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Role of AI, Remote Sensing, and Digital Tools in Regenerative farming : With a Special Focus on West Bengal Region of Eastern India

*Rohit Kumar Choudhury and Shubhadip Dasgupta**

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ABSTRACT

At the present juncture, Indian agriculture faces a bidirectional challenge - meeting the rising food demand of a growing population while ensuring economic stability and environmental sustainability. Prolonged dependence on intensive and conventional farming practices has led to the degradation of soil quality, depletion of soil organic matter, and soil resilience. The yield-centric mindset of farmers, often driven by short-term economic needs, has gradually undermined the long-term productivity and ecological balance of agricultural lands. If continued unchecked, this trajectory risks future food insecurity, increased production costs, and systemic economic vulnerability. In this context, the adoption of alternative farming strategies becomes crucial. Regenerative agriculture represents a transformative approach aimed at restoring soil health, enhancing biodiversity, capturing carbon, improving water use efficiency, and strengthening ecosystem services. The emerging integration of Artificial Intelligence (AI), Internet of Things (IoT), remote sensing technologies, and decision-support systems (DSS) has significantly enhanced the feasibility and scalability of regenerative practices. These technologies enable precision soil health monitoring, real-time assessment of pest and disease outbreaks, optimized irrigation and fertilization, and predictive weather and risk assessment. Remote sensing combined with AI-driven analytics, facilitate continuous and spatially explicit monitoring of soil conditions and crop performance. IoT-based field sensors generate localized, real-time datasets that support adaptive and site-specific management. Such gaps are prominent in regions like West Bengal, where high cropping intensity and diverse agroecological conditions demand region-specific solutions. Strengthening digital infrastructure, capacity building, and inclusive policy support will be essential to realize full-scale adoption. Overall, the synergy of regenerative agriculture with AI, remote sensing, and digital tools holds significant promise for improving farm productivity, economic resilience, and environmental sustainability, while contributing meaningfully to national food security and climate change mitigation goals.

Keywords : Digital Agriculture, Proximal sensing, Soil fertility prediction, Crop monitoring, Machine learning, Future recommendations

Department of Agricultural Chemistry and Soil Science, Bidhan Chandra Krishi Viswavidyalaya, Mohanpur, Nadia, West Bengal-741252, India.
*Corresponding Author Email: dasgupta.shubhadip@bckv.edu.in

Introduction

Increasing population growth has drawn greater attention regarding limited availability of soil and other natural resources which further raises a serious concern about soil security and the earth's carrying capacity (Hartemink and McBratney, 2008). In India, where agriculture contributes 18.33% to the national GDP and employs almost half of the population, the sector have a higher chance to face challenges to meet the food demand for the growing population in near future due to intensive farming practices, soil degradation and changing climate. Therefore, it is crucial to understand and manage soil health to promote sustainable agriculture and innovative farming practices (Biswas *et al.*, 2025; Choudhury *et al.*, 2024; Bhattacharyya *et al.*, 2015). Regenerative farming emphasizes restoring soil health, enhancing biodiversity, improving water retention, and reducing dependence on chemical inputs. Artificial Intelligence (AI), remote sensing, and digital technologies together enable data-driven decision-making that supports these ecological goals. AI, remote sensing, and digital tools play a transformative role in supporting regenerative farming enabling more sustainable practices, higher yields, and improved soil health through data-driven strategies and precision technologies (Olawale *et al.*, 2025). By utilizing satellite imagery, sensor mounted aerial platforms, and spatial analytics, AI algorithms can identify crop types, monitor crop and soil, health, assess growth stages, detect stress caused by pests, diseases, or water deficiency, and predict yields with high accuracy empowering farmers to make informed decisions that enhance sustainability and output (Kulwant and Patel, 2024). This integration enhances real-time monitoring, supports sustainable resource management, and helps farmers optimize inputs such as water, fertilizers, and pesticides while minimizing environmental impacts (Ramirez, 2025; Arogundade and Njoku, 2024). In a climate with increasingly unpredictable weather, it also supports resilience by forecasting extreme events and helping farmers adapt their strategies. Overall, integrating AI into agricultural systems not only streamlines farm operations but also supports global efforts toward food security and environmental conservation (Ali *et al.*, 2025).

Precision Farming and Digital Agriculture- A Component of Regenerative Farming

Precision Farming and Digital Agriculture are closely related concepts in modern regenerative farming strategies that leverage technology for improved productivity and sustainability, but they differ quietly in scope and complexity (O'Donoghue *et al.*, 2024; McLennon *et al.*, 2021; Bronson, 2020). Precision agriculture, commonly called as precision farming, is a management strategy focused on resource optimization with the help of technologies like GPS, sensors, remote sensing (satellite/aerial imagery), and variable-rate application tools to deliver inputs (water, fertilizers, pesticides) precisely where and when needed on a site-specific basis (Mani *et al.*, 2021; Mohamed *et al.*, 2021). It aims to increase resource use efficiency, yield, and quality while reducing environmental impact by minimizing waste and unintended application. Digital Agriculture often called as Smart farming is a more integrated digital approach that applies information and communication technologies (ICT), artificial intelligence (AI), remote sensing, machine learning (ML), robotics, Internet of Things (IoT), and big data analytics across the entire agricultural value chain (Gebresenbet *et al.*, 2023; AlZubi and Galyna, 2023). It incorporates precision farming techniques but extends to autonomous machinery, farm management software, supply chain tracking (blockchain), climate control, market forecasting, and environmental monitoring. Smart agriculture aims to optimize not only production inputs but also logistics, sustainability credentials, and decision-making processes at farm and system levels.

Internet of Things (IoT) in Smart Agriculture

The Internet of Things (IoT) has emerged as a transformative technology in smart agriculture, enabling real-time monitoring, automation, and decision-making to enhance productivity and sustainability (Suma, 2021; Sekaran *et al.*, 2020). IoT systems connect a network of sensors, devices, and machinery through the internet, allowing wireless data exchange and deploy sensors in fields to measure crucial parameters such as soil moisture, temperature, humidity, nutrient levels, and light intensity which provide continuous insights to farmers regarding crop, soil and weather conditions (Suma, 2021; Mat *et al.*, 2018) (Figure1). Thus, IOT can be treated as an integral part of precision farming through which irrigation, fertilization, and pest control can be optimized based on real-time field variability (Sharma and Shivandu, 2024). IoT-enabled systems also include smart irrigation that automatically adjusts water supply based on soil and weather data, thereby reducing water wastage and improving efficiency (Lin *et al.*, 2020). Drones and unmanned vehicles, integrated with IoT networks, help in crop surveillance, pesticide spraying, and mapping of large farmlands (Vashishth *et al.*, 2024; Gao *et al.*, 2020). The integration of IoT with AI and cloud computing enables predictive analytics, early disease detection, and yield forecasting, empowering farmers to make data-driven decisions (Delfani *et al.*, 2024).

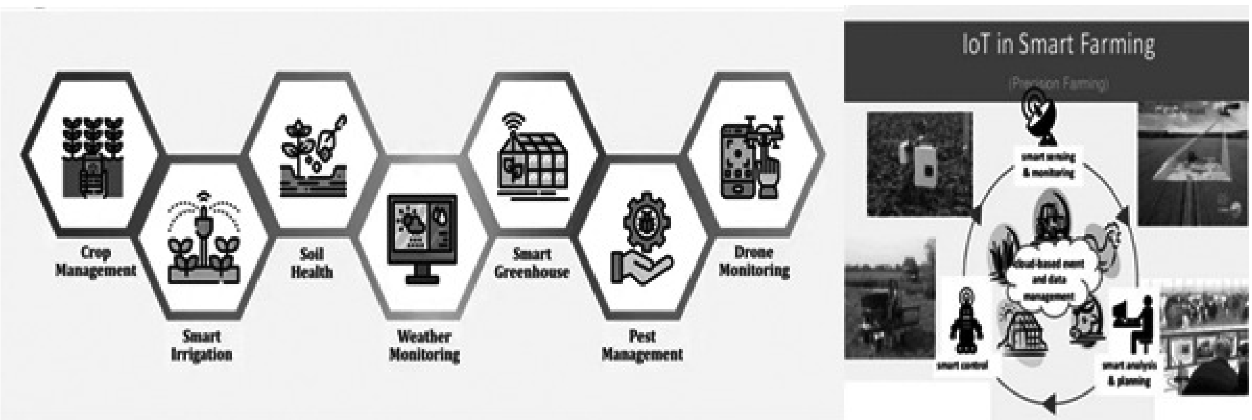


Figure 1. Application of IOT in digital agriculture

Artificial Intelligence (AI) and Machine Learning (ML)

Artificial Intelligence (AI) refers to an advanced computer system that can perform tasks typically alike human intelligence, such as recognizing images, understanding speech, making decisions, and translating languages (Russel and Norvig, 2016). It includes areas like computer vision, data mining, deep learning, image processing, and neural networks (Kale and Patil, 2018). In other hand Machine Learning (ML) is the process through which AI can perform any task based on algorithms that enable computers to learn from provided dataset and can improve their performance without being explicitly programmed for each specific task (Tyagi and Chahal, 2020) (Figure 2). Instead of following fixed instructions, machine learning algorithms analyze patterns in data and adapt to make predictions or decisions based on new input (Figure 3). Machine learning makes

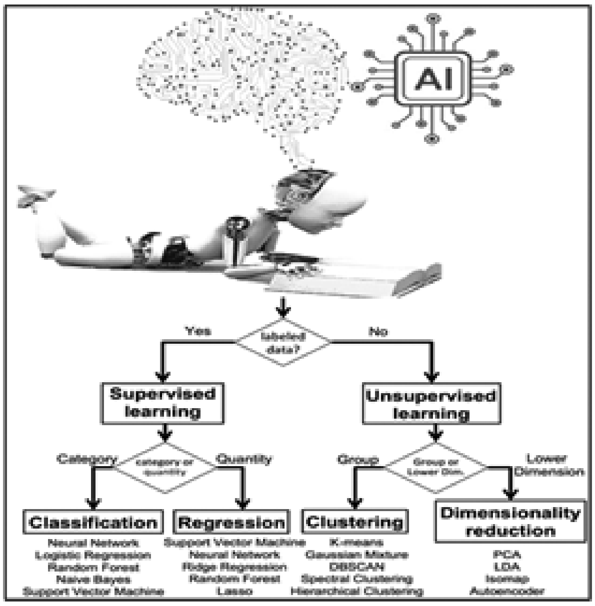


Figure 2. AI and Machine learning based approaches

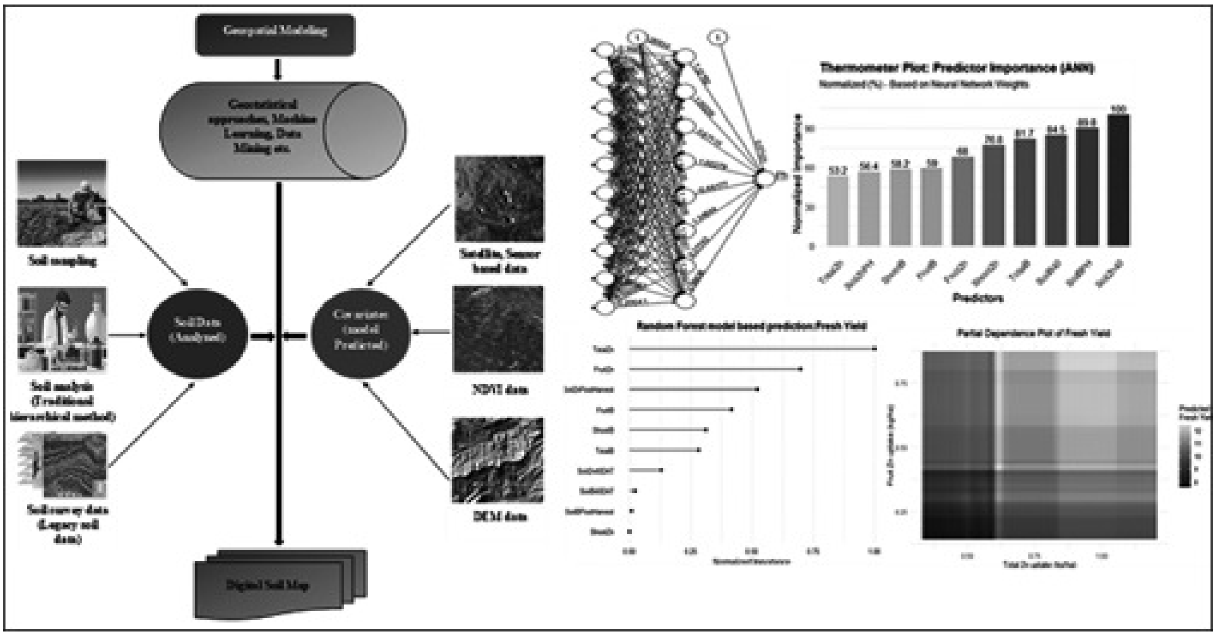


Figure 3. Machine learning and statistical modeling-based approaches to predict several soil and crop parameters (Source : Modified from Choudhury *et al.*, 2025 with permission from the publisher © Springer Nature, 2025.)

able any AI system to learn and improve from experience, making AI systems more flexible and powerful (Rahmani *et al.*, 2021). AI is becoming an essential part of this technological shift. Simply put, AI is a system that can learn and adapt to carry out tasks in real-time, using cognitive abilities similar to the human brain, and importantly, it can operate without needing constant oversight (Maher, 2018).

Applications of AI and other Digital Platforms in Agriculture - Decision Support System (DSS)

A Decision Support System (DSS) is an intelligent, computer-based tool that assists farmers, agronomists, and policymakers in making informed and data-driven decisions for effective farm management (Zhai *et al.*, 2020; Rinaldi and He, 2014). In smart agriculture, DSS integrates data from multiple sources such as IoT sensors, remote sensing, weather stations, GIS, and crop models to analyze complex agricultural scenarios and provide actionable recommendations (Kukar *et al.*, 2019) (Figure 4). The system combines data processing, analytical modeling, and visualization techniques to help optimize irrigation scheduling, fertilizer application, nutrient management, pest management, and crop selection based on site-specific conditions (Gallardo *et al.*, 2020; Mir *et al.*, 2015). Modern DSS platforms leverage ML and AI algorithms to predict crop yield, assess risks, and simulate various management strategies under changing climatic and market conditions (Upadhyay *et al.*, 2025; Suneetha, 2023). Moreover, cloud-based DSS allows real-time access and collaboration, enabling farmers and extension workers to share insights and make coordinated decisions. AI may help Indian farmers to choose the right crop and minimise the risks. As a result, AI is steadily appearing as part of the industry's technological evolution. AI can identify a disease with 98% accuracy (Giri *et al.*, 2020). AI-powered solutions can enhance crop quality and significantly shorten the time-to-market, ensuring greater efficiency and profitability in agricultural production (Soffar, 2019). A brief list of several AI based digital platforms used in the field of Agriculture and Soil science are given in Table 1.

Figure 4. Digital platforms employed in smart farming

Remote Sensing, Proximal Sensing, Aerial Platforms and Satellite Imagery Based Monitoring

Recent advances in sensor design, including higher signal-to-noise ratios and miniaturization, have enabled spectral sensing to operate from satellites, aircraft, unmanned aerial vehicles, and even ground-based platforms. These systems provide near-laboratory quality reflectance data in real-world conditions. Combined with modern multivariate statistical techniques, it can predict the complex

Table 1. Application of several digital tools in smart farming practices

AI/Digital platforms	Type	Application	Reference
Google Earth Engine (GEE)	Cloud-based GIS platform	Crop classification, vegetation dynamics, drought monitoring	Zhao *et al.* (2021); Khan and Mohiuddin (2018)
QGIS	Open-source GIS software	Soil mapping, land use planning, crop health mapping	Choudhury *et al.* (2025)
ArcGIS	Commercials GIS software	Spatial modeling and decision-making	Choudhury *et al.* (2025); Bright *et al.* (2009)
SAGA-GIS	Department of Physical Geography, University of Gottingen,	Germany	Passy and Théry (2018)
ENVI	Harris Geospatial Solutions	Broomfield, Colorado,	Choudhury *et al.* (2025); Bright *et al.* (2009)
AutoCAD Map 3D	Autodesk	San Rafael, United States, California,	Tickoo (2017)
Map Maker Pro (MapMaker)	Map Maker Limited	Argyll, UK Scotland,	Winkelaar and Crosson (2024)
GeoMedia (Hexagon)	Intergraph	Madison, United States, Alabama	Takken (2012)
aWhere	Predictive analytics platform	Weather forecasting, crop sustainability analysis, pest and disease detection	Giri *et al.* (2020)
FarmShots	Predictive analytics platform	Monitoring crop health, pest and disease detection	Giri *et al.* (2020)
Plantix	Predictive analytics and monitoring tool	Crop disease detection, sustainable cultivation, farm advisory	Giri *et al.* (2020)
CropIn	AI + IoT agribusiness platform	Crop monitoring, yield estimation, credit risk mitigation, farm traceability	Giri *et al.* (2020)

mixtures of soil constituents, detect the particular signs and symptoms caused by any insect-pest or disease, monitor soil and crop health, land cover etc. (Dasgupta *et al.*, 2024; Mitran *et al.*, 2024; Ghany *et al.*, 2020) and thus can efficiently be utilized as a powerful non-destructive tool agriculture, environmental monitoring, spectroscopic studies and land management. The significant advancement, however, has been realized through unmanned aerial vehicles (UAVs) outfitted with sophisticated multispectral and hyperspectral sensors. These platforms effectively bridge the critical divide between high-resolution ground measurements and expansive satellite observations. Sensors mounted on UAVs can capture imagery at spatial resolutions frequently less than 5 cm, thus unveiling soil variability patterns that remain undetectable by satellite sensors (Figure 5). Spectral indices derived from remote sensing are widely used for assessing vegetation status, soil fertility, and land degradation. The Normalized Difference Vegetation Index (NDVI) is the most common, exploiting red and near-infrared reflectance to indicate vegetation density, moisture stress, and soil degradation (Zhang *et al.*, 2005; Tucker, 1979) (Figure 6). Additional indices such as Green Normalized Difference Vegetation Index (GNDVI), Ratio Vegetation Index (RVI), Soil Adjusted Vegetation Index (SAVI), and others have been developed to compensate for these limitations and provide more reliable vegetation assessments in varying conditions (Sripada *et al.*, 2006; Gitelson *et al.*, 1996a, b) (Figure7). Variants such as the Enhanced Vegetation Index (EVI) improve sensitivity in dense canopies, while the SAVI and its refinement, the Modified SAVI (MSAVI), reduce soil background influence in sparsely vegetated areas (Novando *et al.*, 2021; Vijith *et al.*, 2020; Huete, 1988). For soil salinity mapping, indices like the Salinity Index (SI), Normalized Difference Salinity Index (NDSI), and Brightness Index (BI) are applied, often outperforming conventional field surveys in delineating salt-affected zones (Zhang *et al.*, 2022; Azabdaftari and Sunar, 2016; Wang *et al.*, 2013) (Figure 8). Normalized Difference Water Index (NDWI), Augmented Normalized Difference Water Index (ANDWI) and Land Surface Water Index (LSWI) provide insights into soil and crop water status, complementing vegetation-based indicators (Jackson *et al.*, 2024; Dasgupta *et al.*, 2023; Christian *et al.*, 2022). In addition, indices such as the Normalized Burn Ratio (NBR), NBR^+ are useful for assessing vegetation disturbance and recovery on degraded lands (Alcaras *et al.*, 2022; Escuin *et al.*, 2008). More advanced indices, including the Chlorophyll Index (CI) and Photochemical Reflectance Index (PRI), provide information on nutrient status and photosynthetic efficiency (Hunt *et al.*, 2011; Garbulsky *et al.*, 2011).

Case Studies-with a Special view on West Bengal Scenario

A notable case study exemplifying the integration of remote sensing with other technologies in agriculture is the Satellite-Based Rice Monitoring (SRM) system (Mani *et al.*, 2021). This system combines RS, crop modeling, web geographic information system (GIS), smartphone technology, unmanned aerial vehicles (UAVs), and cloud computing services such as Amazon Web Services (AWS). The SRM system provides

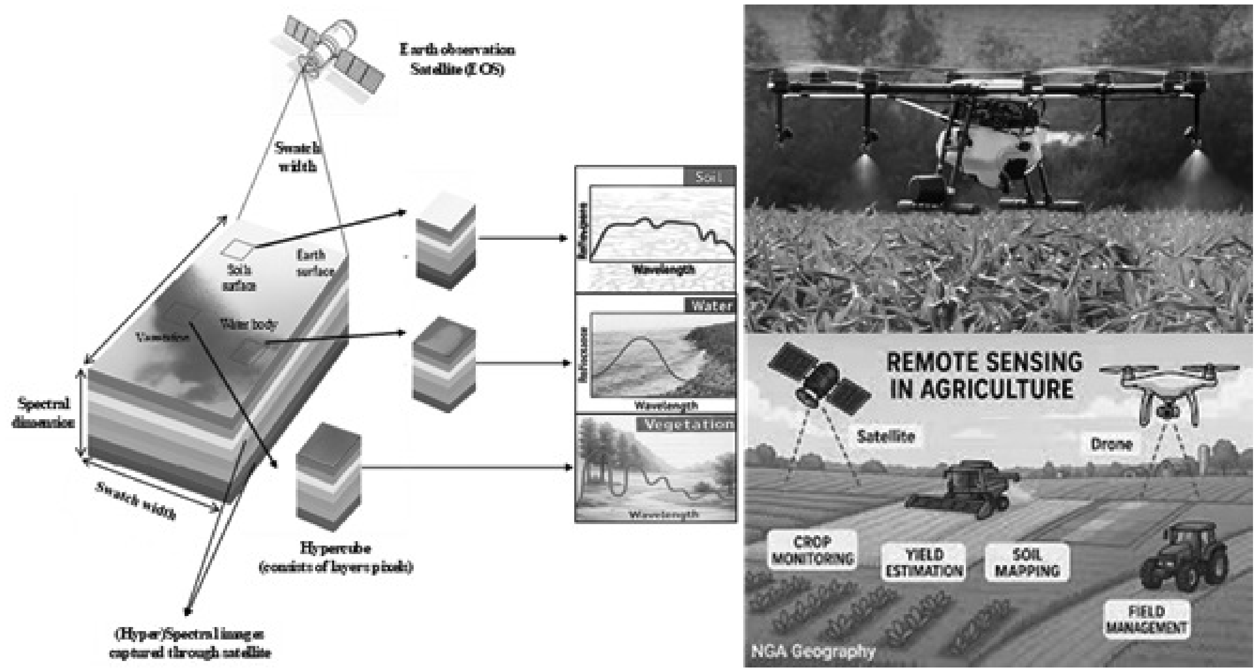


Figure 5. Crop and soil monitoring through satellite and aerial platform based imagery

near-real-time, accurate information on rice growth, yield forecasts, and stress conditions caused by environmental or biotic factors. This integrated approach enables better decision-making and has been applied successfully in several countries, with monitored areas expanding from 1.6 million hectares in 2012 to over 24.5 million hectares by 2016 at an accuracy level exceeding 85% (Sylvester, 2018). In Kalyani, India an ASD Field Spec 4 spectroradiometric study was also carried out in a rice based cropping system to predict the spatial variability in soil organic carbon and nitrogen (available and total) content through PLSR and SVML modelling where it was observed that SVMR model is the best suited model outperforming PLSR for all the soil properties with R^2 values of 0.98, 0.92 and 0.97 respectively for SOC, total soil N and available soil N (Ghosh *et al.*, 2025). Numerous studies also have been done through Portable X-ray Fluorescence spectrometry (PXRFS) for the prediction of various quality attributes of soil (Dasgupta *et al.*, 2022; Weindorf and Chakravarty, 2016; Silva *et al.*, 2021). PXRF-spectroscopy has successfully been implemented to predict the available P, exchangeable Ca^{2+} content (Pelegrino *et al.*, 2022) and available micronutrient content (Andrade *et al.*, 2020) in some tropical soils of Brazil, percentage base saturation (Rawal *et al.*, 2019), SOM content (Silva *et al.*, 2017), textural fractions (Silva *et al.*, 2020); salinity extent (Young *et al.*, 2015), nature of the soil parent material (Mancini *et al.*, 2019) etc. In West Bengal, regional soil micronutrient mapping approach has also been taken by several scientific communities especially based on machine learning and prediction modeling. ML-predicted spatial variability of several micronutrients like Zn, Cu, Fe etc. was assesses and mapped along with their critical values in soil by collecting 1778 soil samples from Indo-Gantetic plains of West Bengal (Dasgupta *et al.*, 2023) (Figure 9). Dasgupta *et al.* (2022) studied on 561 soil samples under rice based cropping system collected from six different agroclimatic zones of West Bengal, India where PXRFS combining with auxiliary variables (e.g., pH, EC, SOC, nature of parent material etc.) have been implemented to predict the available nutrient status (e.g., Ca^{2+}, Mg^{2+}, K^{+}, Zn^{2+}, Cu^{2+}, Mn^{2+} etc.), exchangeable base percentage and sulphur availability index in soil with the help of four machine learning models viz. RF, PLSR, SVMR, Stepwise multiple regression and a combination average model with a good prediction accuracy. Available Mn, B, S, SOC and Sulphur Availability Index in soil were successfully predicted with combine implementation of PXRF spectrometric data, auxiliary soil variables (e.g., Parent material and Agro-climatic characteristics) and microscopic soil images captured through an USB-microscope based on 1133 soil samples collected from five different stated of India and modelled through RF algorithm, the result showed that the combined data source exhibited comparatively a higher accuracy for SOC ($R^2 = 0.87$) and available B ($R^2 = 0.82$) than the individual approaches (Dasgupta *et al.*, 2024) (Figure 10). Nitrogen content in soil was estimated using Hyperion data and the MPLSR algorithm in Udupi, India (Gopal *et al.*, 2015). A digital Soil Quality Index Map was prepared by De *et al.* (2022) based on 450 soil samples from the depth of 0-20 cm from different places of Jalpaiguri, Alipurduar and Cooch Behar district of West Bengal, India which provides a valuable insight in monitoring spatial distribution of soil quality with respect to 19 soil quality indicators (Figure 11). Another DSM programme was initiated by a group of scientists from National Remote Sensing Centre, Hyderabad based on 2012 samples from different regions of Karnataka, India to evaluate and map the nature of soil texture digitally (Mitran *et al.*, 2024). Bhaibai (2023) had carried out a detailed study on the distribution and mapping of the potassium fractions presented in the soil system based on a total of 160 soil samples from two different districts of Teesta Terai alluvial region of West Bengal. Sen (2019) prepared a DTPA extractable Fe map digitally based on 35 composite sample from the district of Cooch Behar, West Bengal, India and Gogoi *et al.* (2017) has developed a digital distribution map of Zn fractions present in soil based on 48 composite samples from the similar study area (Figure 12). A soil organic carbon map was developed digitally through machine learning by Padarian *et al.* (2019). A digital Soil Organic Carbon along with Soil Inorganic Carbon stock map of India have been developed by Sreenivas *et al.* (2016) at a spatial resolution of 250 m. An approach of mapping the salinity classes at Sundarban region, West Bengal was undertaken by Sahana *et al.* (2020). Geospatial data collected via Google Earth Engine was assessed to formulate a soil erosion map of Kharagpur region, Paschim Medinipur, West Bengal, India (Choudhury *et al.*, 2025) (Figure 13).

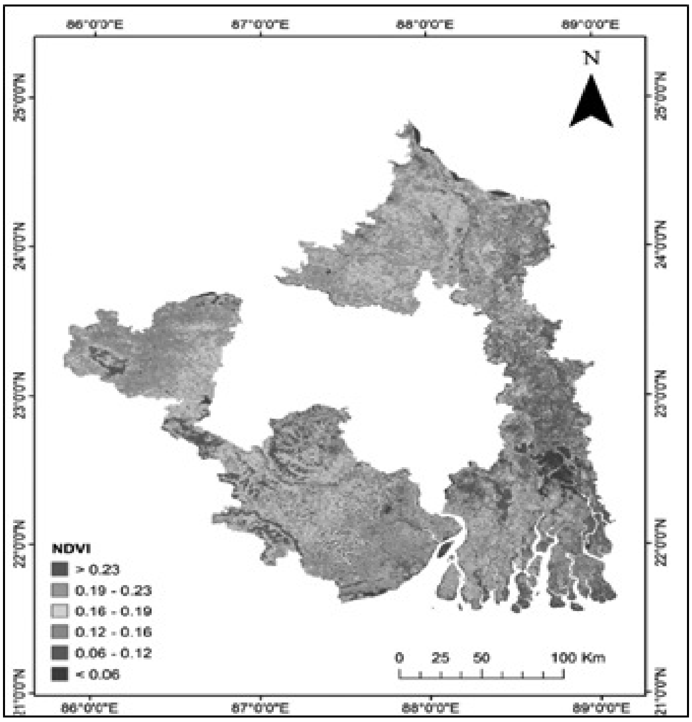
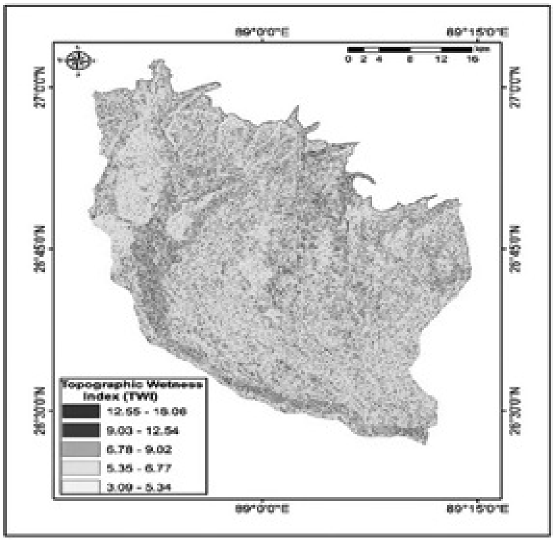


Figure 6. NDVI map of some regions at Indo-gangetic plane, West Bengal (Source : Reprinted from Dasgupta *et al.*, 2023 under terms of the CC-BY license.)



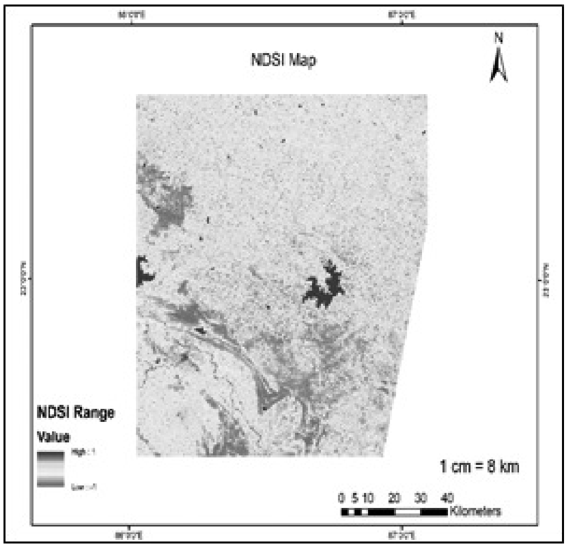


Figure 7 and Figure 8. SAVI map of Jaldhaka river basin, West Bengal and NDSI map (left side) (Source: Reprinted from Raha *et al.*, 2023) and NDSI map Purulia region, West Bengal, India (Prepared with the help of esri ArcMap 10.6) (Right side) (Source: Reprinted from Choudhury *et al.*, 2025 with permission from the publisher © Springer Nature, 2025).

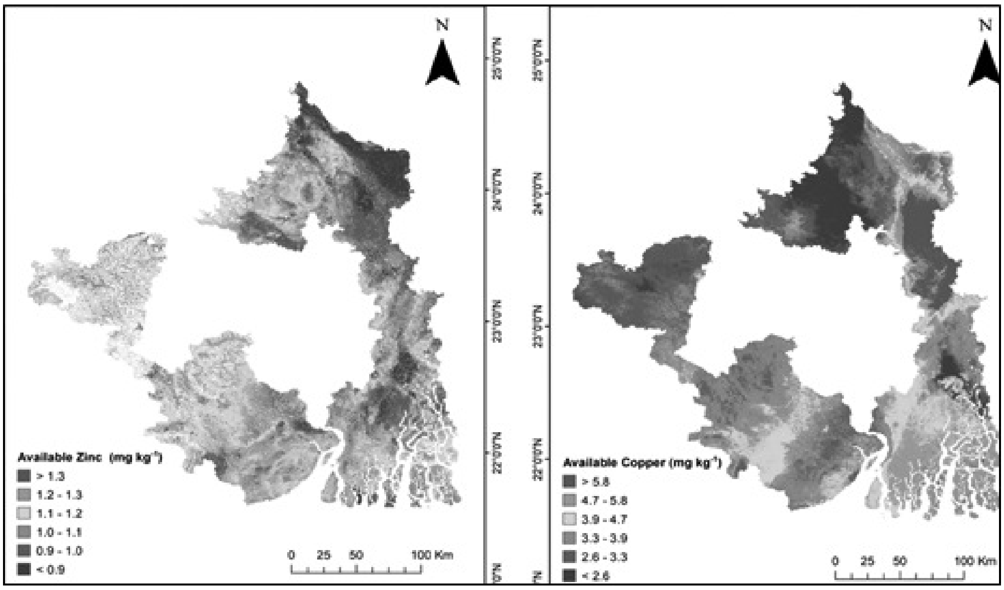


Figure 9. Predicted spatial distribution map of Available Zinc and Copper and Manganese in the soils from some regions of Indo-Gangetic plane, West Bengal (Source: Reprinted from Dasgupta *et al.*, 2023 under terms of the CC-BY license.)

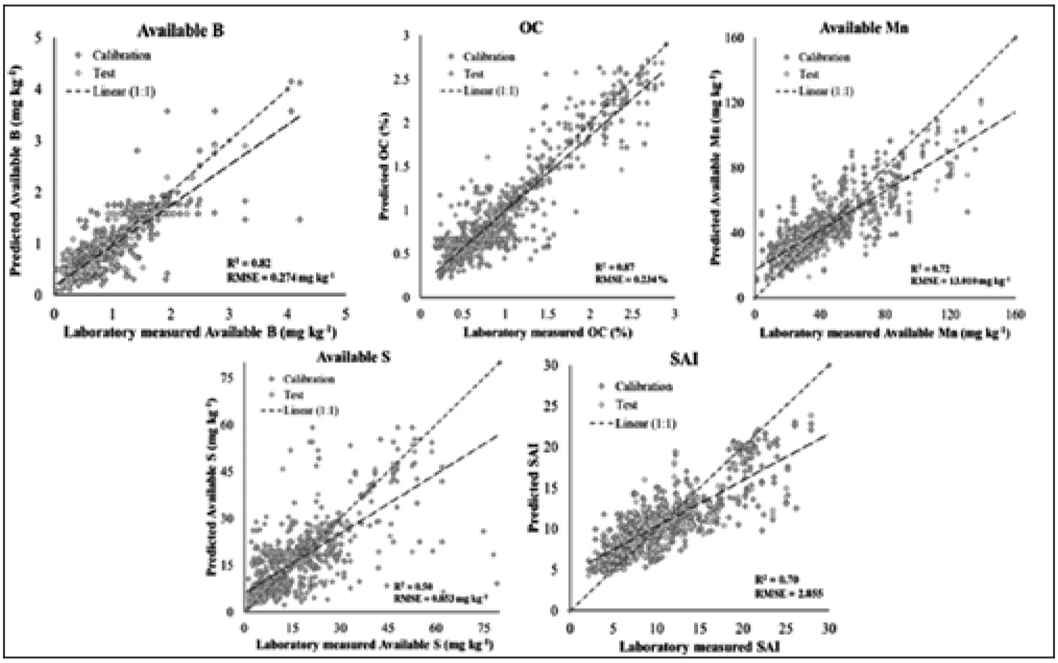


Figure 10. Predicted (RF algorithm based) vs. Observed plots for the available B, SOC, available Mn, SAI (Sulphur Availability Index) extracted from the combined PXRF spectroscopy+USB microscopic approach from soils (Source: Reprinted from Dasgupta *et al.*, 2024 with permission from the publisher © Elsevier, 2024)

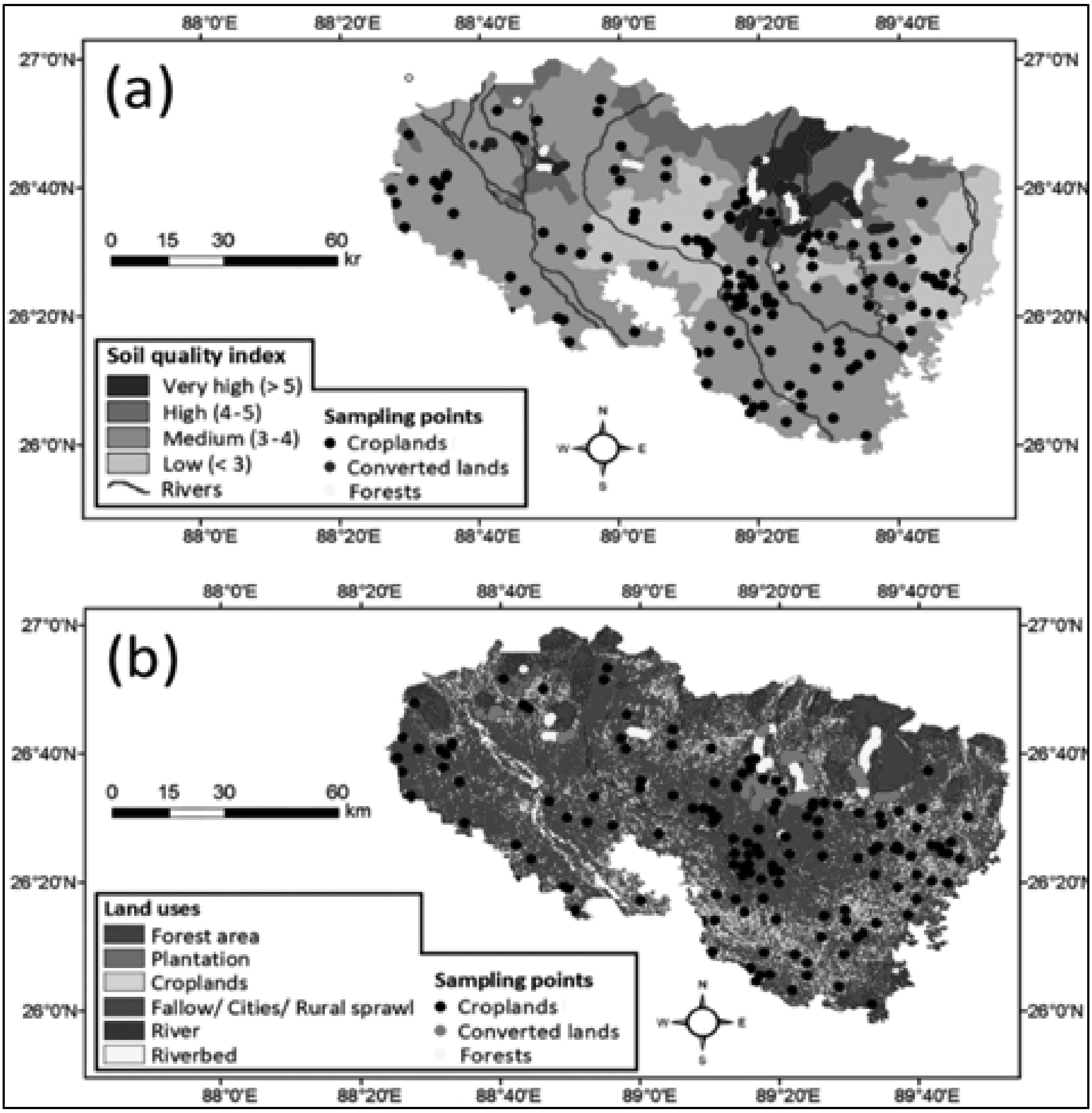


Figure 11. Soil Quality Index (a) and Land Use Land Cover (LULC) map of Cooch Behar region, west Bengal (Source: Reprinted from De *et al.*, 2022 under terms of the CC-BY license.)

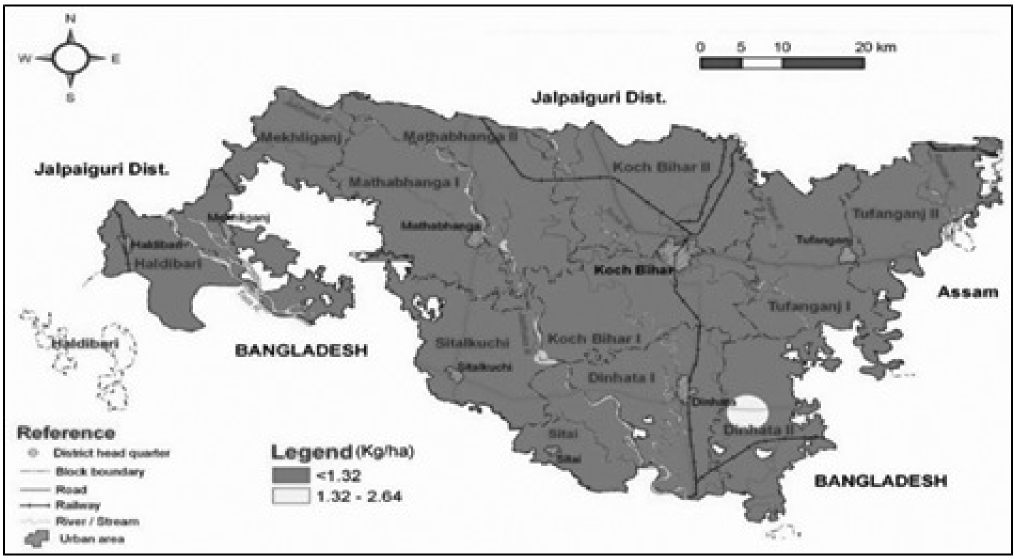


Figure 12. Spatial distribution map of DTPA extractable Zinc (kg ha^{-1}) at 0-20 cm depth in the soils from the study area (Terai region of West Bengal, India). (Source: Reprinted from Gogoi *et al.*, 2017 under terms of the CC-BY license)

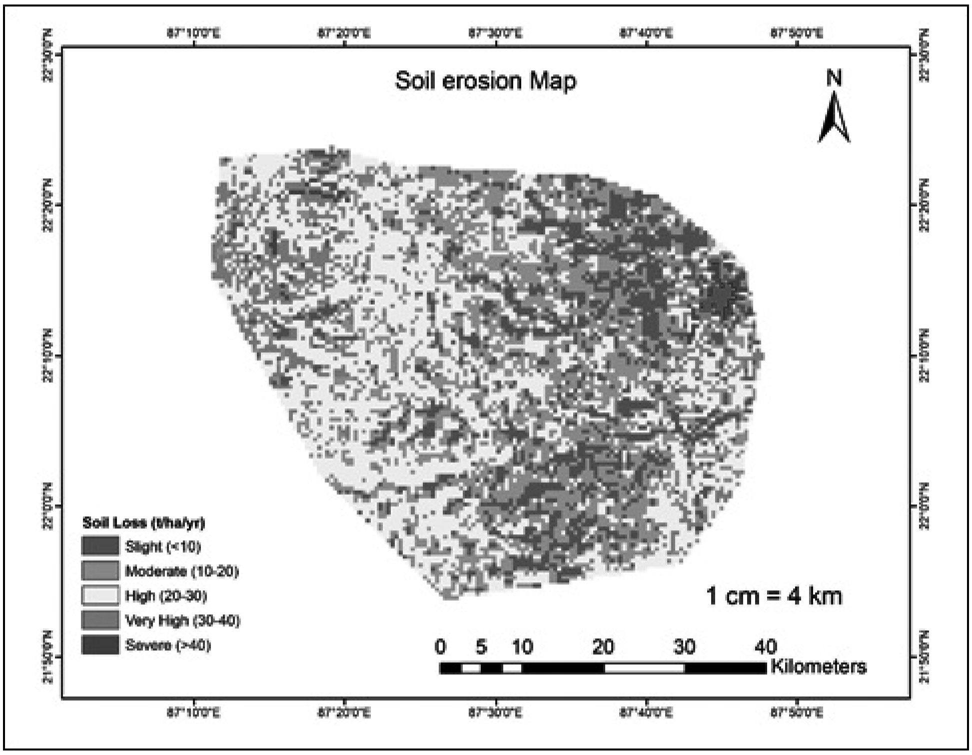


Figure13. Soil erosion map of Kharagpur region, Paschim Medinipur, West Bengal, India (Prepared with the help of Google Earth Engine) (Source: Reprinted from Choudhury *et al.*, 2025 with permission from the publisher © Springer Nature, 2025)

Challenges

While AI greatly advances agriculture by improving its efficiency, yield, and sustainability, simultaneously concerns about its impact on agricultural employment. Agriculture supports the livelihoods of more than 1.5 billion people worldwide. However, as artificial intelligence and robotics take over repetitive field tasks, there is growing concern that these technological advancements could displace many manual laborers, affecting rural livelihoods and traditional farming communities because smart robots and drones can navigate fields, handle crops, and perform complex operations, reducing labor demand. However, AI also creates new job opportunities in data analysis, drone operation, precision farming, and AI system management, which demand higher technical skills. Access to advanced technologies like drones, UAVs, sensors etc. remains costly and thus highlighting the need for increased investment and infrastructure support to make AI tools accessible to small farmers.

Future Recommendation and Scope of Adaptation Particularly for West Bengal Perspective

Future efforts focus on enhancing AI algorithms with deep learning, improving sensor fusion (satellite, drone, ground-based), expanding user-friendly decision support systems, integrating IoT networks, reducing technology costs, and promoting farmer training to boost adoption. In West Bengal, most farming communities (over 82%) belong to the marginal or smallholder category and are economically weaker compared to those in the north-western and southern states of India. Consequently, the adoption of next-generation (Agriculture 4.0) practices, innovative ideas, and resource optimization strategies will not be an easy task for such farmers, as they cannot implement these technologies independently. Moreover, farmers especially those engaged in kharif rice cultivation face persistent challenges related to both yield and income due to inadequate guidance, weather uncertainties, lack of pest and disease forecasting, misidentification of diseases and nutrient deficiencies, and limited marketing facilities. In addition, the absence of reliable soil fertility forecasting systems means that most farmers remain unaware of the nutrient status of their fields, leading to imbalanced fertilizer application, chemical degradation of soil health, and increased input costs per unit area. Therefore, under the prevailing conditions in West Bengal, there is an urgent need to develop efficient and precise systems for real-time monitoring and forecasting of weather, soil, and crop health. These systems should be made freely and easily accessible to all farmers. Government initiatives and collaborative efforts among research institutions, extension agencies, and private sectors will be crucial to achieving this goal.

A) Recommendations for Farmers

I. In season crop health monitoring, yield prediction, pest/disease early warning, irrigation scheduling, and support for crop insurance and market decisions.

II. Near real time crop health and stress monitoring (NDVI/EVI, SAR change detection).

III. Yield forecasting at block level with actionable lead time (4–8 weeks before harvest).

IV. Pest/disease detection and hotspot alerts using edge/phone imagery and UAVs.

V. Soil moisture estimation and precision irrigation scheduling advisories.

VI. Integration with extension services, KVKs, and state agriculture portals.

VII. Establish ground truth networks (KVKs, selected farmer plots) and mobile data collection app.

VIII. Weekly NDVI anomaly maps for rice belts distributed to district officers.

IX. Development of pilot pest detection phone app.

X. Training modules for extension officers on RS dashboards, interpretation, and farmer communication. Hands on workshops for KVKs on mobile data collection and basic model validation.

B) Recommendations for Researchers/ Institutions

I. Development of AI enabled applications where a number of crop android region specific Targeted Yield equations should be programmed. Where by putting the Soil test values, variety name, targeted yield values, farmers can easily determine the optimum fertilizer dose.

II. Smart phone coupled sensors need to be developed which can spectrally determine or indicate the N:K ratio in plant body and detect the chance of Lodging or been infested by BPH or any pest - diseases along with suitable prescription measures.

III. Preparation of region-specific micronutrient fertility maps and identification of their localised deficiencies. So that proper management strategies would be adopted within time.

IV. Special focus should be given on potassium management. Potassium fractions need to be mapped for each agro-climatic zone because at present time the potassium budget ($PNBI_K$- Partial Nutrient Budget Intensity of Potassium) in soils throughout the India is negative due to K-mining and non-labile stocks get exploited day by day.

V. Carbon management strictly need to be brought under spectral monitoring and assessment. Satellite data as well as hyperspectral proximal sensing dada should be processed to determine the emission of carbon from agricultural fields and their lability on long term basis which helps to identify the cropping systems and farming practices which can sequester carbon more efficiently.

VI. Focus also need to be put on spatial delineation of heavy metals (i.e. arsenic, cadmium etc.) and their toxic fractions in soil-water-plant system from their spectral signature and mapped properly for public awareness.

Conclusion

To ensure long-term sustainability of natural resources while maintaining the economic viability of agricultural production, precision farming must be integrated with conventional agricultural practices in a multidimensional and complementary manner. In the coming decades, as global population continues to rise, agriculture will face more challenges pertaining to productivity, environmental resilience, and resource scarcity. Therefore, future agriculture must be more strategic, optimized, and resource-efficient, while generating significantly lower environmental footprints. The goal is to increase or sustain crop production while reducing indiscriminate input use, minimizing soil degradation, and conserving water and other natural resources. This can be achieved through sensor-based monitoring of soil health and fertility, real-time detection of insect-pest infestation and damage boundaries, localized weather forecasting, and site-specific nutrient requirement assessment. In addition, targeted and smart delivery of irrigation water and nutrients, instead of uniform blanket application, can significantly reduce wastage and pollution. When such sensing and monitoring systems are integrated with digital platforms, remote sensing, and AI-driven decision support tools, and made accessible to farmers, cooperatives, and agricultural institutions at affordable scales, the agricultural ecosystem can transition into a truly regenerative, climate-resilient, and smart system. Such a system balances productivity with ecological responsibility, ensuring that agriculture remains both profitable for farmers and sustainable for the planet.

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