SUSTAINABLE AGRICULTURE THROUGH DIGITAL AND BIOTECHNOLOGICAL INNOVATIONS

EDITOR

Basirul Alam Sarker OVY

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AUTHORS

Mahmud Sindid IKRAM
Sumiya Akter MONI
Basirul Alam Sarker OVY
Gunasekar G
Annamalai A
Karthiga A. R
Fathalah ELWAHAB
Mohamed SEDKI
Chetto ABDELAZIZ
Sana El MOUTAOUAKIL
Najiba BRHADDA
Rabea ZIRI

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PREFACE

Agriculture is rapidly evolving as digital technologies reshape how we grow, protect, and manage crops. From AI-powered pest detection to precision irrigation systems, innovation is driving smarter, more sustainable practices across the globe. Yet, these advancements also face barriers—technical, economic, and infrastructural—that must be addressed to ensure equitable access and impact.

This volume explores four key areas where technology meets agriculture: plant protection innovations, remote sensing and AI in South Asia, digital transformation in Morocco's rice systems, and modern pest management strategies. Each chapter highlights how tools like IoT, big data, and machine learning are being adapted to local contexts, offering new solutions to age-old challenges.

Together, these chapters provide a snapshot of agriculture's digital future—one that balances innovation with inclusivity, and sustainability with scalability. They invite readers to consider not just what's possible, but what's practical and necessary for resilient food systems.

On behalf of the Halic Publishing House editorial team, we extend our sincere appreciation to the contributing authors for their valuable insights and scholarly contributions.

Editoral Team
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CHAPTER 1
TECHNOLOGICAL ADVANCEMENTS IN PLANT PROTECTION: POTENTIALITIES AND BARRIERS

[1]Mahmud Sindid IKRAM
[2]Sumiya Akter MONI

[1]Faculty of Agriculture, Bangladesh Agricultural University, Bangladesh, ORCID ID: 0009-0006-6901-8155, ikram.2002161@bau.edu.bd
[2]Faculty of Agriculture, Bangladesh Agricultural University, Bangladesh, ORCID ID: 0009-0006-2540-357X, moni.khan9512@gmail.com

INTRODUCTION

1. A NEW ERA OF DIGITAL AGRICULTURE

Global food security is rising with the rise in population, and a revolution in plant protection becomes necessary to produce more yield with the same area of cultivable land. This chapter explores the technological advancements conducting a shift from traditional pest control to precision-based disease and pest control strategy.

1.1 The Growing Challenge: Global Food Security and Pest Pressure

The most emerging challenge of the 21st century is to ensure food security for the 8 billion consumers of the world. But it is alarming that crop production is at risk because of rapid urbanization, climate change, and attacks by pests and diseases. These biotic and abiotic stresses are threatening livelihoods and stable food supplies by declining crop yield. Conventional agricultural practices rely on calendar-based pesticide application without considering any dose or necessity. Overuse of chemical products is harmful for both the environment and physical condition of the consumers.

1.2 The Shift in Plant Protection

A shift is underway in the field of plant protection. In traditional methods actions are taken after visible symptoms appear. But by using modern technology, disease can be diagnosed before any physical symptom appears. Digital technologies made that possible by ensuring continuous monitoring, data-based decision-making, and site-specific and timely application of chemical fertilizers and pesticides without any human touch. Here decisions are made based on real-time information retrieved from spectral imaging, and chemicals are sprayed using drones or other UAVs to ensure applicator safety.

1.3 Scopes and Objectives

The aim of the chapter is to provide a comprehensive and robust overview of the potentialities of advanced technologies in plant disease management.

It will cover the utilization of remote sensing, IoT, and predictive modeling for surveillance and forecasting possible future danger. It will cover precision agriculture and the potentiality of biotechnology for developing resistant crops. Finally, it will cover challenges faced by the stakeholders in adopting these technologies and provide future directions.

2. THE DIGITAL EYE IN THE SKY: REMOTE SENSING AND MONITORING

Remote sensing is the process of gathering information about a particular object or specific area without making direct contact with it. Information is usually generated in image form based on the radiation emitted from the target object. It is widely used in monitoring and physical analysis of the object by sensing the images taken remotely. This technology is an asset to observe Earth and other planets from remote areas like space through satellites.

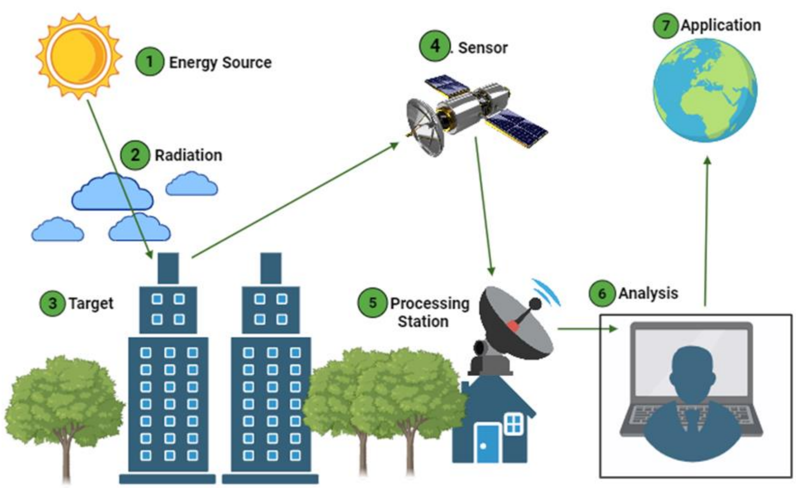

Figure 1. Principles of Remote Sensing with sequential steps

2.1 Satellite Imagery for Large-Scale Surveillance

Spectral sensors installed on satellites or aerial vehicles capture data of vegetation. Gupta et al. (2021) stated that NDVI (Normalized Difference Vegetation Index) is a graphical indicator of remote sensing that measures plant density and health by estimating the difference between red and near infrared light (NIR) reflection. Mahlein (2015) reported that high NDVI values refer to healthier plants, as high chlorophyll content reflects NIR radiation. Based on the severity of the disease, yellow, pale green, brown, or gray patches appear. Sentinel-2 or Landsat satellites can be integrated with machine learning to predict disease outbreaks and severity as well as yield forecasts for crops like rice, wheat, maize, and jute. Disease forecasts will be more precise if data from satellites is implemented with field-based surveys. This is effective for fungal diseases like rice blast and wheat rust, which spread overnight. Fungal infections like rice blast or wheat rust possess yellow to reddish-brown areas on satellite cameras.

Table 1: Color indications of satellite based disease surveillance system

Color (True/False Color or Index Map)	Indications in Crop Field
Dark Green	Healthy and vigorous vegetation
Bright Red	Healthy crops with strong in near-infrared
Yellow / Pale Green	Early stress stage
Brown / Reddish-Brown	Infected or dying vegetation
Gray / Light Brown	Severely infected or dead vegetation
Orange / Red	Severe infestation
Bluish / Purplish Tints	Early pathogen attack or physiological stress not yet visible to the naked eye.

2.2 Spectral Imaging and Thermal Sensors

Spectral imaging reveals detailed plant health signatures. Thermal sensors detect water stress of the canopy by assessing the temperature of vegetation, as higher water levels possess lower temperatures. Integrated application of spectral imaging and thermal sensors can predict stress situations earlier, which ensures enough time to take necessary precautions to skip the calamity.

2.2.1 Spectral Imaging

Multispectral and hyperspectral imaging of remote sensing is mostly effective for monitoring plant diseases on a large scale and predicting future stress conditions of crops before any physical symptom appears. This technology allows for the early identification of potential issues, enabling farmers to implement targeted interventions.

By leveraging these advanced imaging techniques, agricultural practices can become more efficient, ultimately leading to improved yields and sustainability in crop production. The number of broad wavelength bands is limited for multispectral imaging captures (e.g., red, green, blue, and near-infrared). It is widely applicable for calculating vegetation indices like NDVI. NDVI helps to assess crop vegetation and stress. Multispectral cameras enable large-scale farmers to detect infected regions, monitor disease severity, and forecast. is more economically feasible than hyperspectral cameras and easily adjustable with drones.

On the other hand, hyperspectral cameras can capture images of very narrow bands, and sensors can detect stresses earlier by capturing blue or purple tints, which are associated with pathogen attacks prior to the expression of symptoms. Hyperspectral sensors can identify specific biochemical changes. Generally lower chlorophyll content, water stress, or accumulation of secondary metabolites is linked to disease formation. These generate lower NDVI values, which helps in diagnosing specific diseases.

Multispectral imaging offers cost-efficient monitoring, but hyperspectral imaging provides thorough diagnostic precision. Integration of both technologies in precision agriculture can enable rapid disease inspection, forecasting systems, and targeted application with limited doses of control measures. As a result, dependency on chemical pesticides is reduced, which ensures environmental safety and food security.

2.2.2 Thermal and LiDAR Sensors

Thermal sensors are designed for measuring the temperature of crop canopy to detect stress symptoms due to biotic and abiotic factors before they are visible. Higher temperature detected by thermal sensors also indicates water scarcity, and from this response farmers can schedule irrigation according to the moisture status of the plant. LiDAR (Light Detection and Ranging) is a technology that uses pulsed laser lights to generate high-resolution 3D maps of an area of vegetation and the height of the plant canopy. Robust analysis of these 3D maps ensures detection of lodging and insect-pest occurrences. The collaborative approach of thermal and LiDAR technologies fuels precision agriculture by providing real-time monitoring, reducing the use of chemical fertilizers and pesticides, and increasing yield.

2.3 Ground-Based Sensors and IoT Networks

Ground-based sensors and IoT (Internet of Things) networks have opened a new door of plant protection by real-time, site-specific monitoring of soil and crop. Sensors can measure soil moisture, temperature, humidity, nutrient deficiency, and pest occurrences, as well as early diagnosis of diseases. IoT-based initiatives are undertaken in Bangladesh, like iFarmer.Asia. They are leveraging IoT and precision farming techniques to modernize the agricultural sector of South Asia. Intelligent and machine learning-based soil sensors are being used to monitor and analyze soil fertility, pH, and moisture in remote areas.

2.3.1 Automated Weather Stations and Microclimate Monitoring

Automated Weather Stations (AWS) are advanced systems equipped with multiple sensors to continuously record and transmit real-time weather data. AWS provides high-frequency and accurate data and also ensures minimized human error in the field of agriculture, AWS are being used in developed countries for microclimate monitoring. Microclimatic conditions influence pest and disease dynamics, soil moisture, and crop growth. Collaborative efforts of AWS with decision-making tools assist farmers to schedule irrigation, fertilizer application, and plant protection strategies. AWS is also a key contributor to climate-smart agriculture. It provides warnings of natural calamities and predicts disease outbreaks. AWS enables rapid decision-making strategies by monitoring microclimate, which enables authorities to take precautions for combating adverse conditions.

2.3.2 Soil and Plant Health Sensors

In-situ soil and plant health sensors are capable of delivering real-time information on plant disease status, moisture level, and chlorophyll content. Soil sensors measure parameters critical for optimizing irrigation and fertilizer application.

Such parameters include pH, temperature, moisture, salinity, and nutrient content (Adamchuk et al., 2020). Plant health sensors address physiological characteristics such as chlorophyll fluorescence, photosynthetic activity, and stress biomarkers. These sensors can detect nutrient deficiencies, diseases, or drought stress by evaluating air temperature, wind speed, and humidity of the relative area (Farooq et al., 2022). Quantum dots are an example of nanobiosensors, which are used to diagnose diseases. When sensors are integrated with IoT, data derived from ground-based sensors are transmitted to a cloud platform without any wired connection. These data allow researchers to analyze and predict disease or pest outbreaks and suggest precautions. Modern sensors and IoT reduce dependency on blind use of chemicals and assist early-warning surveillance. The linkage of ground-based data with predictive models and IoT strengthens decision-making for precision agriculture.

3. THE POWER OF PREDICTION: DATA ANALYTICS AND MODELING

Technological advancements have pushed the area of plant protection one step closer to sustainable agriculture. Traditionally pest and disease management relied on reactive approaches. Farmers usually responded to visible symptoms of insect or pathogen attack in crops. This procedure often leads to delayed interventions, overuse of pesticides, and economic disadvantages. The implementation of big data, predictive modeling approaches, and decision support systems (DSS) has potential in plant protection. These modern approaches effectively strengthen the capabilities of stakeholders to mitigate risks of environmental pollution, as less chemical fertilizer will be applied if a proper prediction of disease resurgence is made.

3.1 Big Data in Agriculture: Integrating Diverse Data Streams

Big Data in agriculture can be defined as the collection, integration, and analysis of large sets of data from diverse sources. These datasets are often heterogeneous in nature, bearing information on climate records, soil nutrient and moisture status, pest and disease occurrences, genomic data, and socio-economic statistics of the targeted region.

Vast information from diverse sources helps researchers and farmers to identify patterns, optimize resource allocation, and improve yield predictions (Wolfert et al., 2017).

A combination of information from satellite-based vegetation indices and ground sensors can forecast stress conditions of plants in order to take emergency preventive measures before symptoms are visible to the naked eye.Images captured by UAVs and drones enhance the granularity of satellite-based information, as they can capture a close and clear photo of the targeted vegetation. Big Data supports the development of climate-smart agriculture by integrating long-term climate scenarios with current crop growth patterns.

The potential of Big Data is not limited to biophysical sectors alone. Social media algorithms and data submitted by farmers in mobile applications or surveys conducted by the Department of Agricultural Extension also contribute valuable information for making rapid decisions on pest management strategies. Integration of these streams spikes up the predictive capacity of agricultural systems

3.2 Predictive Modeling

Predictive modeling is a combined approach of big data and computational tools. It is a model of estimating the probability and intensity of disease outbreaks by analyzing temperature, humidity, growth stage of crop, and record of previous outbreaks. Degree-day models are an ideal example of predictive modeling where the life cycles of insect pests are predicted to warn farmers about the upcoming vulnerable stages of the pest's population development (Mahlein, 2016). Traditional statistical methods cannot handle complex and nonlinear data sets. Machine learning and artificial intelligence have further developed the field by introducing random forests, support vector machines, and neural network algorithms. These modern algorithms can predict rice blast, wheat rust, and locust outbreaks with precise accuracy. Alongside these, cloud-based platforms continuously update their server with new data to ensure a refined accuracy of their prediction. Farmers usually apply pesticides as insurance measures. Predictive modeling can assure them of the indiscriminate use of chemicals. Science-based forecasts assist in targeted application of treatments with minimum cost and environmental pollution.

3.3 Decision Support Systems (DSS)

Decision Support Systems (DSS) is a practical interface between predictive analytics and on-the-ground agricultural decision-making. DSS platforms compile data from different sources, like sensors, predictive models, and external databases, and later generate location-specific recommendations for farmers. DSS also can advise farmers on the timing of pesticide application, irrigation scheduling, and harvesting. One prominent example is the use of cellular-based DSS applications. They are particularly beneficial for smallholder farmers in developing or remote regions. These platforms collect real-time weather data with local crop information from different reliable sources, like satellites, to deliver tailored advice. In developed countries DSS are linked with early warning systems. Forecasting can alert farmers to upcoming pest or disease risks through SMS or app notifications (Basso & Antle, 2020).

DSS can support government-associated policymakers and agricultural planners by simulating the impacts of different pest management. Collaboration of DSS with Geographic Information Systems (GIS) has the field for enhancing their capacity to visualize disease spread. The success of DSS extremely depends on accessibility, user-friendliness, and reliability of farmers. Proper training and skilled extension personnel are crucial to ensure adoption among smallholder farmers who have bare minimum literacy. DSS can bridge the gap between advanced data analytics and field-level application.

4. PRECISION IN ACTION: TARGETED APPLICATION TECHNOLOGIES

Precision agriculture can be defined as a modern farming practice that uses advanced technology to supervise and manage field variability in crops (Precision Agriculture, n.d.). Precision agriculture is a holistic approach of implementing modern equipment to assure precise and site-specific application of chemical pesticide within a short time and with less labor.

4.1 Variable Rate Technology (VRT) for Pesticides and Biocontrols

Variable Rate Technology (VRT) is a precision agriculture method occupied in supervising site-specific application of inputs. It refers to adjusting the application rate of seeds, fertilizers, pesticides, herbicides, and water across different areas of a field by accessing data from sensors, maps, and GPS (Growers, 2023; EOS Data Analytics, 2024). Map-based VRT depends on reference maps created from satellite imagery, soil tests, yield histories, or multispectral drone analysis. Prescribed maps are uploaded to digital sprayers, and input rates are adjusted according to the demand (Ask IFAS, 2023; EOS Data Analytics, 2024; Advexure, 2022). Sensor-based VRT is operated by accessing real-time data from soil moisture or crop health sensors to adjust the application rates as equipment moves through the field (EOS Data Analytics, 2024; Wikipedia, 2025).

The adoption of Variable Rate Technology (VRT) for pesticides and biocontrols benefits farmers' economic, environmental, physical, and agronomical aspects. VRT minimizes material costs by optimizing pesticide and biocontrol application according to site-specific requirements. As a result, the number of laborers and cost of chemical expenditures are reduced with a maximized yield potential. USDA reported savings of nearly $25 per acre in corn production when VRT was combined with yield mapping (ERS, 2022). VRT restricts chemical overuse and runoff. Reduced chemical exposure regulates greenhouse gas emissions, improves soil health, and decreases water contamination (Eos, 2024). It also protects the applicator from health hazards caused by chemicals. Overuse of chemical products may result in the presence of toxic elements in our food chain. Accumulation of carcinogenic materials can cause cancer also. From an agronomic perspective, VRT enhances precision by applying fungicides or biocontrol agents only in the zones of higher population density of insects or pests. (Farmers Edge, 2021).

4.2 Smart Sprayer Systems

Smart sprayer systems optimize pesticide and herbicide application from the data derived from sensors. The *Smart Apply* LiDAR-based system reduces water requirement by 73%, chemical runoff by 93%, and pesticide air drift by

87% (Smart Apply, n.d.). *ONE SMART SPRAY* technology has a camera mounted on it to address weeds for recommending a spray of selective herbicides (ONE SMART SPRAY, 2023). Sensor-assisted sprayers are capable of reducing herbicide use by 90% (AgTechLogic, 2024). The robotic sprayer's integration with machine learning and crop-health sensors can minimize off-target spraying of chemical pesticides, fertilizers, and herbicides, which can assure environmental safety as well as the safety of the applicator (Farmonaut, 2025).

4.2.1 Sensor-Based Weed Detection and Spot-Spraying

The combined approach of spot spraying and sensor-based weed detection technology contributes to a transformative leap in precision agriculture. It enabled specific herbicide application and drastically lowered chemical application without altering the control efficiency. Previous systems, like **WeedSeeker®** and **WEED-IT®,** consist of near-infrared (NIR) reflectance sensors to address weeds in bare soil based on chlorophyll content. Sensors detect chlorophyll when any vegetation is present and activate nozzles to spray herbicides. In this method, 50-90% less chemical herbicide is required compared to traditional methods (Søgaard & Lund, 2007; Biller, 1998).

Integration of machine vision and deep learning with camera-based spot sprayers, for example, Ecopatch and Deep Agro Sprai, utilizes convolutional neural networks to detect weeds in real time and results in savings of 70–90% herbicide solution (Partel et al., 2019). Robotic treatments like **Solinftec Solix** and retrofit systems such as Carbon Bee's Smart Striker X further combine hyperspectral sensors with pulse width modulation (PWM) nozzles. López-Granados (2011) has reported chemical reductions of up to 98% by adopting this robotics technology (López-Granados, 2011). Deep learning-associated detectors like YOLOv9 and RT-DETR offer high accuracy and rapid inference for embedded spot-spraying applications (Xu et al., 2024).

4.2.2 UAV-Assisted Precision Spraying

UAVs are commonly known as drones, small aerial vehicles without any operator on board. UAVs have the potential to be used as application equipment for pesticides and fertilizers. Drones can ensure uniform and precise spraying of chemical pesticides and fertilizers, leading to less chemical exposure and fewer health hazards. Alongside drones, small aircraft are also effective in spraying applications and observing crop status. Drones equipped with high-resolution RGB, multispectral, or hyperspectral sensors and image analysis capability can precisely differentiate between crops and weeds. Thus, targeted herbicide or fertilizer application only where necessary is ensured (GensTattu, n.d.; I2I Automation, n.d.). This precision technology reduces chemical use by up to 50–95%, improves coverage accuracy, and minimizes drift and environmental contamination (MDPI, 2023; Farmonaut, n.d.; GensTattu, n.d.).

UAV systems are also more advanced in terms of speed and flexibility than other ground-based precision equipment. They can cover 40–80 acres per hour on average, and they can also operate over challenging terrains such as steep slopes or muddy fields (Farmonaut, n.d.; GensTattu, n.d.). As it can be operated remotely using a controller, operators' safety from agrochemicals is ensured. (MDPI, 2023). The integrated approach of UAV imagery with site-specific sprayers (UAV-IS) boosts the efficiency of spray solutions. It can minimize spray area by up to 20-5%, keeping the management efficiency similar. Although some weed patches may be missed compared to blanket applications (Pest Management Science, 2019).

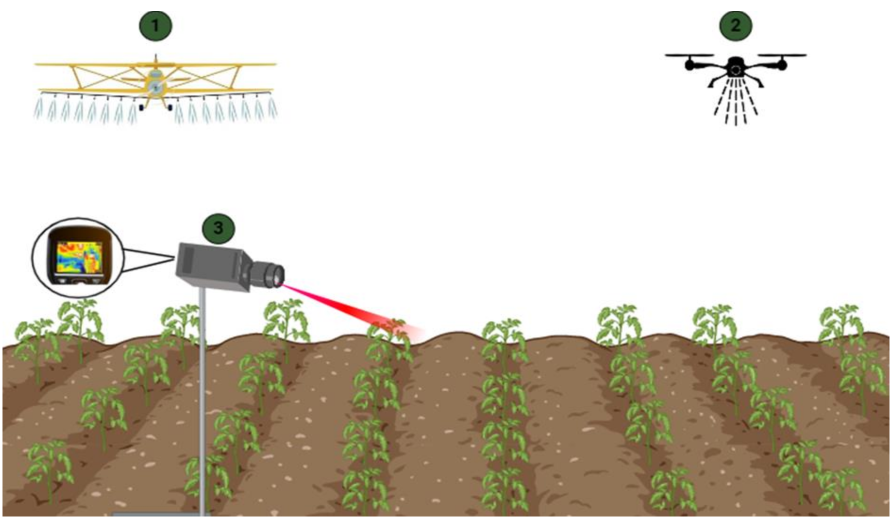

Figure 2. (1) Spraying through aircrafts, (2) Spraying through UAV’s, (3) Thermal sensor mediated camera.

4.3 Automated and Robotic Systems for Physical Control

Automated and robotic systems for physical weed control employ machine vision, AI, and robotic arms to mechanically remove weeds. Application of laser, hot water, or mechanical cutting is also possible to manage weeds by non-chemical means through these technologies. These innovations reduce farmers' dependency on chemical herbicides, address labor shortages, and ensure precise, site-specific application of chemicals (Farmonaut, 2025; LJ Tech, 2024).

4.3.1 Laser Weeding and Electrocution

Laser weeding systems can target weeds precisely by using diode or CO_2 laser energy beams, which destructively cause dehydration and cellular disruption by heating up plant tissues while sparing adjacent crops. Phani et al. (2024) studied with a robot that uses a 1064 nm continuous wave laser, which increases the temperature of weed tissues and results in a changing phase with structural collapse. Machines or robots mounted with laser beams can adjust beam direction and power by using servo-driven mirrors to optimize energy use and robust targeting (Phani et al., 2024).

Weed control with laser beams minimizes soil compaction, reduces harm to beneficial soil organisms, and ensures precise, site-specific application of harmful elements. But some potential risks are found, including fires from residual heat and eye or skin damage from exposure to beams. Installation of smoke detectors, infrared sensors, safety curtains, and laser protector goggles is essential before implementing this technology. A study on electrocution-based weed control requiring electrodes with high voltage has found promising results in trials in controlling taller weeds in soybeans (Michigan State University, n.d.).

4.3.2 Robotic Harvesters and Pruners with Disease Detection

Robotic arms are progressing further by harvesting and pruning as well as detecting diseases for smarter and more selective crop handling. The Harvey robotic sweet pepper harvester is developed as a protected cropping-friendly device to identify, grasp, and harvest peppers efficiently. It ensures a cost-effective strategy compared to traditional ways and maintains regularity of harvesting and crop quality (Lehnert et al., 2017). A robot called AHPPEBot follows phenotyping and pose estimation to detect the maturity of tomatoes and fruit orientation in greenhouses. Thus, precise harvesting with an 86.67% success rate and an average harvest time of just over 32 seconds per tomato is ensured (Li et al., 2024). Uploading reference images of diseases on the machine's cloud server may help to cross-check the field condition with the pre-uploaded images to identify early signs of disease or pest damage on fruits.

4.4 The Future Horizon: Nanotechnology

The technology that deals with the nanoparticles (the particles comprising the size of 1-100 nm) by creating new device or system and innovation so that it can provide precise and accurate application in the field of agriculture, medicine and materials science, and food industry. This subtle nanoscale exhibit unique physical, chemical and optical properties which allow them to behave unlike the larger compounds. Due to their lower surface area, they can be incorporated into the pore spaces where chemical compounds generally can't reach. Nanoparticles are derived organically (dendrimers, liposomes) and inorganically (metal oxides). The inorganic nanoparticles such as (ZnO, TiO2, FeNPs, AgNPs, AuNPs, CuNPs) which have to be synthesized from the chemical or organic sources (Fungi, bacteria, virus, algae, plant extract). Nanotechnology offers sustainable and eco-friendly plant protection by delivering nanofertilizers, nanopesticides, Nanosensors, Nano-priming and so on. Due to their target specificity, encapsulation property, precise action at infection site, optimum dose reduce the uneven disperse and toxicity to beneficial microorganism. Nanoparticles shows antimicrobial properties against plant pathogens while Nano encapsulated biopesticide foster the eco-friendly pest management. Nanotechnology have developed smart sensors to detect early signs of plant stress, nutrient deficiencies, soil condition, water deficiency in advance, allowing need based application in field with proper time interval. Quantum dots have potentiality to be used as a plant disease diagnostic tools. Nanoparticles disrupts the cell membrane of pathogens, generates reactive oxygen species and kills the pathogen.

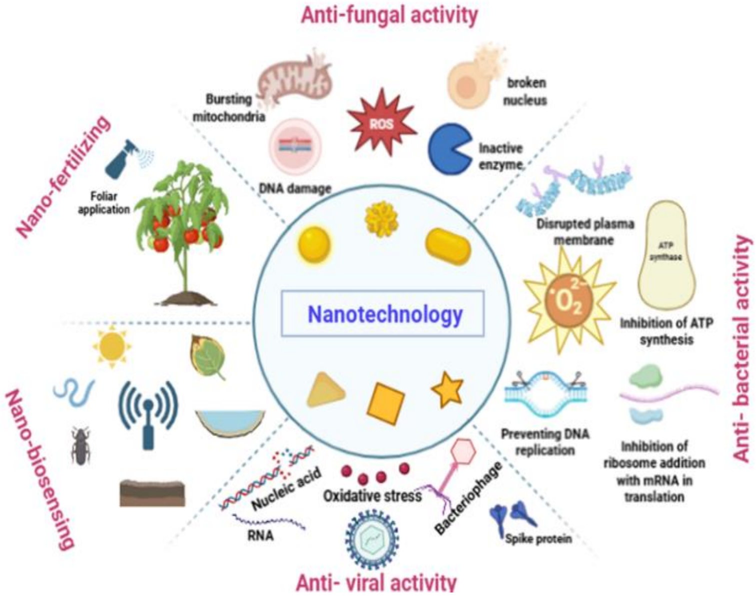

Figure 3. Overview of nanotechnology in plant protection

5. BIOLOGICAL: BIOTECHNOLOGY IN PLANTS

Biotechnology is a field of science that utilizes living organisms, biological systems or cells, and their properties to construct such technologies involved in the welfare of agriculture, the environment, industry, or health and medicine. Biotechnology in plant protection mainly combines the biological objects with the technical approaches in order to develop the resilient crop, improve the productivity and sustainability, and reduce the dependency on the reactive methods. The biotechnological approach in plant protection is highly appreciated due to the application of Bt technology, recombinant DNA technology, gene pyramiding, RNA interference, marker-assisted selection, genetically modified crops, biofertilizers and biopesticides, CRISPR gene editing, biofortification, and so on.

5.1 Advanced Bio-pesticide and Bio-fertilizer

The eco-friendly alternative to the conventional farming system comprises the use of bio-pesticides and bio-fertilizers that provide environmental protection, leading to the reduction of chemical use.

The biopesticide acts as climate-resilient agriculture by combating pests and diseases, whereas the biofertilizer supports a cost-effective method by providing better crop yield and quality. Both biopesticides and biofertilizers are mainly derived from organic materials involving plant debris, plant extracts or parts, microbial components, etc.

Table 2. Types, Origins and Functions of widely used Bio Control Agents

Topic	Types	Organism	Species	Function
Bio-fertilizers	Microbial	Bacteria	*Rhizobium* inoculant	Biological nitrogen fixation
		Bacteria	Azotobacter inoculant	Atmospheric Nitrogen fixation
		Bacteria	Azospirillum inoculant	Atmospheric Nitrogen fixation
		Blue-green algae	Cyanobacterial inoculant (*Anabaena, Nostoc)*	Reducing soil salinity, promoting auxin and amino acid in soil
		Fungus	Mycorrhizae biofertilizer	Phosphorus absorption to root
		Fungus	*Penicillium*	Secrete organic acids for solubilizing phosphates
		Fungus	*Aspergillus*	
		Bacteria	Inoculants for nodulated leguminous trees	Nodule formation in root that enhance the nitrogen uptake
		Actinomycetes	*Frankia* inoculant for some non-leguminous trees	Nitrogen availability
		Earthworm	*Erwinia fetida*	Production of vermicompost
		Earthworm	*Lumbricus Rubellus*	
		Earthworm	*Eisenia hortensis*	
Bio-pesticide (Bio-Fungicide and (Bio-fungicide)	Microbial	Bacteria	*Bacillus thuringiensis*	Controls lepidopterian insects
		Bacteria	*Bacillus subtillis*	Controls lepidopteran and dipteran insects
		Fungus	*Beauveria bassiana*	Controls aphid and thrips
		Fungus	*Metarhizium anisopliae*	Controls grasshopper and beetles, ants

		virus	*Nucleopolyhedrovirus*	Controls moths and butterflies
		protozoa	*Nosema locustae*	Controls grasshopper
		Bacteria	*Pseudomonas fluorescens*	Antagonist against *Fusarium* spp
		Fungus	*Trichoderma viridae*	Controls *Pythium ultimum*
		Fungus	*Trichoderma harzianum*	Inhibit *Rhizoctonia* and *Sclerotium*
		Nematode	*Steinernema spp*	Controls caterpillars
		Fungus	*Gliocladium virens*	Controls *Rhizoctonia solani*
	Bio-Chemical	Chrysanthemum	Pyrethrum	Antifeedant and repellent to tsetsefly and grasshopper
		Solanum	Leptine, solanine	Antifeedant to leafhopper
		Lemon grass	Odomos	Repellent to mosquito
		Apple	Phlorizin	Antifeedant to aphids

5.1.1 Microbial consortia and synergistic formulation

"Microbial consortia" refers to the collaboration of a group of beneficial microorganisms like fungi and bacteria, that coexist and positively interact with each other to enhance plant growth, sustain soil fertility and productivity, promote crop yield, and control disease infection and pest infestation. The synergistic formulation is the optimum mixture of desired microorganisms that are supportive of each other and improve their effectiveness when working together rather than individually. As an example, the amalgamation of arbuscular mycorrhizal fungi (AMF) and Trichoderma produces a symbiotic effect on plant growth and protection (Santoyo et al., 2021).

5.1.2 RNA interference (RNAi)

RNA interference (RNAi) is a predominant biological approach in plants for silencing the gene expression of targeted pathogens, using three different groups of proteins to resist the virulence of pathogens by disrupting their messenger RNA (mRNA). However, pathogens trigger an anti-silencing mechanism to create infection in the invaded host (*Muhammad et al., 2019*). This RNA interference acts as the anti-silencing suppressors by introducing double-stranded RNA (dsRNA) to the pest, resulting in the failure of gene expression both transcriptionally and post-transcriptionally. The dsRNA is cleaved to small interfering RNAs (siRNA) that complement the mRNA sequence of the pest, leading to mRNA degradation and then ultimately stopping the synthesis of essential proteins (Agrawal et al., 2003).

The phenomenon of RNA interference (RNAi) was first unfolded in the early 1990s, when it was proposed that introduced genes subdued the corresponding endogenous genes (Napoli et al., 1990), but Romano and Macino (1992) stated that homologous RNA sequences showed the inhibition of internal genes. The blue rose is the modified rose developed by the application of RNAi, as it prevents the gene responsible for the production of cyanidin in the rose. (Pathak & Gogoi, 2016).

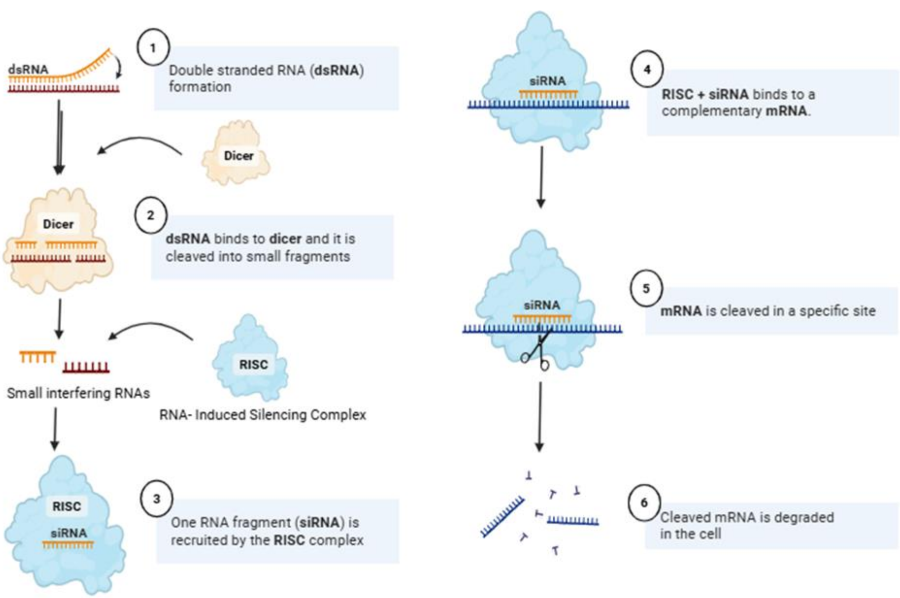

Figure 4. RNA interfering (RNAi) technique for gene silencing in targeted pathogen

5.2 Genetic Engineering for Resistance

Genetic engineering is the manipulation/alteration of the structure of a gene by the support of biotechnology to bring a desired character into an organism, and the derived organism is called a transgenic organism. Genetic engineering in agriculture fosters sustainable food production and food security by ensuring improved crop yield, pest and disease resistance, and drought and stress tolerance. Genetic engineering showed rapid advancement by opening a new door for the opportunities to modify the organic entities' hereditary material (DNA).

Table 3: Essential components of Genetic Engineering (GE)

Name of tools	Types	Examples
Enzyme	Restriction enzyme(RE)	Molecular scissors to cut desired DNA fragments
	DNA Ligase	Joins two DNA molecules
	DNA Polymerase	Synthesis of DNA
	Reverse Transcriptase	Making DNA copy by using RNA as template
Vector	Plasmid	Carry smaller fragment and cause independent replication in bacteria
	Cosmid	Carry larger fragments
	Bacteriophage	Infect bacteria
Host	Prokaryotic host	*Escherichia coli, Bacillus subtillis, Streptomyces sp.*
	Eukaryotic host	*Saccharomyces cerevisiae, Aspergillus nidulans*

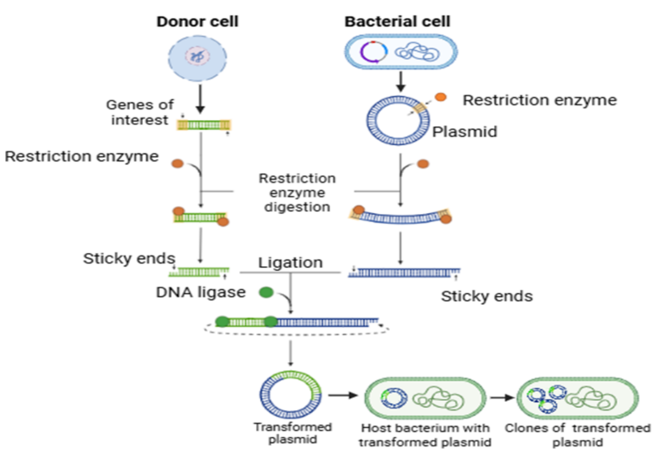

Figure 5. Recombinant DNA technology in Genetic Engineering (GE)

5.2.1 Genetically Modified Organisms (GMO)

Genetically modified organisms (GMOs) in agriculture are plants or animals whose nuclear components have been altered through genetic engineering to donate them enhanced traits.

In 1986, France and the USA conducted the first experiment of genetically engineered necrotic crop, developing genetically modified (GM) tobacco that was expected to be resistant to herbicide (*James & Krattiger, 1996)*. A significant approach in increasing crop production is the improvement of pest management strategies, comprising herbicide-resistant (HR) and insect-resistant (IR) crops, just as transgenic.

Table 4: Some majestic Genetically Modified (GM) crops with their modified traits and the status of crops before modification

Genetically Modified Crops	Genetically Modified traits	Symptoms/Stress/Deficiency occurred before modification
Bt brinjal	Brinjal shoot and fruit borer resistance	Make holes in the surface of fruit and damage the pulp by discharging excreta
Bt cotton	Insect resistant	Damaged pod
Corn	Herbicide tolerance	Onion leafing
Soybean	Insect resistance	Irregular holes in leaf surface
	Herbicide tolerance	Leaf chlorosis and necrosis
Alfalfa	Herbicide tolerance	Shortening of internode length and distorted root
Papaya	Papaya ring spot virus resistance	Mottling / mosaic
Tobacco	Fungal resistance	Leaf spots and wilting
Jute	*Macrophomina* resistance	Stem rot
Citrus	*Xanthomonas* resistance	Citrus canker
Tomato	Abiotic tolerance	Salinity stress
Golden Rice	Enriched in beta carotene	Vitamin-A deficiency

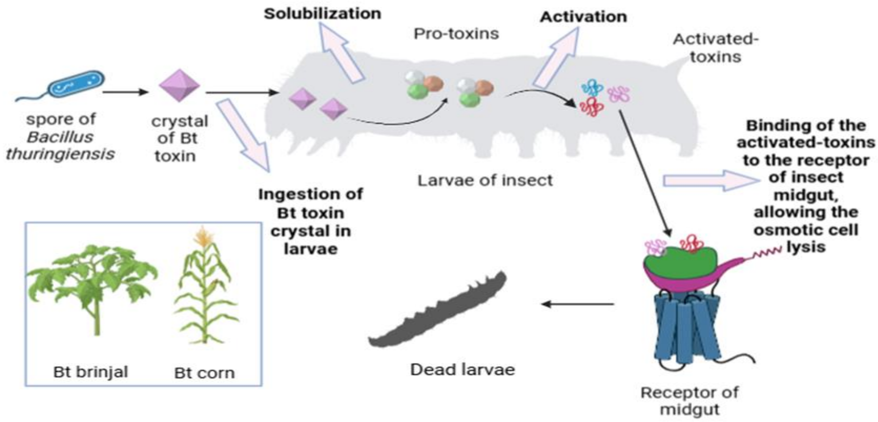

Figure 6. Mode of action of Bt. crystal toxin on insect

5.2.2 Genome Editing: CRISPR-Cas-9 Technique

Genome editing is a type of genetic engineering in which DNA is inserted, removed, modified, or replaced in the genome of a living organism. CRISPR (Clustered Regularly Interspaced Palindromic Repeats) is a technique of genome editing in molecular biology where the genomes of living organisms may be altered or modified, allowing existing genes to be removed and/or new ones added. This method comprises a guide sequence of 20 nucleotides that is complementary to the targeted gene to be edited in order to bind to the cas-9 protein by forming a scaffold (stem-loop) structure.

Horvath and Barrangou (2010) and *Deveau et al. (2010b)* propelled CRISPR-Cas-9 as an adaptive immune system found in most bacteria and archaea that defends against the infections caused by phages, viruses, and other foreign genetic elements. The technique is highly appreciated in biotechnology and medicine, as it enables modifying genomes very precisely and cheaply. Some specific tasks this method can carry out may be the targeted gene mutation and transgene addition, endogenous gene labeling, and gene therapy that are used in the creation of new agricultural products, genetically modified organisms (GMOs), and the solution of mitigating pathogens and pests.

Table 5. CRISPR/Cas-9-mediated improvement in different traits in different crops

Crops	Targeted gene	Desired trait
Rice	*IPA1*	Number of tillers
	GS3, Gn1a	Grain size, grain number, yield
	OsSWEET11, 13	Sugar transport, grain filling
	OsERF922	Magnaporthe oryzae resistance
	OsNAC041	Drought, osmotic, salinity tolerance; stomata & ABA signaling
	ALS, FTIP1e	Imazamox resistance
Tomato	*EJ2*	Larger fruit calyx, higher yield
	SlMlo	Podosphaera xanthii resistance
Wheat	*TaDREB-2, 3*	Drought signaling
	TaMlo	Powdery mildew resistance
Soybean	*FAD2-1A, 1B*	Oil quality, increase oleic acid , decrease linolenic/linoleic acid
Maize	*ARGOS8*	High yield under drought stress
	ALS2	Chlorsulfuron resistance
Cucumber	*elf4E*	PRSMV, ZYMV, CuVYV resistance

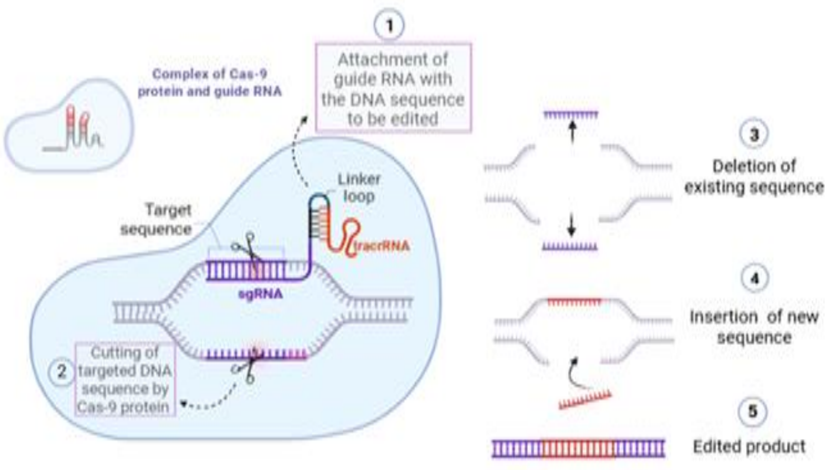

Figure 7. CRISPR-Cas9 genome editing technique

6. DISEASE ASSESSMENT BY ANALYTICAL TECHNIQUES

Spectroscopy, chromatography, PCR, and ELISA can diagnose plant diseases accurately by detecting pathogens, molecular markers, and biochemical changes at molecular levels. These methods ensure fast, sensitive, and quantitative results. Rapid diagnosis, surveillance, and effective disease management strategy can be ensured through this.

6.1 Molecular Diagnosis: PCR

Polymerase chain reaction (PCR) is an analytical technique of molecular biology that is conducted in a laboratory for rapid amplification of a huge number of copies of a gene (a particular region of DNA), used to provide greater molecular detail in research, and often applied in the detection and quantification of pathogens. The compulsory element for PCR is the polymerase enzyme that is capable of synthesizing complementary DNA strands, ensuring the million to billion copies of targeted DNA fragments.

Sankaran et al. (2010) *and* McCartney et al. (2003) felt the necessity of quick, rapid, and particular detection and identification of plant pathogens in efficient plant disease management, as proper control measures cannot be effective unless the diagnosis of disease is specific. The disease caused by *Fusarium oxysporum* f.sp., *Phytophthora fragariae*, *Colletotrichum acutatum*, *Verticillium dahliae*, *Botrytis cinerea*, *Macrophomina phaseolina*, and *Xanthomonas fragariae* in strawberry was detected and identified by the PCR-based method (Mirmajlessi et al., 2015).

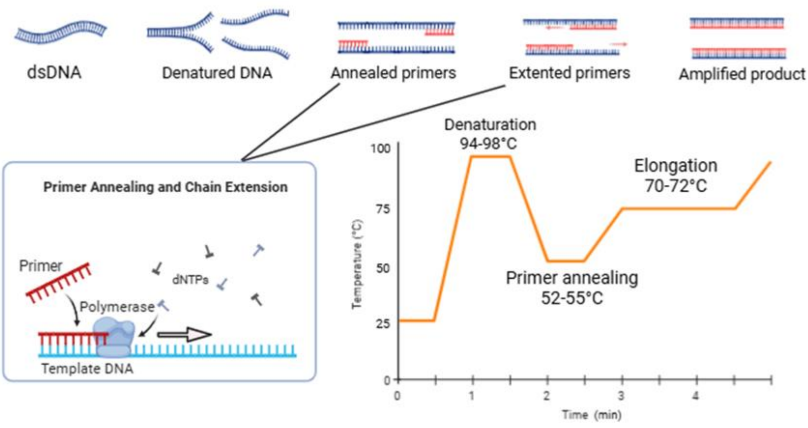

Figure 8. Polymerase Chain Reaction (PCR) technique for amplification of specific section of DNA

6.1.1 Gel Electrophoresis

Gel electrophoresis is the process of quantification of biomolecules (DNA, RNA, and proteins) in order to determine and separate the amount of amplified DNA/RNA (PCR product) present in the sample, running the agarose gel (for DNA and RNA) or polyacrylamide gel-sodium dodecyl sulfate (for proteins) in an electric field, and visualizing the band of molecules based on their fragment length, migration, and concentration. The band is observed under UV light, following the principle of "the more amount of DNA, the more absorbance of the band," where the larger fragments move faster than the smaller ones in the gel matrix.

6.1.2 Next-Generation DNA Sequencing

DNA sequencing in disease detection is a process of precise and rapid determination of the nucleic acid sequence of a pathogen, finding the correct order of four nitrogenous bases (adenine, guanine, and thymine) through high-quality molecular (DNA/RNA) extraction to get a comprehensive understanding of the genomic structure that is responsible for a plant disease, accelerating the biological research and discovery in plant disease management.

The next-generation sequencing technique is able to provide high throughput and high accuracy in the detection of novel pathogens, understanding the plant microbiome details, and tracking the disease outbreak. Sometimes DNA sequencing is done to screen for the presence of desired species, which may be growth-promoting for plants or antagonistic to the harmful pathogens, encouraging sustainable agriculture by ensuring a disease management technique.

6.2 Bioinformatics

Bioinformatics is an advanced technology used for analysis of complex biological study (DNA sequence, amino acids, proteins, genomes) by using mathematics, statistics and computer science to develop software that enable to compare, organize and interpret the data of this molecular properties. It is mostly familiar in the agricultural science with holding the components of transcriptomics, proteomics, metabiomics and analyzing the product comes from PCR, CRISPR-Cas9, Gel electrophoresis, and biotechnology by showing their precise nucleic acid sequencing and then ultimately interpret the database to cope up the frequent challenges in health and agriculture.

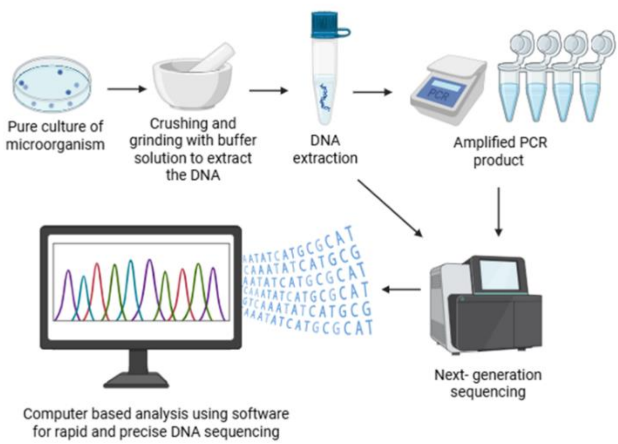

Figure 9. Bioinformatics tools and softwares for analysis of DNA sequence

6.3 Serological Assay: ELISA

Enzyme-linked immunosorbent assay (ELISA) is a clinical analysis for the detection of the presence and concentration of pathogens, including bacteria and viruses, with high specificity and sensitivity, using antibodies (Ab), antigens (Ag), and enzyme-linked antibodies to know the presence of the particular antigen of the desired viruses by the change of the color of the substrate of the enzyme with the aim of preventing the viral epidemiology. The amount of product derived by this detection is proportional to the amount of antigen in the sample (Aydin, 2015).

Scholthof et al. (2011) listed some common viruses in molecular plant pathology, such as Tobacco mosaic virus, Tomato spotted wilt virus, Tomato yellow leaf curl virus, Cucumber mosaic virus, Citrus tristeza virus, Potato leaf roll virus, and Tomato bushy stunt virus Potato virus Y, which were confirmed by this test. ELISA was verified as a standard test for identifying *Xanthomonas campestris* pv. *undulosa (Xcu)* in plant tissues (Frommel & Pazos, 1994).

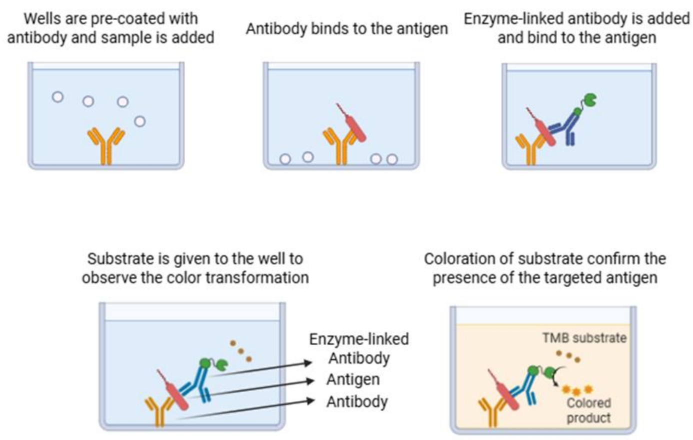

Figure 10. Enzyme-Linked Immunosorbent Assay (ELISA) test

6.4 Bio-Assay: Pathogenicity Test

Robert Koch observed that *Anthrax bacillus, a bacteria* in blood samples of diseased cows, could also introduce similar diseases in mice (Blevins & Bronze, 2010).

This method got high acknowledgement in plant pathology to determine the ability of an organism to cause disease in the healthy and susceptible host. The isolated pathogen from the diseased host is grown in a pure culture, and the cultured pathogen is inoculated into a healthy host to observe if the pathogen is able to show corresponding disease in the healthy host. The test is confirmed when the disease caused by the re-isolated pathogen from the inoculated host becomes identical to the original causative pathogen.

6.5 Marker Assisted Selection for Resistance

Marker-assisted selection is mainly the molecular technique used in breeding programs to find out the traits of interest in plants that are able to resist a particular gene of the pest and pathogen or the abiotic stresses (salinity, drought, submergence*)* (Hasan et al., 2021). The DNA fragments used as markers are closely linked to the disease resistance and stress tolerance gene to carry out the direct selection of a specific characteristic of a plant, and the method is basically based on the genotypic character rather than the phenotypes, allowing more rapid and accurate results not just in the crop improvement but also in disease remediation compared to conventional methods. Selecting the desired trait in plants, compatible for preventing the specific pest and pathogen, confirms the existence of a host resistance mechanism, reducing the use of chemical approaches as a reactive control measure, which facilitates the environmental health by declining the residual effect of pesticides.

7. CHALLENGES AND FUTURE DIRECTIONS

Technological advancements in plant protection face several challenges. High installation costs, lack of knowledge, and insufficient infrastructure restrict adoption in remote areas or developing countries. Some countries have restrictions on importing drones and flying them which is quite troublesome for farmers to get permission regarding this aspect.

7.1 Barriers to Adoption: Cost, Connectivity, and Knowledge Gaps

The adoption of advanced plant protection techniques are frequently hurdled by some barriers such as higher cost, low connection and knowledge gap. High-priced technology, regular maintenance cost and difficulties in operating the tools make the farmers less interested to adopt the modern solution. Also lack of skills and education, unstable electricity and inadequate internet facility restrict the poor and marginal farmers from adoption of this sustainable plant protection. But initial installation cost is the main barrier for smallholder farmers to adopt modern technologies. Small farm size, heterogeneous cropping pattern, unavailability of land tenure and ownership is also keeping small farmers away from adopting PA. Infrastructure and institutional barriers, market imperfections are also playing a considerable role in developing doubts in farmers. Uncertainty of success by adopting new technology and equipment is another problem which should be eradicated by expert and knowledgeable root level extension personnel recruited by government. Government initiatives should be taken to form farmer community groups to ensure a collaborative effort. Alongside this, authority should increase subsidies in this sector by implementing Public-Private Partnership with international donors or NGO's.

7.2 Data Ownership, Privacy, and Cybersecurity

Though advanced plant protection techniques generate valuable agricultural data, lack of privacy, unethical access to third parties and security bring some uncertainty and hinders in sustainable food production as well as plant protection. Often some agrotech companies claim to own the data which is collected by farmers through modern tools as smart sensors, swarm robotics, AI, breaking the privacy of a field trial or an experiment. Marginal farmer also face some barriers to transfer their data properly to the technology providers or the researchers. Cyberattacks on IoT devices or platforms by unethical hacker or security breaches can disrupt the sensitive genomic trial by tampering with critical database.

A multi-layer approach should be implemented by the government and law enforcement agencies.

Initially strict **cybersecurity protocols** including encryption, firewalls, and regular system audits should be introduced to protect personal data (Wolfert et al., 2017). Furthermore clear explanation of data access and terms and conditions should be explained to the farmers before providing to them. Ensuring a secure cloud storage also reduces privacy risks. Proper training and awareness campaigns should be held targeting the farmers to warn them about data safety.

CONCLUSION: PLANNING A SUSTAINABLE FUTURE

Technological integration is a blessing for the shift from conventional practice to precision agriculture to generate sustainable action in global agriculture. The holistic approach of these modern technologies can construct the path toward a sustainable future.

Major Technological Advancements

In this chapter technological transformations in plant protection are discussed in detail. Remote sensing using satellites and drones, the Internet of Things, and the operation principle of ground-based soil sensors in plant protection are explained. Integration of big data with machine learning systems has opened a new door in the sector of predictive modeling, where early prediction of severe diseases and pest occurrences is possible through Decision Support System (DSS). Technologies like Variable Rate Technology (VRT) and smart sprayer systems can calibrate the exact dose of pesticides or herbicides required for a specific site where weed or disease infestation is reported at a higher rate. The smart spray system also ensures applicator safety. Thus less chemical is exposed to the environment with negligible residual value. Also, several biotechnological tools with the potentiality of developing environmentally friendly control agents are discussed to reduce the chemical consumption.

Future Strategies

In the future, proper integration, accessibility, and sustainability will be mandatory. Integration of these assets should be made easier by the policymakers.

Initial installation cost should be minimized by using locally available materials, ensuring proper safety. Security of data of consumers must be ensured by law enforcement agencies. The true potentiality of these technologies will only be known if they are successfully integrated by farmers. Further sustainability will be ensured smoothly if they perform properly.

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CHAPTER 2

REMOTE SENSING AND ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE AGRICULTURE IN SOUTH ASIA

[1]Basirul Alam Sarker OVY

[1]Bsc. Agri. Engg., Msc. Sustainable Agri.& Food Security, Bangladesh, ORCID ID: 0009-0007-2889-632X, basirul.ovy.iifs@gmail.com

INTRODUCTION

Agriculture has traditionally mediated the economy, society, and culture of South Asia. It supports hundreds of millions of people by giving them a livelihood, food, and employment, and, besides, rural revenues. The industry well belongs to the fabric of the region; it has affected the tradition and habits for generations. Besides its socio-cultural value, in nations like Bangladesh, India, Pakistan, Sri Lanka, and Nepal, agriculture bolsters economies by making a large contribution to the gross domestic product, providing raw materials to industry, and even ensuring food security to the rural population. However, agriculture, which lies at the core of the economy in that area, is under increasing pressure and is becoming less and less productive and more and less sustainable. Climate change and environmental destruction form some of the most burning issues. Temperatures have increased and decreased in spurts with these changing climatic conditions, rainfall has been in an unpredictable manner, floods have been a common feature, and droughts have been long-lasting to the extent of destroying varieties of crops. Many years of intensive production of high-yielding soil have worsened the soil fertility, and the extraction of water and ineffective irrigation have resulted in water resource depletion. These strains are compounded by the fact that more and more pests and diseases are becoming common in other climate regimes. The absence of resources, imperfect access to technologies, and money make the farmers, mainly the smallholders, in South Asia, fail to make the necessary adjustments. Consequently, this has made agricultural systems more susceptible to climate variability and environmental degradation. Things are aggravated even by demographic pressure. As South Asia experiences the effects of the growing population, the food demand is expected to rise rapidly in the decades to come. There is pressure on farmers to yield more products on less land, using less water and less energy. Meeting this increased demand and doing so in a sustainable manner is the twofold challenge, i.e., not to speed up environmental degradation. The size and urgency of the problems posed by the current model cannot be resolved through cultural values, localized farming practices, and customary farming. This fact illustrates the significance of the transformational approaches incorporating innovation, productivity, and resilience.

The path to such transformation will be opened by advances in technology, e.g., Remote Sensing (RS) and Artificial Intelligence (AI).

Remote Sensing is the process by which data, in real-time, is synthesized on large scales (e.g., individual plant, field, landscape) of the environment, including crops, soils, water resources, and terrain on satellite, drone, and aerial platforms. They enable the observation of agricultural landscapes on a periodic basis, which provides knowledge that otherwise is unavailable through on-the-ground observation. Artificial Intelligence adds to them, processing bulk data, identifying patterns, and building predictive models to guide decision-making. Collectively, RS and AI assist in shifting from intuition-based methods to the use of data-intensive agriculture. The benefits of the RS and AI combination are tremendous. They can monitor the health of their produce and whether it is being bothered by pests, diseases, or even experiencing water shortages in order to implement timely measures. You may shift the hours you water to conserve more water than is required. Irrigation programs can be modified, and reduced water will be lost in water-crazed areas. The use of satellite data and models powered by artificial intelligence (AI) have the potential to assist statisticians and policymakers in predicting crop yield, allocating resources, and anticipating response to climate-driven crop catastrophes. Not only do these technologies enhance productivity, but also can maintain sustainability goals in a wider context, through less environmental degradation leading to less inputs, less environmental damage, and greater resilience to climate variability. The significance of the RS and the AI is equal as they help to make farming environmentally friendly. Precision agriculture uses these techniques to minimize the wasteful application of fertilizers, pesticides, soil erosion and water savings. Farming activities can be optimized through predictive climate modeling that allows farmers to optimize the systems and practices of cropping with regard to the changes in weather. In this manner, they may serve the purpose of the food production and ecosystem conservation. Nevertheless, there are a few bottlenecks to using the RS and the AI in South Asian agriculture. Smallholders especially lack infrastructure, funds, or digital capabilities to utilize the current technology. The villages of the nation often lack connectivity through the internet, a 24-hour power supply, and access to the latest farm equipment. Second, resistance to change is high, due to allowing sustainable preferences to old ways of doing things, deep-rooted social weeds, and fear of the unknown.

IT solutions to these challenges do not only focus on the technical side, but on enabling policies, targeted investments, and capacity-building to ensure that accessibility and adoption are fair. Nonetheless, there is an increased momentum in the region. Pilots and examples have demonstrated that RS and AI can be applied to agriculture in different ways and in diverse circumstances as flexible and helpful tools. Keeping a watch on rice in Bangladesh, regulating irrigation in India, and improving the productivity of plantations in Sri Lanka are some the examples. These achievements explain that technology can be used effectively to overcome agricultural imbalances common in these areas. As digital literacy improves, so should access by smallholder farmers due to better infrastructure and the reduction in technology tool costs.

The chapter thus explores the application of Remote Sensing and Artificial Intelligence to change the landscape of sustainable agriculture in South Asia. It looks at their current application, points out what they are capable of providing, and what obstacles might prevent their broader application. Starting with the regional lessons and newly emerging opportunities, the chapter argues that RS and AI can be used to promote agricultural productivity and as a central commodity in resilience development, ecosystem conservation, and food security in the long run. Considering the evolving global economy, it is a significant move in the South Asian agricultural transition to a more dynamic, intelligent, and sustainable agriculture that uses these technologies.

1. REMOTE SENSING APPLICATIONS IN AGRICULTURE

One of the most significant technologies transforming farming in South Asia is remote sensing. Remote sensing technologies are also becoming considered as one of the tools to solve the issue of yield variability and climate-related challenges (Lobell and Azzari, 2017). It enables various instruments to assist the farmers and policymakers in monitoring and controlling the farming system at the local, regional, and national scales.

Through remote sensing, satellite, aerial, and drone-based data can be acquired and extensive agricultural regions can be observed repeatedly, to inform sustained measurements of crop health, soil quality, water resources, and land-use change. In South Asia, where small-scale farms are the dominant form, climatic variability in the form of monsoons, droughts, and extreme events can overwhelm the traditional forms of observation and management. Remote sensing is used to detect crop stress sooner, which would be detected by farmers as nutrient deficiency, pest infestation, and water stress before the situation gets out of control and leads to significant crop loss. Satellite data in the form of vegetation indices, including NDVI based on various averaging techniques (NDVI, EVI, SAVI, LAI) have been traditionally used to estimate the plant growth stages, health, and biomass of the plants. Hyperspectral technology provides very fine spectral information, which can be utilized to determine what type of crops are growing, what diseases they are infected with, and what stress they are under. Thermal photography aids in the assessment of evapotranspiration and water stress, making planning of irrigation a simpler task. Simultaneously, LiDAR can give high-resolution topographical maps of soil erosion and micro-topography (relevant in water management). The space architecture of South Asia that has been implemented in remote sensing is a combination of satellites, UAVs, and aerial photography. Satellites, such as Landsat, Sentinel-1 and -2, MODIS, and Planet Scope, have been heavily utilized in crop mapping, phenological monitoring, yield estimation, and soil moisture analysis. It is applied especially during monsoons (in Bangladesh, India, and Sri Lanka) when there is a possibility of clouds usually covering a bigger part of the land, since its signals can penetrate through clouds. So, the scanning of the land surface can be performed even in the case of heavy rains, when it is still overcast. The satellite imagery, complemented by the inclusion of UAV imagery, allows ground-level imaging at high resolution particularly significant in smallholder farmers with non-uniform fields. Among the bibliographies are Principal Component Analysis (PCA), supervised and unsupervised classification, and machine learning algorithms, which have been applied on large-scale databases to achieve practical results. Time series imagery collected through satellites can be utilized to monitor crop phenology and note growth pattern changes due to drought, flooding, or pest attacks.

Another reason why remote sensing is quite important in the process of managing water resources in farming is that it is important in farming. Since RS can estimate soil moisture, evapotranspiration (ET), and water demand by crops, farmers and irrigationists can make appropriate decisions to optimize water utilization, which is essential to water-scarce regions, e.g., Rajasthan and Punjab regions in India, or arid areas in Pakistan. As an illustration, the RS-driven soil moisture estimation demonstrated positive irrigation timing and resulted in 15-25 percent water savings without any reduction in grain yields. Besides this, flood zoning, drought surveillance, and early warning are also ways in which RS can be used to reduce disaster risk. National crop and production data derived using RS data is utilized by South Asian governments and organizations to classify crops, estimate national production, and develop responses to natural disasters - all of which are of national food security and resilience. South Asia also has a lot of pitfalls associated with telemedicine despite its promise. Remote sensing is not problem-free in South Asia despite the potential it has. The monsoon season may be associated with cloud cover staying long enough to make optical images difficult to see. Small farmers often lack the ability to access high-resolution data, and most rural areas lack the capability to support RS, including good energy and internet services. Furthermore, translation of the RS products into actionable information depends on technical expertise, which is not usually available to local ranchers. The Sustainable Agriculture of South Asia through the use of Remote Sensing and Artificial Intelligence (Magar & K. T., 2023).

2. ARTIFICIAL INTELLIGENCE APPLICATIONS IN AGRICULTURE

With AI, farming is transforming with high-level analysis of big data like remote sensors, field sensors, weather sensors, and farmer reports. The agricultural sector has been no exception to the emergence of artificial intelligence, as now complex learning and statistics are required by the data-intensive farming systems. Pattern recognition, Prediction, and Decision support traditional reactive farming into proactive and precision agriculture.

Working in South Asia, where agriculture is becoming more vulnerable to both extremes of climate, extremes of market prices, and pests and diseases, AI can promise to help farmers become more efficient, as well as to manage natural resources more efficiently and enhance food security. Applications of AI in South Asia have a broad spectrum of areas. There are numerous applications such as crop yield prediction, which are increasingly adopting models such as the Long Short-Term Memory (LSTM) networks, Convolutional Neural Network (CNNs) and ensemble-based machine learning models such as probability distribution models as Random Forest and XGBoost where historical crop data, real time weather forecast, soil properties and remote sensing imagery are being combined to yield future yield prediction. The same forecasts guide farmers in their harvesting and storage choices and policymakers in their food distribution strategies, market interventions, and risk coping strategies. Precision agriculture is another field in which AI is playing a central role. With field-by-field information on soil fertility, soil moisture, crop health, and others, AI systems can make decisions on where and when to use fertilizers, pesticides, and water most effectively, i.e., with less waste, the least impact on the environment, and less costly production. As an example, MAI-developed pest detection systems in Maharashtra have allowed cotton farmers to effectively reduce the 30 percent with precision spraying, and they also did not reduce crop yield. AI, which uses UAV images in the tea fields of Kerala and Sri Lanka, is used to monitor the health of plants to forecast yields and deploy the workforce, leading to an increase in productivity and the quality of work. In South Asian agriculture, artificial intelligence can also support climate adaptation plans. Using advanced interaction between climate simulation, soil characteristics, genetics of crops, and water supply, AI solutions propose customized processes, such as drought-resistant crop types, optimal planting time, and optimal irrigation schedules. Integrating AI and remote-sensing introduces an additional decision-support tier since AI models can process large volumes of satellite and drone imagery, including detecting crop stress, pest infestations, or growth pattern deviations. Outside the farm gate, market intelligence and supply chain management based on AI can predict price changes, demand trends, and logistical issues, and result in reduced postharvest losses and increased income security among farmers.

AI application in South Asia is similarly a comparatively recent phenomenon, and although it has the potential to catalyze a range of changes, it has been marked by a variety of obstacles. It is possible that the datasets used in training AI models are very poor. Smallholder farmers have low levels of digital literacy, and this is a barrier to the uptake of AI-powered tools. You have poor power and unstable power, and slow internet connection at times, and again, your deployment is hampered by the infrastructure limitations. The resolution of these barriers will take the form of investments in digital infrastructure, training, and policy advice for farmers to guarantee fair access. However, AI is an innovation in the active gathering of data-driven agriculture that provides sustainable, efficient, and climate-resistant technology that can help to make a difference in food security and agricultural incomes (Krishnababu *et al.*, 2024).

3. CASE STUDIES FROM SOUTH ASIA

Practical application of remote sensing and AI to the agricultural sector can be considered on the example of several South Asian countries and will focus on the issues at the local level and the encouragement of productivity, resource-use efficiency, and climate resistance. Synthetic Aperture Radar (SAR) images provided by Sentinel satellites have been leveraged in rice-based Bangladesh, where seasonal flooding is a major food security risk, to map rice fields during the monsoon, overcoming the cloud cover. Together with AI-driven modeling of the yield, these solutions have helped governmental institutions to predict the harvest of rice with precision, allocate its resources to maximum capacity, and reduce the threat of an agrarian crisis. It can also be applied to keep track of the flood-prone areas so that they are warned early on how to avoid damage to the livelihoods of the people and also mitigate losses on crops. The issue of water stress is already becoming a concern in India, especially in Punjab and Rajasthan, and AI-based irrigation scheduling systems have been incorporated with remote sensing-derived soil moisture data to help them manage water. Research has seen such systems lessen groundwater drawdown and yield loss. Maharashtra can be used as an example, according to which the AI-based pest detection tools have enabled farmers to deal with cotton bollworm attacks in a more effective manner, which has led to a reduction in the quantity of pesticides used, and the general health of crops has improved. An example would be in Kerala, where drones and artificial intelligence are used to assess the health of plants, forecasting yield, and dedicating additional labor, which will result in higher productivity and the resulting high-quality products. Remote sensing and AI have helped Pakistan monitor floods and droughts in Sindh and Punjab, and this has allowed the authorities to predict water scarcity and flood risk. This allows early warning, optimum scheduling of irrigation, and enhanced disaster management. Tea and horticultural business in Sri Lanka: Use RS and AI to cause sickness in the plantation, pests were identified early, and the yield produced was at its best, which is of great help to the efficiency in production and competitiveness on the market. In Nepal, the technologies have been utilized in mountainous areas to identify the place of crops, monitor the growth, and plan food security interventions against remote communities. Bhutan applies AI and remote sensing toward high-altitude horticulture. There is water and nutrient optimization in Apple orchards and citrus orchards. Taken together, these case studies show that RS and AI can be adjusted, in their implementation, to the different agro-climatic regions, crops, and socioeconomic settings in South Asia.

4. CHALLENGES AND LIMITATIONS

Artificial intelligence (AI) and remote sensing (RS) are changing the face of agriculture worldwide by enabling productivity and sustainability and improving decision-making by better managing information. Agriculture is the main income earner of hundreds of millions of people in South Asia, which includes India, Bangladesh, Pakistan, Sri Lanka, Nepal, Bhutan and the Maldives. Among the major benefits of RS and AI, there are enhanced resource distribution, accurate planting schedules, early disease and pest detection in crops, and recommendations on climate risk management. Nonetheless, the deliberate transfer of these technological changes in reality is still a challenge in South Asia, as structural and contextual challenges continue to exist. One of the key problems associated with the implementation of remote sensing and AI in the region is the quality of data and its availability.

Optical remote sensing remains an impediment because of persistent cloud cover despite the availability of satellite images in the present times, more so than it was prevalent in earlier times, particularly during the monsoon season. In the case of countries like Bangladesh, eastern India, and Sri Lanka, where the monsoons may extend to several months, cloud-free images at critical agricultural phases become rare or even unavailable, thus reducing timely crop analysis and early warning. Although synthetic aperture radar (SAR) sensors can operate through the clouds, SAR data is more complicated, costly, and has less use because of technical challenges. In addition, the publicly available satellite data is not always resolved well enough to capture the small and fragmented plots characteristic of South Asian agriculture, like Landsat or Sentinel. This can be reduced by high-resolution commercial sources, which have the disadvantage of high cost that precludes their broad adoption across poorer regions and smallholder farmers. The next challenge is the availability and reliability of contextual ground truth data. Models that can be applied to carry out agricultural monitoring, prediction, and recommendation on the basis of AI demand extensive, accurate, and up-to-date training data. Field data in South Asia often is disproportionate or biased because logistical and financial constraints constrain the accessibility of ground data and can lead to validation and calibration gaps in satellite-based insights or in AI model output. Such a weakness in the strong ground truth restricts the truthfulness and certainty of the RS-AI technologies in farm-level recommendations. Handling and converting big streams of data is a big challenge. Massive satellite recording, weather information, and sensor readings cannot be handled without powerful computer hardware and reliable internet connections. Such resources are not prevalent in rural South Asia. Access to these technologies is limited because not all affordable, high-performance computers exist, which constrains their application to mainly large agribusinesses and research institutes. The predominant agricultural practices in South Asia present additional challenges. The majority of the farms are small (usually less than two hectares), and intercropping is frequent. These minor, uneven plots decrease the usefulness of remote sensing technologies, which tend to be best-suited to large, homogeneous fields.

The fact that field size and configuration vary makes it difficult to automate crop identification, yield estimation, and the presence of stressors like drought or pest infestation. Moreover, a variety of planting and harvesting times and a range of crops both require increased retraining and regionalizing of existing, general-purpose AI models, which typically are trained on data generated by more consistent agricultural environments. Still, socioeconomic aspects are a constraint to the popularization of the applications of remote sensing and artificial intelligence. Even though these tools are used by academic institutions and government agencies to monitor regions, the information that is generated does not always reach the small-scale farmers. Low digital skills, lack of knowledge about the benefits of technology, and unwillingness to make changes in the old patterns of practicing agriculture are the obstacles to the adoption. A majority of the households in the rural areas have feature phones as opposed to smartphones, which limits the access of application-based advisory. There is also the issue of a language barrier since the majority of platforms are created in English and several local languages, which omits a large number of prospective users. The cost factor is one of the major hindrances to remote sensing and artificial intelligence. Smallholders are sometimes unable to afford the cost of data collection, the deployment of sensors, subscriptions to services, and training of personnel, which exacerbates the productivity and adaptation gaps. Even in the case of government subsidies or donor-financed projects that make the first adopters gain access, there is still a concern over the long-term financial viability. Funding often runs out, and access and maintenance often lapse, and without using a feasible local revenue model or a significant level of public investment, large-scale implementation would remain purely an aspiration. Environmental and climatic variability present further limitations. The agriculture of South Asia is acutely sensitive to extreme weather conditions, such as floods, droughts, and cyclones. They not only cause the satellite data to be unreliable (e.g., cloud cover during floods) but also reduce the predictive value of AI models trained on more consistent past data. The erratic nature of these weather events and their severity often surpasses the ability of existing models to predict and act on a real-time basis and occasionally results in inaccurate recommendations that can further undermine confidence in digital solutions among farmers. There are more dimensions of policy and institutional gaps. No standardized models of sharing data between ministries, research organizations, privately-funded firms, and international collaborators are often available. Where they are in place, they can be obstructed by red tape, issues of data privacy and data security, and the absence of interoperability standards. Such deficiencies in their policies result in the redundancy of efforts and the lack of innovation. Added to this is the fact that there is a limited amount of skilled personnel that is knowledgeable in the convergence of data science, agriculture, and technology. Although the talent pool in information technology is large in South Asia, the majority of individuals do not work in the agricultural sector, and agricultural extension agents themselves typically lack the expertise to interpret or explain complex RS or AI results to farmers with limited resources. The technologies of remote sensing and AI are vulnerable to technical constraints. Most AI algorithms lack transparency, which may decrease user confidence and slow adoption. This can cause errors when the training data are not indicative of the conditions on the ground, during rare occurrences like disease outbreaks, or when a system misclassifies the data. This inaccuracy can reduce the trustworthiness of these technologies. Moreover, the uncertainty of the AI tool results is not shared by most of them, which also leads to the possibility of making suboptimal decisions. Lastly, there are ethical and equity issues. The technological solutions of innovations in the fields of the RS and AI in the agricultural sphere can rather unknowingly support the pre-existing disparities in society and gender differences, if they are proposed only to the population that is already privileged with respect to education, land ownership, or access to technological tools. The technology rollouts face the danger of placing more emphasis on the crops or regions that are commercially viable and abandoning the marginalized regions and farmers. Altogether, remote sensing and artificial intelligence can contribute to sustainable agriculture in South Asia, but many obstacles still limit them. These challenges will have to be addressed through inter-sectoral collaboration, more substantial investment in technology infrastructure and human capital, creation of open and trustworthy AI systems, effective policy frameworks, and active integration of the most vulnerable groups in the farming population. Such measures will help to implement fair access to the advantages of these technologies among all farmers in the area.

5. FUTURE PROSPECTS AND ROADMAP

Combining remote sensing and artificial intelligence will change the future of agriculture in South Asia in a profound way, as it will revolutionize the methods of monitoring crops, managing them, and harvesting them. With the proliferation of high-resolution satellite data and drone-mounted sensors, crop health, soil moisture, nutrient content, and environmental stressors will be able to be mapped on a scale never before imagined. With the growth of these data sources, AI models in the form of local climatic conditions, soil composition, and the type of crops will offer predictive information that can predict the attacks of pests, disease outbreaks, and other adverse weather phenomena with the highest precision ever experienced. Such predictive ability will enable the possibility of taking action before the crop damage can reach a critical state, and hence, the losses will be minimized, and the allocation of resources will be streamlined. AI-powered remote sensing data analysis will also stimulate the spread of precision agriculture in the whole South Asia region. Farmers will have the capability of applying fertilizers, pesticides, and irrigation to individual parts of a field, reducing wastage, environmental damage, and maximizing production. These technologies will especially be beneficial in water management as AI algorithms will combine forecasts of rain, soil moisture sensors, and evapotranspiration models to determine the most efficient irrigation times. This will particularly play an important role in areas where there is a persistent shortage of water, thus crops can grow using a minimum number of resources. The improvement of AI will also support the creation of farming plans that are resistant to the climate. Models of machine learning based on past crop performance and climate forecasts will determine the best planting and crop type rotation days and times in each area. These adaptive measures will serve to cushion against the effects of unpredictable monsoons, warming, and sudden droughts that can stabilize the produce and protect livelihoods. With the capability to model various scenarios associated with farming in silico prior to execution, it will enable farmers to make decisions that are based on risk assessment to reduce uncertainty and financial exposure. The smallholder farmers that take up the largest part of the South Asian agricultural sector will also become prominent beneficiaries of AI and remote sensing in the form of mobile and web-based services delivering individualized recommendations. These platforms will connect the gap in knowledge between technology and small-scale farmers by using real-time sensor data to complement satellite imagery in order to provide actionable advice based on the current conditions of individual fields and crops. The farmers will be able to report on observations in the fields on interactive systems, and AI models will integrate such data to make better predictions and recommendations accordingly, in a closed learning loop. Such an inclusion method will augment adoption rates, decision-making, and resilience to climatic and pest-related shocks. On the regional scale, data networks based on remote sensing and AI will be able to detect food production trends, pest migration trends, and climate vulnerability on a scale. These networks will be used by governments and cooperatives to provide subsidies, design insurance plans, and disaster mitigation strategies in more efficient ways. Insurers covering crop losses will use satellite-based evaluations in order to determine damages in near real-time, which will minimize cases of disagreement as well as speed up compensation. Predictive models, when combined with supply chain intelligence, will enable the farmer to plan production according to the demand in the market, decreasing the losses that occur after harvest, stabilizing market prices, and enhancing income security. New technology like IoT-powered sensors and edge computing will be used to supplement remote sensing to offer real-time field-level data, so that AI-driven knowledge becomes accurate and executable. The AI will incorporate data from automated irrigation controls, soil nutrient monitors, and micro-weather stations to enable localized and dynamic decision-making. In the future, the systems will become full-fledged autonomous farm management systems, able to monitor, forecast, and respond to farming needs with little human input. The invention of the integrated digital platforms will further increase the impact of AI and remote sensing on South Asian agriculture. Farm-level monitoring, predictive analytics, market intelligence, and financial services can be incorporated into these sites and can constitute entire decision-support ecosystems. Within one interface, farmers will have the capability to evaluate the performance of their crops, gain access to real-time weather forecasts, optimize resource inputs, network with buyers, and obtain financing.

Low-latency edge processing and cloud-based infrastructure will provide such tools in low-connectivity or remote areas, facilitating inclusivity and wide usage. Crop research and development will also be propelled by remote sensing and AI. Through the constant monitoring of multi-temporal satellite images, field sensors, scientists will be in a position to determine characteristics linked to resilience, high yield, and resistance to pests in the South Asian native crops. Such a data-based method will expedite the breeding program so that varieties of crops that are highly adapted to the specific local situation can be developed, and that with less time and money compared with the conventional manner of trial-and-error. These progressions, along with predictive modeling, will enable region-specific recommendations that can be highly productive and conserve maximum resources. Agricultural supply chains in South Asia will be reinvented with blockchain and digital traceability tools and AI analytics. Crop provenance, quality measurements, and transaction data will be open and verifiable, allowing farmers to bargain for higher prices and gain access to quality markets. This openness will also make it easy to monitor food safety by making sure that the produce that will reach consumers is of good quality and meets the health requirements. Predictive AI-based models will prompt when to plant and harvest with reference to the expected demand by connecting production data with the market, decreasing excess and lowering economic risk to farmers. The next generation will also be characterized by the formation of teams of regional networks, where nations of South Asia share satellite images, artificial intelligence patterns, and agricultural information to track macro-level dynamics and mobilize forces in the event of transboundary forces like locust swarms, floods, or drought. Cross-border collaboration will foster greater regional food security, enable joint disaster management, and foster the emergence of shared best practices of smart agriculture. Such networks will be strengthened through the use of public-private partnerships, where the scaling of the advanced technologies will be made possible, and some smallholder farmers and marginalized communities will not be left behind. These technological advances will be sustained through capacity-building programs. Targeted education programs countering AI and remote sensing will involve training of farmers, extension employees, and local agronomists to understand the AI insights, to operate sensor networks, and to adopt precision farming methods. Such a humanistic approach is a guarantee that the adoption of technology is not in vain but rather purposeful and results in a significant impact on productivity and sustainability.

Such programs will in the long run, produce a generation of digitally literate farmers who can use advanced tools to address the challenges of climate change, increasing population, and scarcity. In other words, the future of remote sensing and AI in South Asian agriculture is on the path to a hyper-predictive, adaptive, and networked system. Combining high-resolution monitoring, predictive analytics, market intelligence and inclusive digital platforms, these technologies will enable agriculture to transform from reactive, subsistence-based activities to a data-driven, resilient, and profitable business. Not only can the combination of these tools improve crop productivity and resource management, but also can empower farmers to stabilize food security in the region, and build a sustainable agricultural economy capable of meeting the needs of the 21st century. The future of AI and remote sensing in agriculture will revolutionize all activities of the farming lifecycle, and thus, in the decades ahead, South Asia will be able to sustain long-term growth, financial stability, and environmental stewardship. The FAO (2021) states that introducing new digital technologies to agriculture is essential in enhancing food security and resilience in such areas as South Asia.

CONCLUSION

The functioning of farming in South Asia has transformed because of remote sensing (RS) and artificial intelligence (AI). They enable it to be manageable, monitored, and enhanced in a way that was not possible in the past. The agro-climate zones, smallholder production, and extreme sensitivity to the effects of climate variability (floods, droughts, and unpredictable rainfall patterns in the monsoon) characterize agriculture in the region. Conventional farming methods, with most of the knowledge depending on personal observations and knowledge, are not enough in this regard to address these problems. RS and AI facilitate both macro-level planning of policies and micro-level management of farms to achieve greater productivity, sustainability, and resilience. Current, spatially specific, and repeated land use, crop, soils, and water information can also be provided by the remote sensing method. In addition to UAVs, satellite platforms like Landsat, the constellations of Sentinel-1 and -2, MODIS, and Planet Scope could be employed as well to monitor on several scales, including field and regional. Plant health, biomass growth, and stress may also be monitored and tracked in real time using vegetation indices such as NDVI, EVI, SAVI, and LAI. Nutrient deficits and water stress can also be identified by the use of thermal sensors and hyperspectral photography. Rice, a vital crop in India and Bangladesh, could be monitored at all times as a result of the ability of the SAR technology to cut through repetitive cloud disturbance. RS helps to map drought- and flood-affected regions, forecast pre-harvest yields, observe phenological stages, provide early warnings, and prepare immediate response actions. Artificial Intelligence is useful in the field of RS, and it is more affordable to process more complex data, to recognize patterns, and construct predictive models. Machine learning models, including RF, XGBoost, CNNs, and LSTMs, consider past production history, RS images, soil data, and meteorological forecasts to make precise predictions for nutrient management, pest and disease detection, yield prediction, to optimize irrigation and fertilization, and to weather forecasting. With the help of predicting the future, AI makes it possible to use smart agriculture to decrease the cost of production, increase crop yields, and minimize environmental harm.

AI is used on a farm level, in supply chain management, market forecast, and disaster response, and is beneficial to food security and economic resilience. RS and AI are illustrated through case studies that are located in South Asia. In Bangladesh, SAR-based rice mapping and AI-based yield prediction have improved planning and minimized the insecurity caused by flooding. In India, RS-based AI-based precision irrigation has optimized water usage and reduced the groundwater table, and pest control uses have reduced pesticide use. In Kerala and Sri Lanka, AI and UAVs are applied in the tea plantations to forecast yield, handle labor very effectively, and improve quality. Pakistan RS and AI are employed to monitor floods and drought in Sindh and Punjab to enable prompt response and irrigation planning. These technologies are used in Nepal and Bhutan to map remote mountain landscapes with crop mapping, enhancing access, resources, and food security planning.

Such case studies indicate how RS and AI are capable of functioning in various crops, climates, and socioeconomic settings to serve as the enablers of sustainable agriculture. But it does not go without its problems either. There is little access to funds, the best AI platforms, and high-resolution photography, and infrastructure is an issue, whether it is electricity or patchy internet. Factors that cause inaccurate predictions include stability and/or field locations, but technological problems like clouding, low-resolution snapshots in fragmented fields, and lack of ground truth data also reduce prediction accuracy. The barriers that slow down the fast adoption are social and human, whereby there is a lack of trust, unwillingness to change into technology, and a lack of skills due to digital illiteracy. Field location capability is a factor in inaccurate forecasts; however, technology problems, including cloud effects, low-resolution shots on discontinuous fields, and the absence of ground truth data, also reduce prediction accuracy. Some of the social and human barriers that slow the pace of quick adoption include skepticism, reluctance to adopt technology, and the absence of digital literacy. These are data ownership, privacy and fair access issues that render it difficult to use extensively. The absence of inclusive measures would allow AI and RS to increase inequality and encourage giant commercial farms instead of small farms. There would be some helpful prescriptive statements to resolve those issues and to enjoy the best of RS and AI.

The farmers will be asked to hire the services of the extension agencies, take part in the training, and use cheap digital technologies. The information can be packaged into mobile applications (RS and AI-based) to assist with precision management at the farm level. Policymakers can invest in digital infrastructure, such as the presence of good internet and renewable energy in rural regions, in addition to developing new policies that safeguard the privacy of information, its owners, and access to and sharing of information, as well as the minimum rights of people to access and control their own information. Smallholder farmers would be better able to access high-resolution imagery, AI platforms, and drones with subsidies or financial aid. Matching Interest No experience and no model would be of any use in case they could not cope with low-res or partial data; that is something that researchers and technologists should take seriously in order to guarantee applicability in the case of limited-resource scenarios. Additionally, systems by which research institutions establish partnerships with the public and private sector can support the level of emerging technologies, knowledge sharing, and capacity building. The new technologies, such as autonomous UAVs, edge AI, high-resolution satellites, and IoT-based sensors, can enhance the precision and accuracy of current agricultural automation, monitoring, and decision-making. Besides the adoption of resilient/sustainable practices, the frameworks of long-term monitoring and evaluation of socioeconomic and environmental impacts are to be developed to connect adoption and sustainability, equity, and resilience over time. Climate resilience and ecological sustainability will also be achieved through encouraging crop diversification, conservation agriculture, and precision resource management. We conclude that AI- and RS-based solutions are integrative and offer transformational possibilities to inclusive, efficient, and resilient South Asian agriculture. Real-time information, rich analytics, and forecast modeling allow farmers, policy makers, and analysts to optimize resources, maximize yields, and mitigate risk linked to environmental pressures and climate change. There should be the execution of promising strategies and recommendations such that all the farming communities, including the smallholders, benefit from the benefits of RS and AI. These are: capacity development; policy frameworks, infrastructure investment, and use of inclusive technology.

South Asia can grow socially inclusive, economically viable, environmentally sustainable, and productive agricultural systems, which are pursued strategically. The fronts that these systems can support are the' livelihoods of farmers, climate change effects, and food security. With RS and AI being adopted as important elements of agricultural planning and management, the region will ultimately be in a position to enjoy a resilient, climate-smart, and sustainable future in farming.

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CHAPTER 3
AGRICULTURAL PESTS: CLASSIFICATION, IMPACT, AND MANAGEMENT STRATEGIES

[1]Gunasekar G
[2]Annamalai A
[3]Karthiga A. R

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[1]Tamil Nadu Agricultural University, Department of Agricultural Entomology, (TNAU), Coimbatore, Tamil Nadu – 641 003, India, gunaselanbschonorsagri07@gmail.com, ORCID ID: 0009-0007-2566-8348.
[2]Tamil Nadu Agricultural University, Department of Agricultural Entomology, (TNAU), Coimbatore, Tamil Nadu – 641 003, India.
[3]Annamalai University, Faculty of Agriculture, Chidhambaram, Tamil Nadu – 608 002, India.

INTRODUCTION

Agricultural pests are organisms that interfere with the growth, health, or yield of crops by directly feeding on plants or indirectly transmitting pathogens. These pests include insects, mites, nematodes, rodents, birds, and weeds that compete with crops for resources. Globally, pests pose a serious threat to food security, with estimates suggesting that 20–40% of potential crop yield is lost each year due to pest infestations (FAO, 2021). With the global population expected to surpass 9.7 billion by 2050, reducing pest-induced losses is essential for ensuring food availability and minimizing hunger. While chemical pesticides have historically dominated pest control strategies, their overuse has led to environmental pollution, pest resistance, and negative health impacts on humans and livestock (Pimentel & Burgess, 2014). Therefore, modern pest management emphasizes integrated approaches that combine biological, cultural, mechanical, and chemical tactics in a sustainable manner. This paper provides a comprehensive overview of the classification of agricultural pests, their impacts on agriculture and society, and the management strategies employed to mitigate their effects.

1. CONCEPT AND DEFINITION OF AGRICULTURAL PESTS

The term "pest" is relative and context-dependent. In agriculture, a pest is any organism that interferes with human interests by causing damage to crops, reducing yield or quality, transmitting diseases, or competing for resources. Pests can include animals, plants, fungi, or microorganisms. However, not all organisms in a crop ecosystem are pests; many play beneficial roles such as pollination, nutrient cycling, and biological control. An organism becomes a pest only when its population density exceeds a level that causes measurable economic damage. Two fundamental concepts govern pest management decisions: the Economic Injury Level (EIL) and the Economic Threshold Level (ETL). The Economic Injury Level is defined as the lowest pest population density capable of causing damage greater than the cost of control measures. The Economic Threshold Level, slightly lower than the EIL, is the pest density at which action must be taken to prevent populations from reaching the injury level.

These concepts underscore the importance of decision-making in pest control and challenge the notion of complete eradication, which is neither ecologically desirable nor economically feasible. Pests can be further categorized as major pests, minor pests, regular pests, occasional pests, or key pests depending on their occurrence and severity of damage. Major pests cause significant economic loss consistently across seasons, while minor pests only infrequently cross the threshold of economic importance. Regular pests appear predictably on certain crops every season, while occasional pests occur sporadically under favorable conditions such as unusual weather. Key pests are those species that determine pest management practices due to their consistent and damaging presence. Understanding these categories is essential for prioritizing control efforts and resource allocation in pest management programs.

2. CLASSIFICATION OF AGRICULTURAL PESTS

2.1 Based on Taxonomy

Taxonomy provides a systematic framework for grouping agricultural pests based on their biological characteristics. Broadly, pests are divided into invertebrates and vertebrates, each containing several ecologically and economically important groups. Such classification is critical for designing specific and targeted management strategies (Hill, 2008; Pedigo, 2014).

2.2 Invertebrate Pests

Invertebrates constitute the largest and most damaging category of agricultural pests. Within this group, insects dominate, but mites, nematodes, and mollusks also play significant roles in crop loss.

a. Insects

Insects are the most economically important invertebrate pests, representing over 70% of known pest species (Dent, 2000). They attack crops at different growth stages and feed on various plant parts such as leaves, stems, roots, flowers, and fruits.

Examples:

- *Helicoverpa armigera* (cotton bollworm) – highly polyphagous, damaging cotton, chickpea, tomato, and pigeon pea.
- *Spodoptera litura (tobacco caterpillar) – a serious pest of vegetables, pulses, and oilseeds.*
- *Nilaparvata lugens (brown planthopper) – a major rice pest, causing hopper burn and transmitting viral diseases.*

These insect pests not only cause direct feeding damage but also transmit plant pathogens, thereby intensifying crop losses.

b. Mites

Mites are small arachnids, many of which infest horticultural and field crops. They feed by piercing and sucking cell sap, leading to chlorosis, bronzing, and premature leaf drop.

Example: *Tetranychus urticae* (two-spotted spider mite), a cosmopolitan pest of cotton, vegetables, and fruit crops.

Impact: Heavy infestations reduce photosynthesis, induce physiological stress, and decrease yield quality.

c. Nematodes

Plant-parasitic nematodes are microscopic, soil-dwelling roundworms that feed primarily on roots, disrupting nutrient and water uptake.

Examples:

- *Meloidogyne incognita* (root-knot nematode) – causes galls on roots of tomato, okra, and other vegetables.
- *Heterodera avenae* (cereal cyst nematode) – attacks wheat and barley.

Impact: Nematode infestations result in stunted growth, chlorosis, and increased susceptibility to fungal and bacterial pathogens.

d. Mollusks (Slugs and Snails)

Mollusks are significant pests in moist, irrigated, or high-rainfall areas. They rasp plant tissues, creating irregular feeding holes on leaves and seedlings.

Examples: *Deroceras reticulatum* (grey field slug), *Achatina fulica* (giant African snail).

Impact: Seedling mortality in vegetable nurseries, delayed crop establishment, and contamination of produce with slime.

2.3 Vertebrate Pests

Vertebrates, though fewer in number compared to invertebrates, can cause extensive localized damage, particularly in cereal fields, orchards, and storage structures.

a. Rodents

Rodents are among the most destructive vertebrate pests, responsible for direct crop loss in fields and stored produce.

Examples: *Rattus rattus* (black rat), *Mus musculus* (house mouse), *Bandicota bengalensis* (lesser bandicoot rat).

Impact: In fields, rodents cut seedlings, gnaw stems, and feed on grains; in storage, they contaminate food with urine, droppings, and hair, causing economic and health hazards.

b. Birds

Several bird species feed on seeds, fruits, and young seedlings. Though some birds act as natural enemies by preying on insects, others cause serious damage.

Examples: *Passer domesticus* (house sparrow), *Psittacula krameri* (rose-ringed parakeet).

Impact: Sparrows consume germinating grains, while parrots attack ripening fruits such as guava, mango, and maize cobs.

c. Wild Mammals

Large mammals, particularly in forest–agriculture interface zones, raid crops, causing severe localized destruction.

Examples: *Sus scrofa* (wild boar), *Axis axis* (spotted deer), *Elephas maximus* (Asian elephant).

Impact: Grazing, uprooting, and trampling of standing crops; in some areas, wild boar incursions cause near-total crop loss.

3. BASED on TYPE of DAMAGE

Another useful way to classify agricultural pests is according to the type of injury or feeding damage they cause to crop plants. The mode of feeding directly influences the nature and severity of crop losses. By recognizing these categories, farmers and researchers can design specific management practices aimed at minimizing damage and preventing secondary infections (Dent, 2000; Pedigo, 2014).

3.1 Defoliators

Defoliators are pests that feed extensively on leaf tissue, leading to reduced photosynthetic capacity and stunted plant growth. Severe infestations may result in complete defoliation, delayed flowering, and poor yield.

Examples:

- *Spodoptera litura* (tobacco caterpillar) – a polyphagous pest of soybean, cotton, groundnut, and vegetables.
- *Helicoverpa armigera* (cotton bollworm) – consumes leaves in the early stages before boring into reproductive parts.
- *Epilachna vigintioctopunctata* (epilachna beetle) – skeletonizes leaves of solanaceous vegetables.

Impact: Reduced photosynthesis → lowered biomass accumulation → yield losses of 30–80% under severe infestation.

3.2. Borers

Borers attack internal plant tissues by tunneling into stems, fruits, or seeds. Their concealed feeding habit makes them difficult to control with foliar insecticides.

Examples:

- *Chilo partellus* (maize stem borer) – bores into maize stems, weakening plants and reducing grain filling.
- *Scirpophaga incertulas* (yellow stem borer) – a major rice pest, causing “dead heart” (young tillers) and “white ear” (empty panicles).

- *Leucinodes orbonalis* (brinjal fruit and shoot borer) – tunnels into brinjal shoots and fruits, reducing market value.

Impact: Disrupted nutrient transport, plant lodging, poor grain filling, and marketable yield losses.

3.3 Sucking Pests

Sucking pests insert their stylet mouthparts into plant tissues to extract sap. They weaken plants by depleting nutrients, introducing toxins, and transmitting viral and phytoplasma diseases.

Examples:

- *Aphis gossypii* (cotton aphid) – causes leaf curling and sooty mold development.
- *Bemisia tabaci* (whitefly) – vector of cotton leaf curl virus (CLCuV) and tomato yellow leaf curl virus (TYLCV).
- *Amrasca biguttula* (cotton jassid) – causes “hopper burn” symptoms on cotton.
- *Nilaparvata lugens* (brown planthopper) – causes hopper burn in rice and transmits grassy stunt and ragged stunt viruses.

Impact: Reduced vigor, wilting, leaf curling, virus transmission, and indirect yield losses exceeding direct feeding damage.

3.4. Root Feeders

Root feeders damage underground plant parts such as roots, rootlets, and tubers. Their activity is often unnoticed until severe damage occurs.

Examples:

- Termites (*Odontotermes obesus*) – attack sugarcane, wheat, and groundnut, feeding on roots and underground stems.
- White grubs (*Holotrichia consanguinea*, *H. serrata*) – feed on roots of groundnut, sugarcane, and maize, causing wilting.
- Root-knot nematodes (*Meloidogyne incognita*) – induce gall formation on roots, restricting nutrient flow.

Impact: Reduced water and nutrient absorption, stunted growth, wilting, and plant death in severe infestations.

3.5. Fruit and Seed Feeders

These pests directly damage reproductive structures, reducing both yield and quality.

Examples:

- *Helicoverpa armigera* – feeds on developing pods of pulses, squares and bolls of cotton, and fruits of tomato.
- *Sitophilus oryzae* (rice weevil) – damages stored grains.
- *Leucinodes orbonalis* – damages brinjal fruits.

Impact: Loss of marketable produce, reduced seed viability, contamination of food grains, and economic losses.

3.6 Tissue Miners and Gall Formers

Some pests create tunnels within plant tissues or induce abnormal growth.

Examples:

- *Phyllocnistis citrella* (citrus leaf miner) – creates serpentine mines on citrus leaves.
- *Orseolia oryzae* (rice gall midge) – induces gall formation, leading to "silver shoot" symptoms.

Impact: Reduced photosynthesis, malformation of tissues, and poor yield.

3.7. Vector Pests (Indirect Damage)

Certain pests cause minimal direct damage but are highly destructive as vectors of plant diseases.

Examples:

- Whiteflies (*Bemisia tabaci*) – transmit viral diseases in cotton, tomato, and cassava.
- Leafhoppers (*Nephotettix virescens*) – transmit rice tungro virus.
- Aphids (*Myzus persicae*) – transmit more than 100 plant viruses.

Impact: Epidemics of viral diseases leading to large-scale crop failures.

4. BASED ON ECOLOGY

From an ecological perspective, pests can be grouped based on their host range and feeding adaptability. Such classification provides insights into pest behavior, host–pest interactions, and the complexity of management strategies. The major categories include polyphagous, oligophagous, monophagous, and migratory pests (Pedigo, 2014).

4.1 Polyphagous Pests

Polyphagous pests are capable of feeding on a wide range of host plants belonging to different families. Their broad dietary adaptability makes them economically important and difficult to control. For example, the cotton bollworm (*Helicoverpa armigera*) is one of the most destructive polyphagous pests in Asia and Africa. It infests more than 180 plant species, including cotton, pigeon pea, chickpea, sorghum, maize, and tomato (Sharma, 2005). Its ability to switch hosts across seasons allows it to survive throughout the year, thereby complicating management efforts. Similarly, the fall armyworm (*Spodoptera frugiperda*), recently invasive in Asia, feeds on maize, rice, sugarcane, and several horticultural crops (Goergen *et al*., 2016). These pests demand integrated management approaches combining host plant resistance, natural enemy conservation, and targeted insecticide applications.

4.2 Oligophagous Pests

Oligophagous pests feed on a few closely related plant species, typically within the same family. They exhibit moderate host specificity, which reduces their ecological range compared to polyphagous species. An example is the diamondback moth (*Plutella xylostella*), which primarily attacks cruciferous crops such as cabbage, cauliflower, and mustard (Furlong *et al*., 2013). Similarly, brinjal shoot and fruit borer (*Leucinodes orbonalis*) is restricted largely to solanaceous crops. Although their host range is narrower, oligophagous pests can still cause heavy yield losses when their preferred crops are cultivated intensively across large areas.

4.3 Monophagous Pests

Monophagous pests specialize in feeding on a single host species or a very limited number of hosts. Their population dynamics are closely tied to the availability of the specific crop. The rice gall midge (*Orseolia oryzae*) is a classic monophagous pest that attacks only rice, inducing characteristic galls that severely reduce tillering and yield (Bentur *et al*., 2012). Another example is the sugarcane woolly aphid (*Ceratovacuna lanigera*), which feeds exclusively on sugarcane. Although monophagous pests have a restricted ecological niche, they can cause devastating epidemics in monocropping systems where their sole host plant is grown extensively.

4.4 Migratory Pests

Some pests exhibit unique ecological behavior as long-distance migratory species. Migratory pests are capable of moving across vast regions, often in swarms, and inflicting sudden and widespread crop losses. The desert locust (*Schistocerca gregaria*) is the most destructive migratory pest, with swarms capable of traveling hundreds of kilometers per day and consuming massive quantities of vegetation (Latchininsky, 2013). Similarly, the brown planthopper (*Nilaparvata lugens*) in Asia demonstrates seasonal migration patterns, moving across rice ecosystems with the monsoon winds (Denno & Roderick, 1990). Migratory pests are particularly challenging because their management requires international cooperation, early warning systems, and coordinated response strategies rather than localized control alone.

5. ECOLOGICAL SIGNIFICANCE

Ecological classification highlights how feeding range and mobility shape pest risks**.** Polyphagous pests pose year-round threats across cropping systems, oligophagous and monophagous pests threaten specialized crop ecosystems, while migratory pests cause sudden transboundary invasions. Effective management of pests therefore requires integrating ecological knowledge with crop management practices, forecasting models, and global monitoring systems.

6. BASED ON SEASONAL OCCURRENCE

Seasonal occurrence is another important criterion for classifying agricultural pests. The abundance and activity of pests are not constant throughout the year but vary with changes in environmental factors such as temperature, humidity, rainfall, and photoperiod. These climatic parameters directly influence pest life cycles, reproduction, and survival, resulting in distinct seasonal patterns of infestation (Pedigo, 2014).

During summer months, high temperatures and relatively dry conditions favor the multiplication of certain pests. For instance, red spider mites (*Tetranychus urticae*) are notorious for thriving under hot and dry environments, leading to severe outbreaks in crops like cotton, okra, and vegetables. Similarly, whiteflies (*Bemisia tabaci*) tend to proliferate during warmer periods, causing both direct feeding damage and indirect losses by transmitting plant viruses (Naranjo & Ellsworth, 2009).

The rainy season (monsoon period) is typically associated with high humidity and lush vegetation, providing favorable conditions for the proliferation of lepidopteran pests. Examples include the rice stem borer (*Scirpophaga incertulas*), rice leaf folder (*Cnaphalocrocis medinalis*), and fruit borers (*Helicoverpa armigera*). These pests inflict significant yield losses in cereals, pulses, and horticultural crops during wet months (Kumar *et al.*, 2013). Standing water and increased plant density during the rainy season further create microclimates that support pest development and pathogen spread.

In cooler months (winter season), pests adapted to lower temperatures become dominant. Aphids (*Aphis gossypii*, *Myzus persicae*) are classic winter pests that colonize crops such as mustard, potato, and pulses, thriving under mild and cool conditions (Dixon, 1998). Similarly, mustard sawfly (*Athalia lugens proxima*) occurs predominantly during cooler climates, causing severe defoliation in oilseed crops. Many storage pests such as grain weevils (*Sitophilus oryzae*) and bruchids (*Callosobruchus chinensis*) also exhibit peak activity in relatively cooler, dry conditions when harvested grains are stored.

This classification underscores the ecological adaptability of pests to different seasonal environments. Understanding these patterns is crucial for developing timely pest monitoring and forecasting systems.

For example, forecasting models integrate weather data with pest biology to predict outbreaks, enabling farmers to adopt preventive measures before pest populations reach economic injury levels (Prasad & Prabhakar, 2012). Moreover, aligning pest control strategies with seasonal occurrence can reduce pesticide overuse, ensure eco-friendly management, and optimize crop protection.

7. IMPACT OF AGRICULTURAL PESTS

7.1 Economic Impact

Agricultural pests cause significant economic losses by reducing crop yields, lowering produce quality, and increasing production costs. According to Oerke (2006), global crop losses due to pests, including insects, pathogens, and weeds, amount to nearly 40% of potential yield. In rice, one of the world's most important cereals, insect pests such as the brown planthopper (Nilaparvata lugens) and stem borers can reduce yields by 20–60% under outbreak conditions (Heong et al., 2015). Post-harvest pests such as the rice weevil (Sitophilus oryzae) and pulse beetle (Callosobruchus chinensis) damage stored grains, leading to additional losses ranging from 10–30% depending on storage conditions (Boxall, 2001). Furthermore, pest outbreaks increase the cost of cultivation, as farmers spend more on pesticides, labor, and preventive measures, which directly affects profitability.

7.2 Ecological Impact

Beyond direct crop losses, pests disrupt ecological balance in agroecosystems. For example, outbreaks of invasive pests such as the fall armyworm (Spodoptera frugiperda) have been reported to threaten biodiversity by displacing native insect herbivores (Goergen et al., 2016). Pest infestations often lead to the indiscriminate use of synthetic pesticides, which reduce populations of beneficial natural enemies such as predators, parasitoids, and pollinators (Geiger et al., 2010). This imbalance may trigger secondary pest outbreaks, where minor pests become major threats due to the elimination of natural checks and balances. Climate change further complicates pest ecology by altering their distribution, population dynamics, and host range (Deutsch et al., 2018).

7.3 Social Impact

The consequences of pest infestations extend into the social sphere. Farmers experiencing repeated crop losses due to pests often face financial instability, indebtedness, and reduced livelihood security (Prasad & Rao, 2018). In regions where smallholder farmers dominate agriculture, pest outbreaks can cause local food shortages, contributing to malnutrition and poverty. Moreover, excessive pesticide use poses health risks to farm workers and consumers, with studies linking pesticide exposure to neurological disorders, cancer, and reproductive health problems (Alavanja et al., 2013). Thus, pests not only undermine agricultural productivity but also pose serious challenges to rural welfare and public health.

8. CASE STUDIES

Several pest outbreaks highlight their devastating potential. The brown planthopper (N. lugens) has historically caused massive rice yield losses in Southeast Asia, leading to widespread food shortages in the 1970s and 1980s (Heong & Hardy, 2009). The desert locust (Schistocerca gregaria) continues to threaten food security in Africa and the Middle East, with the 2019–2020 outbreaks affecting millions of hectares of farmland (FAO, 2020). Similarly, the recent invasion of fall armyworm in Africa and Asia has jeopardized maize production, causing yield reductions of up to 50% in heavily infested fields (Day et al., 2017). These examples underscore the urgent need for sustainable pest management strategies.

9. MANAGEMENT STRATEGİES FOR AGRİCULTURAL PESTS

9.1 Cultural Control

Cultural practices are among the oldest and most sustainable pest management methods. Techniques such as crop rotation, intercropping, and altering planting dates reduce pest survival and reproduction (Kumar & Kalita, 2017). For example, crop rotation with non-host plants disrupts the life cycle of root-feeding nematodes, while intercropping maize with legumes reduces stem borer infestation. Sanitation practices, including the removal of crop residues and weeds, eliminate alternative pest habitats.

The use of resistant crop varieties has also proven effective, such as the deployment of rice varieties resistant to brown planthopper (Khush, 2001).

Cultural control refers to the modification of agricultural practices and cropping systems to reduce the survival, reproduction, and spread of pests. It is one of the oldest and most widely practiced pest management strategies, emphasizing prevention rather than direct suppression. By creating unfavorable conditions for pests and favorable conditions for crops, cultural methods significantly reduce pest pressure and often lower the need for chemical inputs (Pedigo & Rice, 2009). One of the most effective cultural practices is crop rotation, which involves alternating crops with different pest associations. For example, rotating cereals with legumes helps break the life cycle of cereal pests such as stem borers and cutworms, since the alternate crops do not serve as hosts. Similarly, continuous monocropping of cotton or rice is known to promote pest build-up, while crop rotation interrupts pest adaptation (Norris & Kogan, 2005).

Sanitation practices, including removal and destruction of crop residues, volunteer plants, and weeds, play a critical role in cultural control. Many pests survive in plant debris after harvest, such as pink bollworm (Pectinophora gossypiella) in cotton stubbles or rice stem borers in straw. Timely removal or burning of residues eliminates overwintering sites, thereby reducing pest populations before the next crop season (Kogan, 1998).

Planting time adjustment is another cultural strategy that minimizes pest damage. Early sowing of sorghum and maize can help escape peak infestation of stem borers, while staggered sowing of rice often facilitates pest spread. Synchronizing sowing and harvesting within a region can also limit pest carryover between fields. This practice has been successfully adopted in managing brown planthopper (Nilaparvata lugens) outbreaks in Asia (Heinrichs, 1994).

Intercropping and mixed cropping provide habitat diversification that suppresses pest populations by disrupting their host-finding behavior and enhancing natural enemy activity. For instance, maize intercropped with cowpea reduces fall armyworm (Spodoptera frugiperda) damage due to altered pest movement and predator attraction (Cook et al., 2007).

Trap cropping, where a highly attractive plant species is grown alongside the main crop to divert pests, is also a common cultural tactic. Mustard as a trap crop in cabbage fields attracts diamondback moth (Plutella xylostella), reducing damage to the main crop.

Soil tillage and water management can directly influence pest populations. Deep ploughing exposes soil-dwelling pests such as white grubs and cutworms to predators and desiccation. In rice ecosystems, alternate wetting and drying can suppress stem borers and rice hispa while conserving water resources (Pathak & Khan, 1994).

The adoption of resistant or tolerant crop varieties is often considered a cultural strategy when integrated with farming practices. Varieties bred for resistance to pests such as brown planthopper in rice or maize streak virus vectors are widely deployed and significantly reduce pest losses. Overall, cultural control measures are preventive, cost-effective, and environmentally benign. However, they require regional coordination, farmer awareness, and timely implementation to be effective. When integrated with biological, mechanical, and chemical control, cultural practices form the foundation of Integrated Pest Management (IPM).

9.1.1 Mechanical And Physical Methods

Mechanical and physical methods represent some of the oldest and most eco-friendly strategies for pest management. These methods rely on direct removal, trapping, or exclusion of pests without the use of synthetic chemicals, making them highly suitable for smallholder and organic farming systems. The most basic example is manual collection, where insect larvae, egg masses, or adult pests are hand-picked and destroyed. Though labor-intensive, hand collection remains effective for managing large and visible pests such as caterpillars, grasshoppers, and beetles in small plots or kitchen gardens (Pedigo & Rice, 2014).

Trapping is another widely used mechanical method. Light traps are effective in monitoring and reducing populations of nocturnal insects like moths and beetles. Similarly, pheromone traps utilize species-specific sex pheromones to lure and capture male insects, thereby disrupting mating and reducing reproduction rates (Witzgall et al., 2010).

Sticky traps are employed for small flying insects such as whiteflies, aphids, and thrips in greenhouse environments. These devices are particularly valuable as part of integrated pest management (IPM) programs because they help farmers monitor pest density and make informed decisions about control measures.

Physical barriers are also commonly employed to protect crops from pests. Netting and row covers exclude insects such as aphids and flea beetles from vegetables, while tree banding with sticky substances prevents climbing pests like caterpillars and ants. Mulching suppresses soil-dwelling pests and conserves soil moisture, while reflective mulches deter aphids by confusing their host-finding behavior (Diaz & Fereres, 2007). Soil solarization, which involves covering moist soil with transparent polyethylene sheets to trap solar heat, effectively reduces populations of soil-borne pests and pathogens by elevating soil temperatures to lethal levels (Katan, 2014).

Despite their benefits, mechanical and physical methods are often criticized for being labor-intensive and less practical for large-scale farming. However, they remain important components of sustainable pest management, especially in resource-poor regions where chemical inputs are either unavailable or undesirable. With the advent of modern technology, many of these traditional approaches are being refined. For instance, automated insect traps equipped with sensors and cameras are now being developed to monitor pest populations more efficiently in precision agriculture systems (Shelton et al., 2020). In conclusion, mechanical and physical methods offer safe, environmentally friendly, and cost-effective alternatives for pest suppression. While they may not be sufficient as standalone strategies in large-scale commercial farming, their integration with cultural, biological, and chemical approaches ensures more sustainable pest management outcomes.

9.2 Biological Control

Biological control, often termed biocontrol, is the deliberate use of natural enemies—predators, parasitoids, and pathogens—to suppress pest populations, thereby reducing their damage to crops. It is considered one of the most sustainable and eco-friendly pest management strategies since it harnesses naturally occurring organisms and reduces dependence on synthetic pesticides

(Lenteren, 2012). Unlike chemical methods, biological control does not leave harmful residues in the environment and can provide long-term pest suppression once natural enemies are established.

Predators are an important group of natural enemies used in biocontrol. Ladybird beetles (Coccinellidae) are well-known predators of aphids, mealybugs, and scale insects. Lacewings (Chrysoperla carnea) and predatory mites (Phytoseiulus persimilis) are widely used in horticultural systems to regulate soft-bodied pests such as whiteflies and spider mites (Hajek, 2004). Predators are particularly valued for their ability to consume large numbers of prey over their lifetime, making them highly effective in reducing pest outbreaks.

Parasitoids, another key component of biological control, are insects that lay their eggs inside or on the body of a host insect, eventually killing it. Species of Trichogramma are among the most extensively used parasitoids, released to parasitize the eggs of lepidopteran pests like stem borers and bollworms (Smith, 1996). Similarly, Aphidius colemani is a parasitoid wasp that targets aphids in greenhouse systems. Augmentative releases of these parasitoids, particularly in rice, cotton, and maize, have proven to reduce reliance on pesticides and improve yields.

Microbial control agents represent another dimension of biological pest management. Bacteria such as Bacillus thuringiensis (Bt) produce insecticidal crystal proteins toxic to lepidopteran and coleopteran larvae, while entomopathogenic fungi such as Beauveria bassiana and Metarhizium anisopliae infect and kill a wide range of insect pests (Sharma et al., 2017). Viral agents, particularly nucleopolyhedroviruses (NPVs), have been successfully deployed against pests like the cotton bollworm (Helicoverpa armigera). These biopesticides are increasingly commercialized and form a growing segment of environmentally safe pest management solutions.

Biological control can be implemented through three main approaches: classical, augmentative, and conservation biocontrol. In classical biological control, exotic natural enemies are introduced into regions where pests have invaded, as in the case of introducing parasitoids to control cassava mealybug in Africa (Neuenschwander, 2001).

Augmentative control involves the mass rearing and periodic release of natural enemies to boost their populations in crop fields. Conservation biological control emphasizes habitat management, such as maintaining floral resources and hedgerows, to enhance the survival of natural enemies already present in the ecosystem (Gurr et al., 2012). Despite its advantages, biological control faces challenges such as the time required for natural enemy establishment, variability in field performance due to environmental factors, and limited farmer awareness. Nevertheless, when integrated with cultural, mechanical, and chemical tactics in an IPM framework, biological control offers a cost-effective and ecologically sustainable solution to pest problems.

Biological control harnesses natural enemies of pests, including predators, parasitoids, and microbial pathogens. Ladybird beetles (Coccinellidae) and lacewings (Chrysopidae) effectively suppress aphid populations, while parasitoids like Trichogramma chilonis are used against lepidopteran egg masses (Lenteren, 2012). Microbial control agents such as Bacillus thuringiensis (Bt), nuclear polyhedrosis viruses (NPVs), and entomopathogenic fungi (Beauveria bassiana) have shown considerable success in managing lepidopteran and coleopteran pests (Sharma et al., 2017). Conservation biological control, which involves habitat management to support natural enemy populations, is gaining traction as a sustainable IPM strategy.

9.3 Chemical Control

Chemical control has historically been the most widely adopted method for managing agricultural pests due to its rapid effectiveness and ease of application. Synthetic insecticides, fungicides, and herbicides are routinely used to reduce pest populations in both field and storage systems. In crops like cotton, rice, and vegetables, insecticides such as organophosphates, carbamates, pyrethroids, and neonicotinoids have been extensively used to suppress key pests, including bollworms, stem borers, and sucking insects (Pimentel & Burgess, 2014). The success of chemical pesticides lies in their ability to provide immediate results, protect crops during critical growth stages, and facilitate large-scale pest control operations where other methods may be impractical.

However, reliance on chemical control has raised serious concerns regarding sustainability and safety. One of the major challenges is the development of pest resistance. Over 600 arthropod species are reported to have developed resistance to at least one class of insecticides (Sparks & Nauen, 2015). For example, the cotton bollworm

(Helicoverpa armigera) has evolved resistance to multiple chemical groups, complicating its management across Asia and Africa. In addition, the phenomenon of pest resurgence—where suppressed pest populations rebound rapidly after pesticide application due to the elimination of natural enemies—further undermines chemical control efficacy (Kogan, 1998).

Another limitation of chemical pesticides is their negative environmental and health impacts. Excessive pesticide residues in soil, water, and food not only harm non-target organisms such as pollinators and beneficial predators but also pose health risks to farm workers and consumers. The World Health Organization (WHO) estimates that about 25 million agricultural workers in developing countries suffer from pesticide poisoning annually (WHO, 2019). Furthermore, pesticide drift and leaching contaminate ecosystems, leading to biodiversity loss and groundwater pollution (Aktar et al., 2009).

In response to these concerns, modern chemical control emphasizes safer and more judicious pesticide use. Integrated approaches recommend applying pesticides only when pest populations exceed economic threshold levels (ETLs), thereby reducing unnecessary applications (Pedigo & Rice, 2014). Selective pesticides, which target specific pests while sparing natural enemies, are being promoted. Biopesticides such as neem (Azadirachta indica) formulations, insect growth regulators (IGRs), and microbials like Bacillus thuringiensis are increasingly being incorporated into pest management programs as safer chemical alternatives (Isman, 2006). Moreover, international conventions such as the Stockholm Convention have restricted or banned highly hazardous pesticides, urging countries to adopt eco-friendly substitutes.

Thus, while chemical control continues to play a vital role in pest management, its long-term sustainability requires careful regulation, improved farmer awareness, and integration with non-chemical approaches to reduce ecological risks and safeguard human health.

10. INNOVATIVE APPROACHES IN PEST MANAGEMENT

In recent decades, the limitations of conventional pest management strategies—such as pesticide resistance, resurgence, and environmental hazards—have accelerated the development of innovative approaches that integrate modern science and technology. These new methods aim to enhance sustainability, precision, and environmental safety while reducing reliance on chemical pesticides.

One of the most promising innovations is the use of genetically modified (GM) crops that express insecticidal traits. For example, Bacillus thuringiensis (Bt) crops such as Bt cotton and Bt maize produce Cry toxins that are lethal to major lepidopteran pests like the cotton bollworm (Helicoverpa armigera) and European corn borer (Ostrinia nubilalis) (James, 2014). These crops have reduced pesticide applications, increased yields, and provided significant economic benefits to farmers. However, challenges such as pest resistance development and ecological concerns necessitate the incorporation of refuge strategies and continuous monitoring (Tabashnik et al., 2013).

Another innovative approach is RNA interference (RNAi) technology, which involves silencing essential pest genes through double-stranded RNA molecules. This method offers high specificity, targeting only the intended pest species while sparing beneficial insects and other organisms (Baum et al., 2007). Field applications of RNAi-based sprays and transgenic plants are under development, showing potential against pests like the western corn rootworm (Diabrotica virgifera virgifera).

Sterile Insect Technique (SIT) has also emerged as a successful biotechnological strategy. It involves mass-rearing and sterilizing male insects using radiation or genetic methods before releasing them into the field. When these sterile males mate with wild females, no viable offspring are produced, gradually reducing pest populations. SIT has been effectively used against fruit flies (Ceratitis capitata), tsetse flies, and screwworms (Dyck et al., 2021). Recent advancements in genetic engineering, such as RIDL (Release of Insects carrying a Dominant Lethal gene), have further improved SIT efficiency.

Nanotechnology is another frontier in pest management. Nanopesticides, which involve encapsulating active ingredients in nanocarriers, improve pesticide solubility, stability, and targeted delivery, reducing off-target effects and pesticide residues in food and the environment (Kah et al., 2019). Additionally, nanoparticles such as silver and silica are being investigated for their direct insecticidal properties.

Digital agriculture has also transformed pest management through Artificial Intelligence (AI), machine learning, and precision agriculture tools. Remote sensing, drones, and automated imaging systems allow real-time pest detection and population monitoring (Liakos et al., 2018). AI-based decision-support systems provide farmers with tailored recommendations, optimizing pesticide use and improving ecological sustainability. Smartphone-based pest diagnosis apps have made pest identification and management accessible to smallholder farmers, especially in developing countries.

Lastly, climate-smart and ecological engineering approaches represent innovative cultural and biological integrations. Habitat manipulation techniques, such as planting nectar-rich flowering strips along crop borders, enhance natural enemy populations while reducing pest colonization. Similarly, push–pull technology in maize and sorghum systems uses repellent intercrops to “push” pests away and trap plants to “pull” them in, reducing stemborer and fall armyworm infestations (Khan et al., 2014). Together, these innovative approaches represent the future of pest management combining biotechnology, nanotechnology, automation, and ecology to create more resilient and sustainable agricultural systems. Their integration with classical methods in an IPM framework ensures not only effective pest suppression but also food security and environmental safety.

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CHAPTER 4
DIGITAL TRANSFORMATION IN RICE AGRO-SYSTEMS: LEVERAGING IOT, AI, AND BIG DATA FOR SUSTAINABLE AGRICULTURE IN MOROCCO

[1]Fathalah ELWAHAB
[2]Mohamed SEDKI
[3]Chetto ABDELAZIZ
[4]Sana El MOUTAOUAKIL
[5] Najiba BRHADDA
[6]Rabea ZIRI

[1]University Ibn Toufail, Faculty of Sciences, Laboratory of Plant, Animal, and Agro- Industry Productions, B.P. 242, 14000Kenitra, Morocco, fathalah.elwahab@uit.ac.ma, ORCID ID: 0000-0002-3154-361X.
[2]Regional Center of Agricultural Research of Kenitra, B.P. 257, 14000 Kenitra, Morocco.
[3] Regional Center of Agricultural Research of Kenitra, B.P. 257, 14000 Kenitra, Morocco.
[4]Laboratory of Natural Resources and Sustainable Development, Department of Biology, Faculty of Sciences, Ibn Tofail University, BP 133, Kenitra 14000, Morocco.
[5]University Ibn Toufail, Faculty of Sciences, Laboratory of Plant, Animal, and Agro- Industry Productions, B.P. 242, 14000Kenitra, Morocco.
[6] University Ibn Toufail, Faculty of Sciences, Laboratory of Plant, Animal, and Agro- Industry Productions, B.P. 242, 14000Kenitra, Morocco.

INTRODUCTION

Rice (*Oryza sativa* L.) is a staple food crop that plays a crucial role in Morocco's agricultural strategy, particularly in the Gharb Plain, which represents the country's main rice-growing region (Abdelghani et al., 2022). Despite its importance for national food security and rural livelihoods, rice production in Morocco faces multiple challenges. Water scarcity, intensified by recurrent droughts and inefficient irrigation practices, remains a critical constraint (FAO, 2023). Declining soil fertility, climate change impacts, and the prevalence of major diseases such as rice blast caused by Magnaporthe oryzae further threaten yield stability and grain quality (Zhao et al., 2023; Li et al., 2023).

To address these challenges, digital agriculture has emerged as a transformative approach, integrating advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data analytics. These tools enable real-time monitoring of crops, optimize resource management, support precision farming practices, and enhance overall productivity (Kumar et al., 2022).

The primary aim of this chapter is to examine how the digital transformation of rice agro-systems can contribute to sustainable and resilient production in Morocco. Specifically, it seeks to analyze the current challenges faced by rice farmers, explore the potential applications of IoT, AI, and Big Data in overcoming these challenges, and present practical case studies demonstrating the impact of these technologies. By integrating traditional farming knowledge with modern digital tools, this chapter highlights strategies to improve yields, reduce environmental pressures, and enhance the resilience of rice production in the Gharb Plain.

Through this approach, the chapter contributes to a broader understanding of how digital innovations can strengthen Moroccan rice agro-systems and support national food security objectives in a semi-arid and resource-constrained environment.

Through this case study, the chapter bridges the gap between theory and practice in smart agriculture and provides a replicable model that can be applied across similar agricultural regions in North Africa and beyond.

1. MACHINE LEARNING APPLICATIONS IN SMART FARMING

Machine learning (ML), a subfield of artificial intelligence (AI), plays a transformative role in precision agriculture by enabling systems to analyze large volumes of heterogeneous data, identify patterns, and make predictive or prescriptive decisions with minimal human intervention (Liakos et al., 2018). In recent years, ML has been applied across various domains of agriculture, offering significant improvements in efficiency and sustainability. Common applications include crop yield prediction using regression models, random forests, or deep learning networks; disease and pest detection based on convolutional neural networks (CNNs) trained on large image datasets; and irrigation scheduling or water stress classification utilizing support vector machines (SVM) and decision trees. Additionally, ML techniques have been successfully employed for weed detection and precision spraying through the integration of image-based computer vision systems. A key strength of ML lies in its ability to dynamically adapt to changing environmental conditions. For instance, time-series models trained on continuous inputs from IoT sensors—such as soil moisture, temperature, and humidity—can accurately forecast drought stress several days in advance, allowing for timely intervention (Kaur et al., 2022). These capabilities position ML as a central component of intelligent decision-support systems in agriculture, particularly when integrated with real-time data collected through IoT infrastructures.

In the context of the Gharb Plain, Morocco, this study harnesses such ML capabilities by integrating IoT-collected environmental data to develop predictive models tailored for local agro-climatic conditions. The system analyzes real-time sensor data to optimize irrigation schedules and monitor crop health, significantly enhancing water use efficiency and crop productivity in this water-stressed region. This case study exemplifies how combining ML with IoT infrastructure can deliver intelligent decision-support tools, fostering sustainable agricultural practices adapted to the specific challenges of Moroccan farming landscapes.

This figure illustrates the yield forecast accuracy of two approaches: the conventional method, based on farmers' experience and manual observations, and the digital system using Artificial Intelligence (AI). The results show that forecast accuracy remains limited to approximately 55% in the conventional system, whereas the AI-based approach reaches over 90%. This clearly demonstrates the contribution of machine learning algorithms in reducing uncertainties related to climate variability, soil fertility, and disease outbreaks. Such high accuracy enables farmers to better anticipate production and optimize input management.

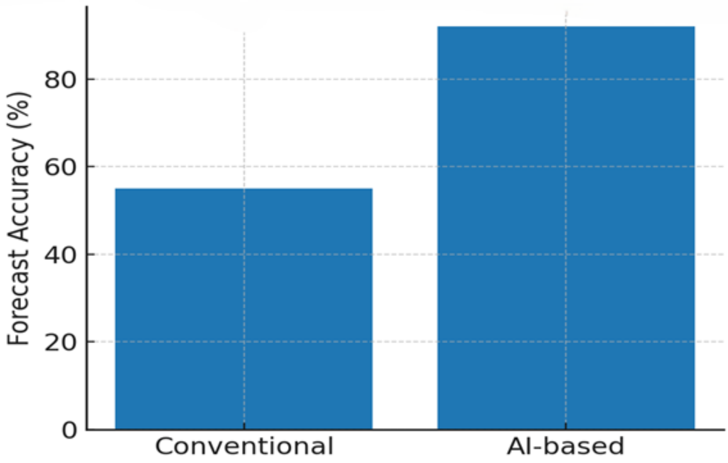

Figure 1. Comparative yield forecast accuracy between conventional and AI-based systems

2. IOT APPLICATIONS IN RICE AGRO-SYSTEMS

The application of Internet of Things (IoT) technologies in rice agro-systems has revolutionized crop monitoring and management by enabling real-time, data-driven decision-making, improving resource efficiency, and enhancing yield and quality outcomes.

Table 1 presents typical examples of IoT sensors commonly used in rice farming systems. Soil moisture sensors, such as capacitive sensors, are employed to monitor soil water content and optimize irrigation scheduling, improving water use efficiency. Temperature and humidity sensors, including DHT22 devices and IoT nodes, provide real-time climate monitoring, helping farmers anticipate stress conditions and adjust management practices.

Leaf wetness sensors, usually optical, are essential for early detection and prediction of plant diseases, such as rice blast (*Magnaporthe oryzae*). Finally, nutrient sensors, based on ion-selective technology, allow continuous monitoring of soil nutrient levels, enabling precise fertilizer application and minimizing environmental impacts. Collectively, these IoT devices form the backbone of precision agriculture in rice systems, facilitating data-driven decision-making and sustainable crop management.

Table 1. Examples of IoT Sensors in Rice Farming

Parameter	Sensor Type	Application
Soil moisture	Capacitive sensors	Irrigation management
Temperature & Humidity	DHT22, IoT nodes	Climate monitoring
Leaf wetness	Optical sensors	Disease prediction
Nutrients	Ion-selective sensors	Fertilizer optimization

3. AGRONOMIC PRODUCTIVITY AND FERTILITY CAPACITY

In many countries, precision agriculture is still commonly referred to as satellite-based agriculture or site-specific crop management, due to its reliance on satellite and aerial imagery, climate forecasting, predictive modeling, and productivity indicators. By integrating these parameters, artificial intelligence (AI) plays a key role in advancing agro-technologies and improving crop profitability. Machine learning (ML) enables this by learning from past experiences, analyzing input and output data, and facilitating highly precise crop production (Fig. 1) (Liu, 2020).

Moreover, the adoption of intelligent models can address issues such as crop health disorders and nutrient deficiencies in the soil (Hamrani et al., 2020). AI technologies also support the development of phytosanitary models, enhancing the management of soil health and optimizing fertilizer application rates (Mahlein, 2016). By minimizing the risks of soil and plant degradation, AI helps align agricultural production with market demands, maximizes the productivity of various soil types (Patrício & Rieder, 2018), and contributes to improved crop mapping for more informed decision-making (Fig.2).

The detection of crop diseases is a critical aspect of effective rice management, and modern technologies have significantly improved this process. This figure compares the effectiveness of traditional visual inspection with automated AI-based detection methods. Visual inspection, which relies on the expertise of farmers or technicians, achieves an accuracy of approximately 60%, presenting a high risk of errors and delayed interventions. In contrast, AI-based detection, which integrates imagery from UAVs, optical sensors, and image recognition models, reaches an accuracy of 95%. These results highlight the importance of automation and real-time monitoring for early detection of diseases such as *Magnaporthe oryzae*, thereby reducing yield losses and improving overall crop management.

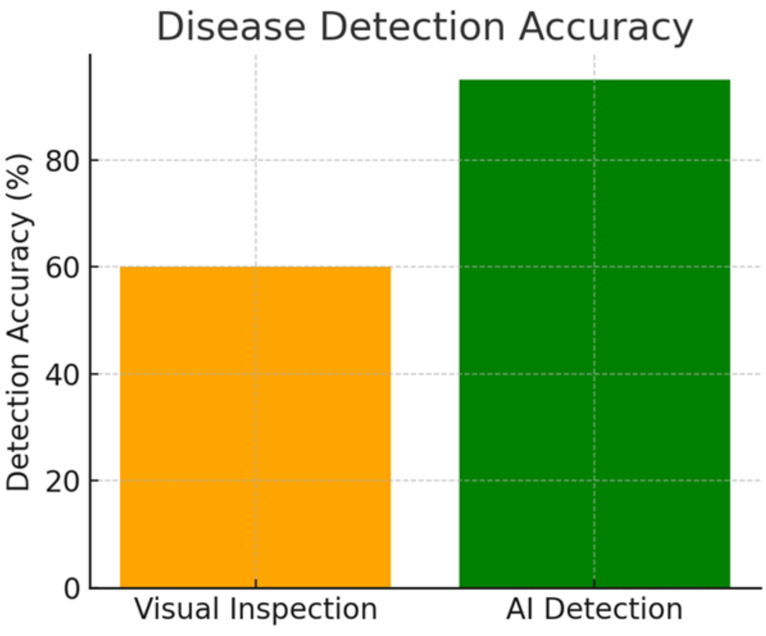

Figure 2. Accuracy of disease detection methods in rice farming.

Projecting future rice productivity is essential for assessing the impact of digital technologies on sustainable agriculture. This figure 3 illustrates the projected rice yield (in tons per hectare) under two scenarios: the conventional system and the digital system integrating IoT, AI, and Big Data.

In the conventional scenario, productivity shows only a slight increase, rising from 4.5 t/ha in 2025 to 4.8 t/ha in 2040. In contrast, the digital scenario demonstrates a significant growth, reaching 6.3 t/ha in 2040, representing an increase of nearly 35% compared to the conventional system. These results highlight the critical role of digital technologies in sustainably enhancing rice productivity while accounting for water constraints and biotic pressures.

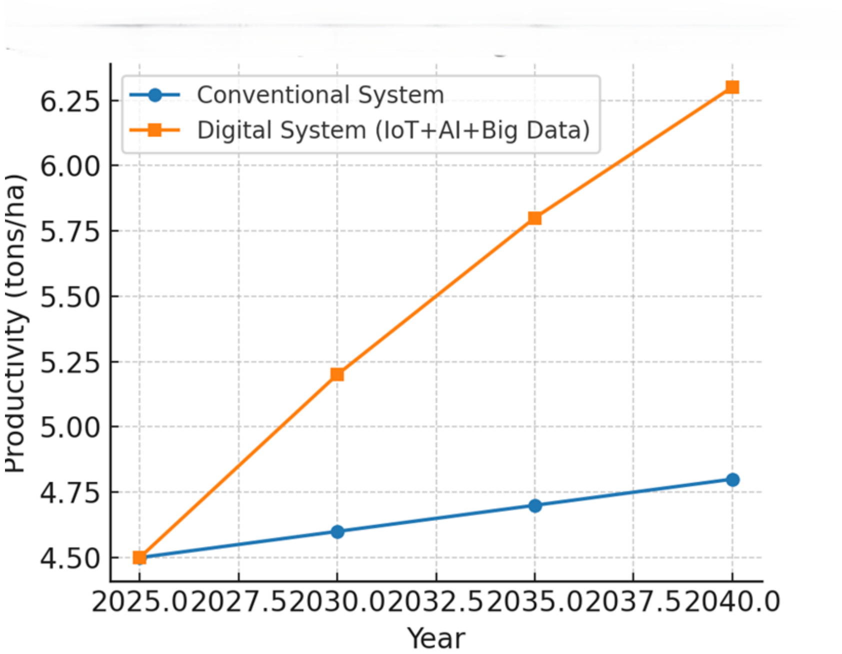

Figure 3. Projection of rice productivity under conventional vs digital systems

4. THE ROLE OF DRONES AND ROBOTS IN AGRICULTURAL AUTOMATION

The Gharb Plain, one of Morocco's most productive agricultural regions, provides an ideal environment for implementing drones and robotic technologies in farming. Characterized by extensive rice, vegetable, and cereal fields, the region faces challenges such as labor shortages, irregular rainfall, and pest pressures (Elwahab et al., 2024). Drones are increasingly used for aerial monitoring, enabling farmers to assess crop health, detect early signs of disease, and optimize irrigation through multispectral imaging (Zhang et al., 2023). As illustrated in Figure 4, drones perform multiple functions in agriculture, including crop mapping, variable-rate spraying, and field surveillance.

Precision spraying, particularly in rice paddies, is gaining popularity in the Gharb Plain, helping to reduce pesticide use and minimize environmental impacts (Ahmed et al., 2022). On the ground, robots and autonomous tractors assist in sowing, weeding, and harvesting operations, increasing efficiency and reducing reliance on manual labor (Khan et al., 2024). Additionally, robotic systems are being introduced in greenhouse agriculture — a rapidly expanding sector in the Gharb — to automate climate control, irrigation, and fertilization processes (Benhadi et al., 2023). These innovations promote sustainable, data-driven agriculture and position the Gharb Plain as a leader in smart farming in Morocco (Elwahab et al., 2025).

Figure 4. Drone applications in agriculture (Unpaprom et al., 2018)

In addition, drones facilitate field mapping and crop scouting, enabling farmers to efficiently monitor large agricultural areas in a fraction of the time required for manual surveys. They can generate digital elevation models, assess plant density, and detect pest infestations early, improving overall farm management.

Beyond rice, drones are increasingly deployed in greenhouse monitoring, orchards, and large-scale cereal or vegetable farms to enhance data-driven decision-making.

Overall, drones play a critical role in the transition toward precision agriculture, enabling sustainable, efficient, and environmentally friendly farming practices. Their integration with AI, IoT sensors, and Big Data analytics further amplifies their value by providing actionable insights for optimized crop production.

CONCLUSION

Digital transformation offers a transformative pathway for enhancing the sustainability, resilience, and productivity of rice agro-systems in Morocco. The integration of IoT-based sensing, Artificial Intelligence (AI), and Big Data analytics enables real-time monitoring, precise resource management, early detection of diseases such as Magnaporthe oryzae, and accurate yield forecasting. Case studies from the Gharb Plain demonstrate that AI-driven approaches can significantly improve yield prediction accuracy, reduce water consumption, and optimize input use compared to conventional methods.By bridging traditional farming knowledge with cutting-edge digital tools, Moroccan rice producers can overcome critical challenges related to water scarcity, soil fertility decline, and climate variability. The adoption of digital agriculture not only enhances productivity but also contributes to environmental sustainability and national food security.

Future perspectives include scaling up these technologies across the country, integrating climate-smart agriculture practices, and developing policies to support farmers in adopting digital solutions. Continued investment in digital infrastructure, farmer training, and research collaborations will be essential to fully realize the potential of IoT, AI, and Big Data in transforming rice production systems in Morocco.

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