended for precision variable rate application of liquid pesticides, fertilizers and herbicides (Gonzalez-de-Soto *et al.*2016; Narmilan *et al.* 2022; Nahiyoon *et al.* 2024, Maheswaran, *et al.* 2024; Sunil *et al*. 2024)).
- The technology was first realized in Japan in the 1980s when unmanned helicopters armed with spraying equipment and pesticide tanks were used to spray crop fields. Characteristic modern-day spraying drones have a tank capacity of over ten litres of liquid pesticide with a release rate of over a litre a minute, permitting them to cover a hectare in ten minutes. Nevertheless, to leverage drone technology fully as a spraying platform, the spraying needs to be paired and synchronised with the imaging, processing and automated analytics capabilities to discourse the affected areas or plants with precision. Such an method would lead not only to the improvement of dosage in the affected areas but also to a reduction in the overall use of chemicals within the area.
- **Insect activity and Diseases spread** (Reddy *et al*. 2023; Upadhye *et al*. 2023; Nahiyoon *et al.* 2024)
- **Crop maturity** (for harvest). Drone-enabled NDVI index values help to specify the precise timing for harvesting.
- **Assessment of soil colour and ground cover** (Liu *et al*. 2020; Alsalam *et al*.2026)

- **Yield estimation:** Multispectral and hyperspectral aerial and satellite imagery benefits in generating Normalised Difference Vegetation Index (NDVI) maps, which can distinguish soil from grass or forest, detect plants under stress, and distinguish between crops and crop stages (Medar *et al.* 2019; Akbarian *et al.*2023; Das *et al*. 2023). There are robust associations between crop yield and NDVI data measured at certain crop stages. Hence, tracking the crop growth at key stages will help to deliver an precise estimate of the crop yield and also to address issues early. Estimation of yield by UAV-based RS is a modern technique in the sugarcane industry. Two months beforehand harvest was discovered to be the best period for yield estimation utilising remote sensing data



Fig. 9. Drone spraying system

- **3D mapping for land levelling or development**
- **Soil and field analysis** –Mapping and imaging capabilities of drone platforms with a range of sensors can be used throughout the whole production process to plan production better and therefore improve productivity. Before the vegetation cycle starts, drone technology can be used to assess soil condition, and thus, potential yield can be achieved by monitoring soil health. The key application in assessing soil condition is the actual 3D

mapping of the terrain with precise soil colour coverage. This helps to assess the soil quality as well as the moisture and water flow precisely. After getting precise 3D maps for soil, planting can be planned, and nutrient status can be analysed for further operations.

- **Irrigation** – Drones with hyperspectral, multispectral, or thermal sensors can identify which parts of a field are dry or need improvement.
- **Estimation of crop loss:** Drones are also increasingly used in the agricultural insurance and assessment sector, including in insurance claims. Drone imagery is very useful in giving an accurate estimate of loss. Advanced geospatial NDVI products can also be used in the case of natural disasters or destruction of crops to precisely estimate the level of losses by comparing the pre-disaster state of vegetation with the damage that occurred. Precise documentation of damages, followed by precise estimation of the reduction in estimated yields, can be used in insurance procedures. Companies such as Skynet are using drones to provide agriculture survey services to insurance companies and the state governments of Maharashtra, Gujarat, Rajasthan and Madhya Pradesh.
- **Livestock management**

  Cattle ranchers, with a large area of land to cover, have used UAVs to determine the location of their livestock, and some have found UAVs useful for conducting regular surveys of fencing.

For these applications, the drone platform needs to be fitted with the appropriate sensors for the task and supported with the appropriate software to analyse the data collected. There is now an obvious move towards the commercialisation of agricultural drones that include a package of hardware and software specifically tailored to agricultural industries. Agricultural drone systems have also been brought to market by leading drone manufacturers to undertake a variety of tasks such as aerial spraying and seeding, bird scaring and water sampling.

(II-e) Applications in sugarcane agriculture

The sugar industry is the second-largest agro-based industry in India. Sugarcane is being cultivated in a 5-million-hectare area in India (Gomathi *et al.* 2023). The crop canopy of sugarcane reaches more than two meters in height at harvest. In other main crops like paddy, cotton, etc., where the crop canopy reaches a maximum level of one-meter height, it would be easy to survey and identify the disease occurrence and micronutrient deficiency symptoms and advocate necessary remedial measures in real time. Whereas in sugarcane, once the crop grows beyond one meter in height during the 4th month after planting, it would be difficult to either enter the dense field or to scan the field from a distance to measure the crop status. As per the ISSCT report, 10-15 % of the sugarcane crop is lost every year due to diseases. The crop loss due to micronutrient deficiencies like iron and zinc are estimated to cause huge crop losses that might have been evaded had it been assessed and suitable remedial measures applied at the early stage of this occurrence (**Fig. 10**). Further, data collection on other crop-related information like flowering, leaf canopy and architecture, irrigation, mapping soil and nutrient availability *etc* are also time-consuming and labor intensive in a crop like sugarcane. Harnessing the advances in IT and aviation technologies like drone technology for the surveillance and management of such disorders can save the crop from huge yield and monetary losses (Bhatt *et al.* 2024; Vinayaka *et al.* 2025).

Drones are unmanned aerial vehicles, which are obtainable in the market in various shapes and sizes to suit the user's requirements. A suitable drone, which can be operated remotely with a GPS-aided camera, can be employed for this purpose. The drone fitted with a high-resolution real-time camera or a multi-spectral camera has the potential to acquire real-time images and record videos or to acquire multispectral images, which capture images from infrared in addition to the visual spectrum, which could be utilised to spot the variations among healthy and detrimental crops. These unmanned aerial vehicles can be put into use to fly over the fields to survey the

sugarcane crops every week, every day or even for a particular hour, helping us map selected sugarcane crops with micronutrient deficiency for its management. A Quadcopter Drone (Model/Make: DJI-INSPIRE 1) capable of capturing 4K video, 12-megapixel photos and transmitting an HD video signal (up to 2 km) was utilized to capture the field images of the sugarcane crop leaves at ICAR-Sugarcane Breeding Institute (SBI), Coimbatore. It is equipped with a retractable landing gear, and it can capture an unobstructed 360-degree view from its camera. The built-in camera has an integrated gimbal to maximise stability and weight efficiency. With the help of sensors on vision positioning technology, the drone can perform hovering more precisely, even when there is no GPS signal available. It is equipped with a 4500 mAh intelligent flight battery, which supplies power for flying the drone. The drone was flown over different experimental fields at ICAR–SBI, Coimbatore, to capture images of healthy sugarcane leaves (**Fig. 11**) and sugarcane leaf with iron deficiency symptoms (**Fig. 12**) were recorded. While flying over the sugarcane field, along with capturing real-time crop images, the real-time videos were also recorded at different heights varying from 2 m to 100 m. The disease and micronutrient symptoms inside the sugarcane field could be diagnosed using the images and videos captured using the drones. The field images of the sugarcane leaves can be processed using MATLAB software for defining the colour



Fig. 10. Drone flying over healthy sugarcane field at ICAR-SBI, Coimbatore



Fig. 11. Drone flying over sugarcane field with iron deficiency symptom



Fig. 12. Close view of field images captured by drone

value through RGB values, L*a*b* values, Hue saturation value (HSV) and YCbCr values to clearly distinguish the sugarcane leaves with visually distinct symptoms on micronutrient symptoms and disease symptoms from healthy one based on the digital colour value (Arumuganathan *et al.*2026).

A multispectral camera (Make/Model: MicaSense RedEdge 3) which is capable of simultaneous capture of five discrete spectral bands to generate precise and quantitative information on the vigour and health of crops was utilized to capture the field images of sugarcane crops (**Fig. 13 and Fig. 14**). It is connected with a GPS module for geo-tagging of the captured images so that it records the information on geographical location of the captured images. This multispectral camera is provided with a calibrated reflectance panel, and images are captured directly by this overhead panel immediately before and after

each flight for better results. The geotagged images captured using the drone are normally stitched into a single ortho mosaic image using software like Pix-4D. Various vegetation indices namely *Normalized Difference Vegetation Index* (NDVI), Normalized Difference Red Edge Index (NDRE) and *Optimized Soil Adjusted Vegetation Index* (OSAVI) for field images of sugarcane crop captured using multispectral camera (Mica Sense- Red Edge) equipped with Drone (DJI- Inspire 1) can be mapped using the software PIX4D and MICA SENSE-ATLAS(Arumuganathan *et al*.2026).

The NDVI algorithm takes advantage of the fact that green vegetation reflects less visible light and more NIR, while sparse or less green vegetation reflects a greater portion of the visible and less near-IR (Narmilan *et al.* 2022). The range of values obtained is between −1 and +1. Only positive values correspond to vegetated zones; the higher the index, the greater the chlorophyll content of the target. The NDVI map of the sugarcane field with different treatments is shown in **Fig. 15.**



Fig. 13. Drone system equipped with multispectral camera flying over sugarcane field

NDRE is an index that can only be formulated when the Red edge band is available in a sensor. High values of NDRE represent higher levels of leaf chlorophyll content than lower values. Soil typically has the lowest values, unhealthy plants have intermediate values, and

healthy plants have the highest values. The NDRE map of the sugarcane field is shown in **Fig. 16.**

Usefulness of drone in irrigation experiment

Drone's theatres a vibrant role in capturing comprehensive data and images for sugarcane fields, predominantly in experiments concerning diverse irrigation methods. These UAVs can quickly identify zones of water deficiency or excess, permitting focused irrigation that augments water-use efficiency. Besides, drone surveillance supports early stress detection, improves yield predictions, and progresses decision-making for sustainable irrigation management in sugarcane cultivation (**Fig.12 and Fig. 14)**.

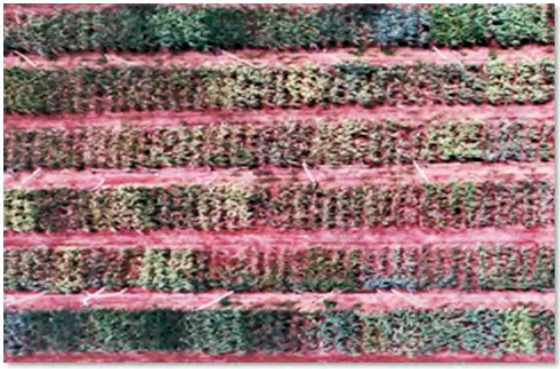


Fig. 14. Aerial view of field layout recorded with a drone with different irrigation treatment

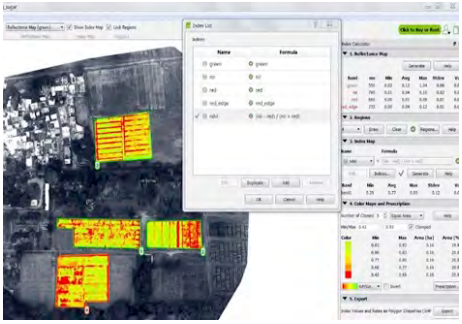


Fig. 15. NDVI map of sugarcane field

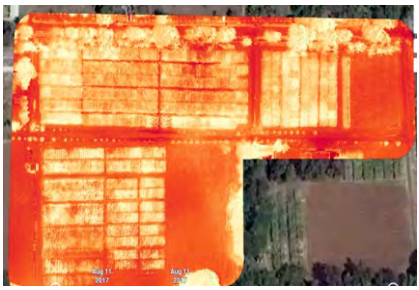


Fig. 16. NDRE map of sugarcane field

OSAVI maps variability in canopy density, and it is robust to variability in soil brightness. This index is best used in areas with relatively sparse vegetation where soil is visible through the canopy and where NDVI saturates (high plant density). The soil adjustment coefficient (0.16) is selected as the optimal value. OSAVI values can range from -1 to 1. High OSAVI values indicate denser, healthier vegetation, whereas lower values indicate less vigour. OSAVI map of the sugarcane field is shown in **Fig. 17.**

UAVs are a great example of a technology that allows farmers to focus on future possibilities rather than the limits of the present. UAVs in sugarcane industries offer numerous major benefits, including reduced labour, expenditure, and resources throughout sugarcane management. Sugarcane growth monitoring and yield prediction have traditionally relied on the farmer's expertise gained via visual examination. Sugarcane cultivation is frequently challenging to manage due to a lack of human resources. In conjunction with other precision farming approaches, state-of-the-art remote sensing technologies for quick sugarcane mapping and growth monitoring may considerably enhance sugarcane management. The use of extremely high spatial resolution UAV data for determining sugarcane crop monitoring and management is potentially a promising application. UAV data, combined with crop growth models, provide locally effective solutions for sugarcane monitoring and yield estimates at the field scale. Numerous countries are

conducting UAV-related trials on various crops. As a result, various research projects utilising UAV applications might be undertaken in the sugarcane industry. Future technologies will extend endurance and payload, improve human-UAV interaction, and develop clear norms and regulations for UAVs' safe and secure use. Additionally, by integrating artificial intelligence with UAV technology, the UAV will make judgments independently of humans. As a consequence, it is obvious that the use of UAS in sugarcane industries is still in its beginning and that there is a great opportunity for further growth in terms of both technologies (UAS and AI) and application possibilities such as the detection of exotic pests and disease and mapping of pest incidence.

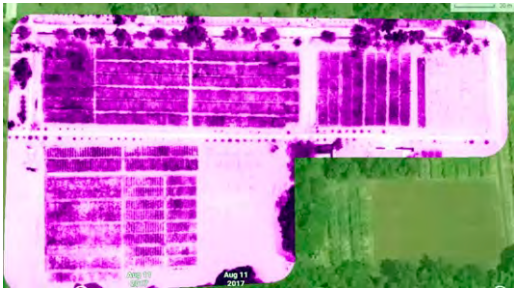


Fig. 17. OSAVI map of sugarcane field

Drones in agriculture are merely a low-cost aerial camera platform, armed with an autopilot using GPS and sensors for gathering relevant data. They can be related to a regular point-and-shoot camera for visible images, but whereas a regular camera can afford some information about plant growth, coverage and other things, a multispectral sensor expands the utility of the technique and allows farmers to realize things that cannot be seen in the visible spectrum, such as moisture content in the soil, nutrient deficiencies, pest infestations, plant health and stress levels. With the world population expected to reach 9 billion by 2050 and agricultural consumption expected to increase by 70 per cent over the same period, agri-producers need to embrace emerging technological advancements such as UAVs. Drone technology aids in scanning the inaccessible

areas of the fields from a remote distance and also in imposing remedial measures remotely. This will not only help to avoid time delays in diagnosis and rectification but also enhance the input use efficiency and the economic returns of the farmer. This technology will also help to cover a larger area in the shortest time. Particularly, sugarcane is a crop grown under contract with sugar factories, and extension services are provided by the factory personnel; it is easy to implement such technologies immediately in farmers' fields. In addition, UAVs create openings for ICT entrepreneurs supporting the agriculture sector, which could attract and engage educated youth in rural areas. This is especially true among younger people who are eager to embrace cutting-edge technologies and establish businesses based on them. The fusion of advanced aerial information acquired with the help of drones with data from other sources, such as weather forecasts and soil maps, can help to refine the final information and enable the farmer to take full advantage of the farm and maximise the yields to their natural limits.

Conventional methods of monitoring sugarcane fields take a significant amount of human effort and time to complete successfully. Therefore, using UAVs with advanced sensors enables a farmer to assess sugarcane (Barbosa Júnior et al. 2022; Ruwanpathirana *et al.* 2024) health within a short time with less labour. UAVs can be equipped with different sensors that detect the wavelengths of light absorbed and reflected by plants, resulting in the production of color images and maps to identify sugarcane health. According to the map produced by image processing, a farmer can easily identify and investigate an unhealthy area in the field and propose a suitable solution using a GPS-enabled smartphone or other computer. Sensors mounted on UAVs may collect a variety of data for estimating leaf color, plant height, lodging, canopy cover, stand count, flower count, and fruit count. Additionally, spectral sensors may be used to determine the nitrogen content of leaves, yield, leaf area index, chlorophyll content of leaves, and plant biomass. Around 31% of research and publications are performed to estimate the yield in the sugarcane industry. Next to yield prediction, detection and mapping

of crop lines were conducted in sugarcane crops. Also, UAVs are used for the application of agrochemicals, measurement of canopy, identification of pests and diseases, measurement of canopy temperature, estimation of vegetation indices, measurement of height, and weed detection for sugarcane management

With rapid adoption and continuous innovations, drone technology will become more and more accessible to the common farmer. However, adequate training and awareness are a must for its deeper penetration into the rural masses. The future of UAVs in precision agriculture comes down to farmers being ready and willing to try out the technology for themselves. Regulation will continue to evolve, and new advances will keep changing our conception of what drones can do. Getting involved now helps farmers acquire an understanding of the tremendous potential of drones and also allows them to determine their way forward.

Section-III
Role of Unmanned Aerial Vehicles in Cotton Precision Farming

Cotton is a major fibre crop of global significance, which is cultivated in tropical and subtropical regions of more than 70 countries. Cotton production in India during 2020-21 is 37.1 million bales of 170 kg (25.6% of world cotton production) from 13.35 million hectares (41% of world cotton area). Though India is the world's number one in terms of area and production, its productivity is very low (473 kg lint ha^{-1}) compared to the world average (766 kg lint ha^{-1}) and countries like China (1943 kg lint ha^{-1}), USA (909 kg lint ha^{-1}) and Brazil (1727 kg lint ha^{-1}). The low productivity of the cotton crop in India is mainly attributed to factors like being predominantly grown as a rainfed crop under aberrant weather conditions, low/medium soil fertility status and lack of integrated crop management practices, pest and disease problems, higher labour cost and non-availability of labour in time, etc. For achieving sustainable and secure cotton yields, genetic variation (G), environmental conditions such as climate (including

annual variability) and location (E), together with farm agronomic management (M) and their interactions (G x E x M) are very important. Genetic improvements in cotton yield continue in the world through the concerted efforts of breeders, but to realise the potential of these improvements in farmers' fields to meet global demands will require improved agronomic practices, especially precision farming technologies.

The modern farming industry in our country is at a turning point. With the development of more advanced farm management techniques, such as precision agriculture, industry professionals now have more tools than ever to improve the accuracy and efficiency of processes (Pathak *et al.,* 2020). The advent of the Internet of Things (IoT) and Unmanned Aerial Vehicle (UAV) technology, combined with image data analytics, provides promising precision agriculture solutions like the creation of spatial maps of fields, operational monitoring of crop conditions, evaluation of germination, spraying of agrochemicals, predicting crop yields, etc.

(III-a) Drone-based multispectral imaging for precision nitrogen management in cotton

Nitrogen status can vary spatially within a field; however, detecting that variability by ground-based data collection methods has many limitations, including spatial resolution. Unmanned aerial systems (UAS) can provide a better understanding of where variability exists in the field, on time and with good spatial resolution. Unmanned aerial systems can be equipped with many different sensor types that can record large amounts of data quickly. A UAS's ability to record a dense amount of data that is georeferenced provides the capability of analysing data with geographic information systems (GIS) software, which can then be correlated to ground sampling data (Vellidis *et al.* 2004). Multispectral imagery is used to record the reflectance of different bands of the electromagnetic spectrum. Generally, most of the spectral bands that multispectral sensors capture is between 400 nm and 1000 nm. Visible light is between 380 nm and 750 nm, and plants use light between 400 nm and 700 nm for photosynthesis. The

most common multispectral bands used for remote sensing are blue (460 nm), green (550 nm), red (660 nm), red edge (735 nm), and near infrared (790 nm). The bandwidths of each of these spectra captured by multispectral sensors can vary depending on the capability and resolution of the sensor and on the calibration.

Spectral data recorded from plants have been used to create different ratios or vegetative indices. A popular vegetative index is the normalised difference vegetation index (NDVI), which has been used to predict mid-season N requirements for cotton (Arnall *et al.* 2016). NDVI uses the NIR and red spectra and the formula is: NDVI = (NIR-red)/ (NIR + red). The strongest wavelength correlations with leaf N concentration, lint yield, and plant total N content were noted near 700 nm by Raper and Varco, (2015). Nitrogen deficiency causes a decrease in leaf chlorophyll content, resulting in an increase in spectral reflectance between 550 nm and 710 nm (Zhao *et al.* 2010). One of the most sensitive regions to changes in chlorophyll content is the red edge, and Raper and Varco (2015) found that other vegetative indices that include the red edge showed a stronger correlation to N status than NDVI.

Results of a field experiment conducted during the *kharif* 2021 season at ICAR- Central Institute for Cotton Research, Regional Station, Coimbatore, using drone-based multispectral imaging indicated that multispectral data can be a viable method for detecting N levels in cotton (Raja *et al*. 2026). The Normalised Difference Red Edge



Plate 1: Cotton crop monitoring using DJI-Phantom 4 Multispectral Drone

(NDRE) Index and leaf N% at different crop stages exhibited a better coefficient of determination than NDVI and leaf N%. The field-level management zone maps can be generated based on these vegetation indices, and these maps can be used in variable rate applicators for variable rate application of nitrogenous fertiliser to cotton crops.

(III-b) Drones for Agrochemical Spraying

Also, the crop monitoring process, another major use of UAVs in precision agriculture is the agrochemical spraying in agricultural fields. Agricultural drones have the features of high efficiency and consistent manoeuvrability, and could rapidly retort to sudden pests and diseases and large-scale spraying needs (Lan and Chen, 2018). Furthermore, the drones will not touch the crops, which could evade the economic losses triggered by mechanically crushing cotton. With the progress and improvement of the real-time kinematic (RTK) high-precision positioning technology and terrain-following technology, agricultural drones have been widely used as spraying tools in China in recent years, particularly for low crops, such as wheat, rice, and cotton (Chen *et al.* 2020). In India also drones are being used for spraying of agrochemicals, and clear-cut guidelines are laid down by the Government of India. For numerous field crops, including cotton, standard operating procedures (SOPs) have been formulated for insecticide spraying (Reddy et al. 2023). In addition to insecticide spraying, drones can also be used for growth regulator application and harvest aid application in cotton grown under a high-density planting system (Raja *et al.* 2026).



Plate 2: Agrochemical spraying using a drone in cotton

(IV) Artificial intelligence in plant phenomics:

The Food and Agriculture Organisation (FAO) has specified that by 2050, there will be about 10 billion people, and the food demand will rise by 70% (FAO, 2017). Under the changing climate, declining soil fertility, dwindling natural resources, urbanisation and environmental safety, sustaining food production is highly imperative to match the demand of the projected population, and artificial intelligence plays a major role in bridging the demand for food through precise phenotyping/phenomics. Phenomics is a transdisciplinary field that investigates phenotypic variation in organisms, with a primary focus on their morphological, physiological, and biochemical characteristics (Sahoo et al., 2022; Aparatana et al., 2023). In other words, phenomics encompasses the comprehensive analysis of phenomes or phenotypes at the genome-wide scale, focusing on the physical, physiological, and biochemical traits of an organism. The field of phenomics provides a link between different traits and gene variants or alleles (Slikker *et al.* 2007). High-throughput phenomics is known for efficient phenotyping in various crops with less space and less manpower on a real-time basis. Further through HTP, the same number of inputs, viz., water and nutrients, can be applied, and the efficient genotypes are identified. It is also useful to clearly understand the genomic region linked with physiological efficiencies.

The utilisation of high-resolution RGB, IR, NIR, multispectral and hyperspectral cameras for capturing various images related to morphological, biometric, and physiological data has led to the unravelling of complex scientific information in a useful way related to biomass, crop yield, stress tolerance, etc. Artificial intelligence is being reported to be an effective tool which has enabled present-day science to encompass into areas previously unexplored and provided ease of execution. AI utilises the large repository of data/big data of the images from the high-throughput phenomics, and through machine learning and deep learning, the complex data are analysed, and results are obtained in a meaningful way.

The images obtained from the RGB camera help in the derivation of crop biomass, chlorophyll content, leaf rolling compactness, rate of senescence, and growth parameters viz., RGR, NAR, AGR, pixel no vs leaf area, projected shoot area vs biomass. Different imaging cameras and AI tools inclusively (**Fig.18**) play certain specific roles and thus help in the determination of morphometric and physio-biochemical features of the large breeding population of various crops in a short period.

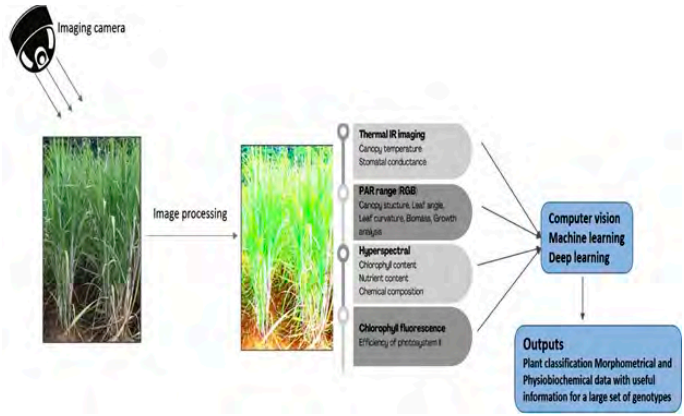


Fig. 18. Different imaging cameras and AI tools in the determination of morphometric, physio-biochemical features

(IV-a) Challenges for artificial intelligence in agriculture:

- Adoption of AI-based drip irrigation by the farmers, particularly in the subtropical north, is certainly a difficult task to achieve given the easy availability of irrigation water. It requires precise automation and validation.
- AI measures the status of plant nutrients in the soil through satellite images and makes recommendations accordingly. Nevertheless, it needs validation with proper soil sampling and analysis.

- The low offer and high cost of Robots, drones, sensors, and AI gadgets optimised for the efficient use of water, herbicides, and pesticides delivery to the crops is a challenge to developing countries. The cost of hardware and software is reasonable. However, it seems to be unaffordable to the small farmers who occupy larger areas of Indian agriculture.
- Dissemination and commercialisation of developed technology is a practical challenge for the reach of artificial intelligence in agriculture.
- Sometimes the training process seems to be overfitting/ underfitting, and the created models need to be retrained to reduce the error.
- One of the big and main challenges is the digitisation and mapping of small and medium-sized agriculture production units.
- Workforce ageing is considered one of the important challenges. For the improvement of competence, it is necessary to invest in and train farmers through workshops and other meetings.
- Functioning of devices/gadgets in harsh field environments is a challenge for artificial intelligence in Indian agriculture. Environmental variability is a great threat to sensors and their data.
- Data quality, availability, privacy, integrity and interoperability need to be addressed. Need extra care for excess/big data management.
- Heterogeneity of farmer fields and sector imperfections of the cropping system pose significant challenges for AI.
- Job replacement is also a big threat to AI.

(V) Artificial Intelligence (AI) and its impact on Indian and world agriculture

Artificial Intelligence (AI) is transforming agriculture in India and across the globe by improving crop productivity, optimizing resource

use, reducing operational costs, and promoting sustainable agricultural development through precision farming, automation, and data-driven decision-making systems. (https://farmonaut.com, https://farmingfirst.org/).

Table 2: Impact of Artificial Intelligence on Modern Agriculture

Institution	Year	Key AI-in-agriculture aspect	Reference
FAO	2025 2026	FAO notes that AI and digital agriculture can drive global agri-food-system transformation, support precision farming, and strengthen climate resilience. It also emphasizes that innovation is essential for sustainability, food security, and resilient agri-food systems.	Food and Agriculture Organization of the United Nations. (2025). *Digital agriculture and AI innovation roadmap for the global agri-food systems transformation.* FAO. Food and Agriculture Organization of the United Nations. (2026). *Digital agriculture and AI innovation.* FAO.
ITIAayog	2018	The integration of computer vision, machine learning, and cognitive computing enables intelligent farming	NITI Aayog. (2018). *National strategy for artificial intelligence.* Government of India.

Institution	Year	Key AI-in-agriculture aspect	Reference
		systems that enhance crop productivity, improve quality, and minimize resource wastage. By supporting precision agriculture, these technologies create a data-centric ecosystem that delivers real-time field insights, optimizes resource utilization, and strengthens market connectivity. Agribots perform crop management tasks such as weeding, fertilization, and harvesting, reducing fertilizer costs and labor requirements. Further, smart drones, Soil sensors, Weather forecast, autonomous tractor etc plays a major role in agriculture sustainability.	

Institution	Year	Key AI-in-agriculture aspect	Reference
ICAR	2025	ICAR has encouraged AI, IoT, and ML in agriculture through training, webinars, and partnerships.	Indian Council of Agricultural Research. (2025). *Training programme on development of AI-based Android applications in agriculture; Webinar on artificial intelligence for smart agriculture; ICAR-CCARI signs MoU with Business Kendra to promote AI, IoT and ML in coastal agriculture.*
ICRISAT	2025	AI and ML are being used to provide climate advisories, monitor plant health, and support farmers' decision-making.	International Crops Research Institute for the Semi-Arid Tropics. (2025). *ICRISAT and partners launch AI-powered climate advisory initiative to boost farmer resilience.* ICRISAT.
CGIAR	2023, 2026	CGIAR emphasize that AI as a transformative tool for agriculture, with	CGIAR. (2023, August 8). Artificial intelligence: How could it transform

Institution	Year	Key AI-in-agriculture aspect	Reference
		use cases in breeding, crop monitoring, and policy support. CGIAR is occupied with partners to use AI for crop development and agricultural innovation.	*agriculture?* CGIAR. CGIAR. (2026, April 20). CGIAR and Google leverage AI to develop the crops the world needs the most. CGIAR.
CIMMYT	2024	AI and digital technologies are being used more often in crop breeding, data analysis, and the expansion of agricultural innovation.	International Maize and Wheat Improvement Center. (2024). *[Use the exact CIMMYT article/report title from your chosen source]*. CIMMYT.
IRRI	2024	AI contributes to rice breeding, remote sensing, and decision-making, thereby improving the efficiency of rice-based production systems.	International Rice Research Institute. (2024). IRRI.

Institution	Year	Key AI-in-agriculture aspect	Reference
NAAS	2021	AI helps in computing complex big data generated from various agriculture research viz., genomics, phenomics etc. and agro-based manufacturing and services.	NAAS 2021. Big Data Analytics in Agriculture. Policy Paper No. 101, National Academy of Agricultural Sciences, New Delhi, pp16.

The table 2 exemplifies how artificial intelligence is rapidly redesigning the agriculture sector in India and globally, leading to robust market growth by 2025. In India, the widespread integration of AI is anticipated to result in billions of dollars in market value, with distinguished gains in crop yields, efficiency, and reduced costs for farmers. On the world stage, the increasing market size and rapid adoption rate highlight AI's essential role in driving sustainable agriculture, elevating productivity, and enabling significant changes in farming methods across regions.

VI. Way Forward

Scientific advancement in current years has led to the application of artificial intelligence (AI) to ease the work of humans in many sectors including agriculture. AI is going to play a major role in agriculture performing tasks in an accelerated and accurate manner with reduced cost of cultivation.

1. Artificial Intelligence / Machine Language (ML) based models may be established for major crops for crop monitoring, yield estimation and yield forecasting using remote sensing technology

which is essential for effective decision-making to maximize the efficiency of soil and water usage in sustainable agriculture.

2. AI based Community Micro Irrigation System can be a good opportunity to adopt by the farmers
3. AI is a disruptive technology that increases the efficiency of crop and livestock management and AI can be combined with precision and digital tools to improve crop productivity, increase resource use efficiency and minimize losses.
4. AI maybe given due importance during the pre-production phase of sugarcane, post-harvest & processing phase and distribution sector in sugar industry.
5. New AI tools may be developed for the Phenomics study and make the existing AI tools more robust.
6. AI may be used for identification of sensitive physiological process, desiccation tolerance threshold through spectral and hyper spectral signatures.
7. Successful AI-based models may be studied and adopted by the sugar mills for sugarcane harvesting systems and improvement in sugar recovery.
8. Efforts may be made to make AI technology to become more and more available to the common farmer and adequate scientific information is indispensable for different crops for the enhancement of crop productivity.
9. System approaches (e.g., Sustainable Agricultural intensification, Circular Biosystems and Broader– Health) provide multiple options and holistic solutions to address food, nutrient, climate, water security and biodiversity.
10. Provides database evidence for decision-making in all aspects of agri-food systems (from management, Yield prediction, Market analysis and pricing).

11. The combination of AI with precision and digital agriculture tools will help improve productivity, increase resource use efficiency and minimize losses, thus supporting sustainable agricultural intensification and improving lives and livelihoods.
12. There are many encounters, including the cost of services, the need for more knowledge, some technological limitations, adoption issues, maintenance, privacy and security concerns and many others.
13. Need a large database/dataset for the proper model with optimum fitting, while using AI, ML and deep learning.
14. Inter-institute collaboration is essential for the efficient use of AI. Combinations of subject matter specialists and AI experts would be helpful in reducing the errors which results in better models.

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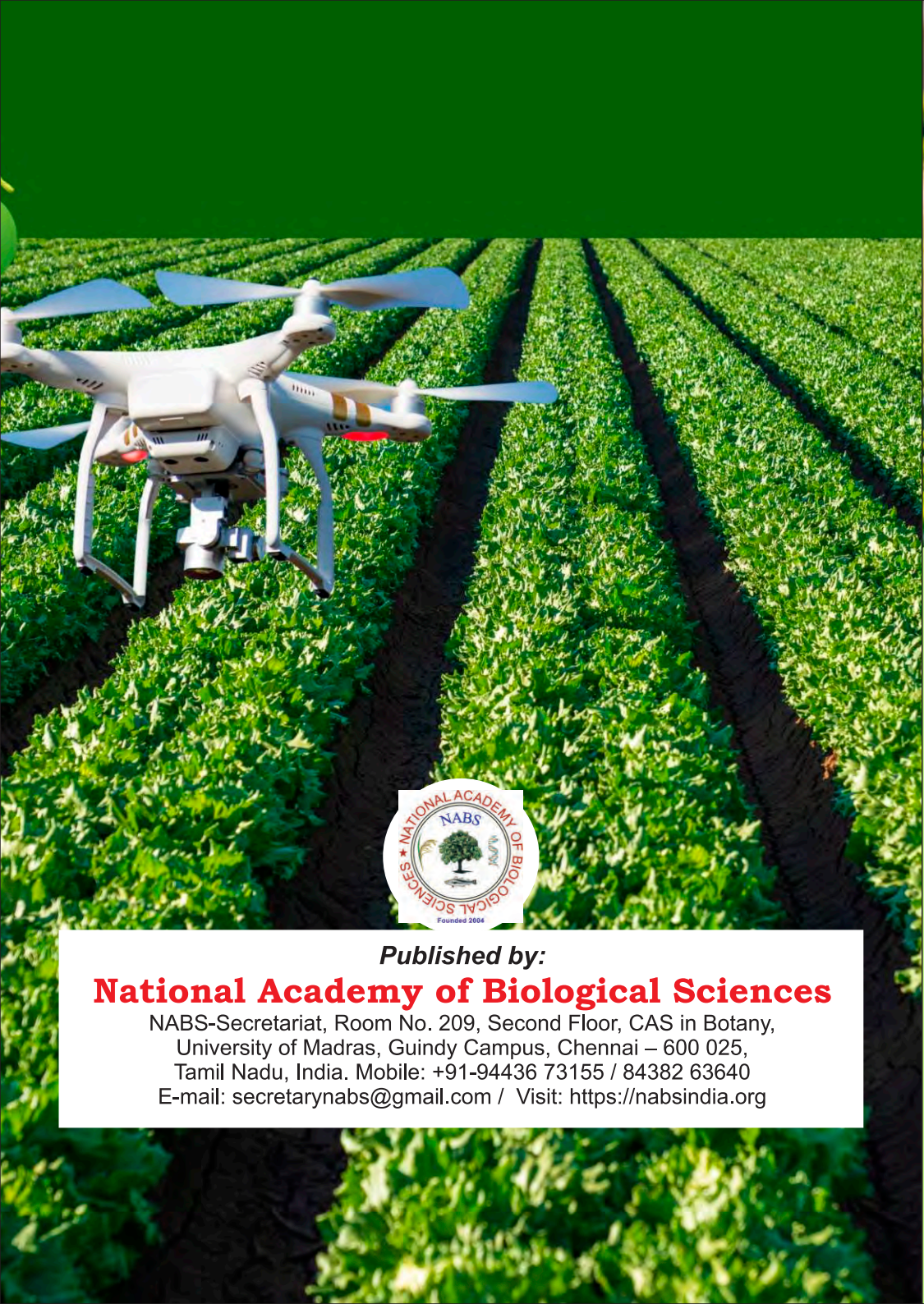
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