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Editor(s) in Chief

Prof. Ujjwal Kumar Nyogi
Prof. Moumita Mukherjee

ADAMAS TECHNICAL REVIEW

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Prof. Ujjwal Kumar Neogi,
Director, School of Smart Agriculture

Prof. Moumita Mukherjee,
Dean, Research and Development

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Editorial

Welcome to Vol 3. , Issue 1 (July - December ,2026) of the Adamas Technical Review. This bi-annual publication showcases the forefront of technological and interdisciplinary exploration. Within these pages, our peer-reviewed journal stands as a beacon of research and innovation, offering a rich and diverse collection of research papers, insightful articles, illuminating case studies, comprehensive reviews, and promising student research contributions, each meticulously selected to reflect the dynamic landscape of modern advancements.

Adamas Technical Review serves as a vital conduit for knowledge dissemination and collaborative discourse. We provide a platform where academics, researchers, students, and industry professionals converge to share groundbreaking insights and foster a collective understanding of the challenges and opportunities that lie ahead. The contributions featured in this edition address critical issues within science, engineering, and technology, offering innovative solutions and theoretical frameworks that push the boundaries of current knowledge.

We extend our deepest gratitude to our esteemed contributors, whose dedication and intellectual rigor have enriched this issue with invaluable scholarship. Their commitment to excellence is the cornerstone of our journal's success. We also acknowledge the tireless efforts of our distinguished editorial board and meticulous reviewers, whose unwavering commitment to academic integrity ensures the highest standards of quality and rigor.

To our valued readers, we express our sincere appreciation for your continued support and engagement. Your interest fuels our pursuit of scholarly advancement and inspires us to continually strive for excellence.

It is our earnest hope that this edition of the Adamas Technical Review will serve as a catalyst for further research, igniting meaningful discussions and fostering a spirit of intellectual curiosity. We remain steadfast in our dedication to promoting scholarly excellence and cultivating a culture of innovation as we collectively navigate the ever-expanding frontiers of knowledge.

Happy reading.

Dr. U. K. Neogi
Editor-in-Chief
Adamas Technical Review

Dean (Research & Development)
Office of the Dean (R & D)
Adamas University Campus
Kolkata - 700126, WB, India

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Adamas Knowledge City
Barasat - Barrackpore Road,
P.O. - Jagannathpur,
North 24 Parganas,
Kolkata - 700126,
West Bengal, India

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+91 1800 419 7423 dean_rd@adamasuniversity.ac.in www.adamasuniversity.ac.in

Foreword from the Editor-in-Chief

It is with great pride and anticipation that we present the latest edition of the *Adamas Technical Review*, the tri-yearly research journal of Adamas University, Kolkata. This publication stands as a testament to our unwavering commitment to fostering a culture of inquiry, innovation, and interdisciplinary dialogue across the scientific and technological landscape.

In a world increasingly driven by data, research, and rapid technological advancement, the role of academic institutions as hubs of original thought and rigorous experimentation becomes more vital than ever. *Adamas Technical Review* serves as a platform where scholars, researchers, and practitioners can converge to share insights, challenge conventional boundaries, and inspire new avenues of exploration.

This issue encapsulates a diverse range of contributions—from applied sciences and engineering breakthroughs to novel interdisciplinary studies—that reflect the vibrant intellectual ecosystem nurtured at Adamas University. Each article has undergone a meticulous review process, ensuring academic rigor and relevance to both academia and industry.

We are deeply grateful to our contributors for their valuable work, to our reviewers for their discerning assessments, and to the editorial board for their unwavering dedication in bringing this journal to life. Their collective efforts continue to elevate the standards of scholarship and underscore the university's mission to advance knowledge that serves both local and global communities.

As you delve into these pages, we invite you to engage with the ideas presented, question assumptions, and perhaps, find inspiration for your own research journey. May this journal be a catalyst for conversation, collaboration, and continued discovery.

Warm regards,

Moumita Mukherjee 11/04/2025

Prof. Moumita Mukherjee
Professor & Dean (Research & Development)
Editor-in-Chief
Adamas Technical Review
Adamas University, Kolkata – 700126

RESEARCH PAPERS

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Precision Farming vs Traditional Farming: A Comparative Analysis for Sustainable Agricultural Development

Soumi De

School of Smart Agriculture
soumi.de1993@gmail.com

Abstract — *Agriculture remains the backbone of food security and rural livelihoods worldwide. Traditional farming practices have sustained agricultural production for centuries through experience-based decision-making and generalized resource application. However, increasing challenges such as climate change, resource depletion, declining soil fertility, water scarcity, and rising production costs necessitate more efficient agricultural systems. Precision farming has emerged as a technology-driven approach that utilizes Geographic Information Systems (GIS), Global Positioning Systems (GPS), Internet of Things (IoT), remote sensing, drones, artificial intelligence, and big data analytics to optimize farm operations. This study compares precision farming and traditional farming in terms of productivity, resource efficiency, environmental sustainability, and economic viability. A quantitative research framework is proposed using farmer surveys and expert interviews. The findings suggest that precision farming significantly improves crop productivity, reduces input costs, enhances environmental sustainability, and strengthens climate resilience. Despite challenges related to high investment costs and technological barriers, precision agriculture represents a transformative pathway toward sustainable agricultural development.*

Keywords — *Precision Farming, Traditional Farming, GIS, IoT, Sustainable Agriculture, Smart Farming, Resource Efficiency, Agricultural Innovation*

1. Introduction

Agriculture contributes significantly to food security, employment generation, and economic development. Traditional farming relies on farmers' experience, intuition, and generalized management practices. Although effective in many contexts, traditional farming often fails to address field variability, leading to inefficient use of water, fertilizers, pesticides, and labor.

Precision farming represents a revolutionary shift toward data-driven agriculture. By integrating advanced technologies such as GIS, GPS, IoT sensors, drones, remote sensing, machine learning, and predictive analytics, precision agriculture enables site-specific management of crops and resources. Farmers can monitor crop health, soil moisture, nutrient levels, pest infestations, and climatic conditions in real time, thereby optimizing productivity and sustainability.

The transition toward precision agriculture is increasingly important in developing countries where population growth and climate uncertainty place additional pressure on agricultural systems. This study explores the comparative advantages and limitations of precision farming and traditional farming while examining their implications for sustainable agricultural development.

2. Background of the Study

Global food demand is projected to increase significantly by 2050. Simultaneously, agricultural land availability is declining due to urbanization, environmental degradation, and climate change. Traditional farming methods frequently result in excessive resource consumption and environmental impacts.

Precision agriculture emerged during the 1990s with advancements in GPS and geospatial technologies. Recent developments in AI, cloud computing, sensor technologies, and drone-based monitoring have accelerated its adoption. Governments worldwide, including India, have introduced digital agriculture initiatives promoting precision farming to enhance agricultural productivity and resource conservation.

Figure 1: Conceptual Framework

TraditionalFarming	**Precision Farming**
|	|
Experience-Based Decisions	Data-Driven Decisions
|	|
General Input Application	Site-Specific Input Application
|	|
Lower Resource Efficiency	Higher Resource Efficiency
|	|
Moderate Productivity	Enhanced Productivity
|	|
Environmental Stress	Sustainable Agriculture

3. Objectives of the Study

1. To compare precision farming and traditional farming practices.
2. To examine the impact of precision farming on crop productivity.
3. To evaluate resource-use efficiency in precision agriculture.
4. To assess environmental sustainability outcomes.
5. To identify barriers to precision farming adoption.
6. To recommend strategies for promoting sustainable agricultural transformation.

4. Literature Review

Table 1: Selected Literature Review (2016–2025)

Author(s)	Year	Key Findings
Zhang et al.	2016	Precision agriculture improves input efficiency and yield.
Gebbers& Adamchuk	2017	Site-specific management enhances farm profitability.
Wolfert et al.	2017	Big data analytics transforms agricultural decision-making.
Liakos et al.	2018	AI significantly improves crop monitoring accuracy.
Kamilaris & Prenafeta-Boldú	2018	IoT enhances real-time agricultural management.
Sharma et al.	2019	Precision irrigation reduces water consumption.
Pathak et al.	2020	Drone technologies improve crop health assessment.
Javaid et al.	2021	Industry 4.0 technologies accelerate smart agriculture adoption.
Kumar & Singh	2023	Precision farming enhances climate resilience among farmers.
Patel et al.	2024	Digital agriculture contributes to sustainable farming systems.

Research Gap

Most previous studies focus on technological applications independently. Limited research comprehensively compares precision farming and traditional farming regarding productivity, sustainability, economic viability, and adoption challenges within developing agricultural economies.

5. Research Questions

RQ1: How does precision farming affect agricultural productivity compared to traditional farming?
RQ2: Does precision farming improve resource-use efficiency?
RQ3: What environmental benefits are associated with precision agriculture?
RQ4: What factors influence farmers' adoption of precision farming technologies?

6. Hypotheses

H1: Precision farming significantly increases crop productivity compared to traditional farming.
H2: Precision farming significantly improves water, fertilizer, and pesticide use efficiency.
H3: Precision farming positively influences environmental sustainability.
H4: Technological awareness significantly affects farmers' adoption of precision farming technologies.

7. Research Methodology

Research Design

The study adopts a descriptive and explanatory research design using quantitative methods.

Population

The target population includes farmers, agricultural extension officers, agronomists, and agricultural technology experts.

Sampling Technique

Stratified random sampling will be employed.

Sample Size

- Farmers: 250
- Agricultural Experts: 30
- Extension Officers: 20

Total Sample = 300 Respondents

Data Collection Methods

Primary Data

- Structured questionnaire survey
- Expert interviews
- Focus group discussions

Secondary Data

- Research journals
- Government reports
- FAO publications
- Ministry of Agriculture reports

Figure 2: Research Methodology Flow Diagram

Literature Review
↓
Research Gap Identification
↓
Research Objectives
↓
Hypothesis Development
↓
Questionnaire Design
↓
Data Collection
↓
Data Analysis
↓
Interpretation
↓
Conclusion & Recommendations

8. Variables of the Study

Independent Variables
- GIS Usage
- IoT Adoption
- Drone Utilization
- Data Analytics
- Farmer Awareness

Dependent Variables
- Crop Yield
- Resource Efficiency
- Environmental Sustainability
- Adoption Intention

9. Data Analysis Techniques

The following statistical techniques will be applied:

Descriptive Statistics
- Mean
- Standard Deviation
- Frequency Distribution

Inferential Statistics
- Correlation Analysis
- Multiple Regression Analysis
- ANOVA
- Independent Sample t-Test

Structural Analysis
- Structural Equation Modeling (SEM)

Statistical Software
- SPSS 29
- AMOS 24
- SmartPLS 4
- Microsoft Excel

10. Proposed Analytical Model

Precision Farming Technologies
(GIS + IoT + Drones + Analytics)
↓
Resource Optimization
↓
Enhanced Productivity
↓
Environmental Sustainability
↓
Farmer Adoption & Profitability

11. Expected Outcomes

- Increased agricultural productivity through data-driven management.
- Reduction in water, fertilizer, and pesticide consumption.
- Enhanced soil health and environmental sustainability.
- Improved profitability among farmers.
- Better climate resilience and risk management.
- Increased adoption of digital agriculture technologies.
- Policy recommendations for large-scale precision agriculture deployment.

12. Discussion

The integration of advanced technologies into agriculture has transformed conventional farming practices. Precision farming enables farmers to respond proactively to field variability and environmental conditions. While traditional farming remains relevant for resource-constrained farmers, hybrid approaches integrating traditional knowledge with modern technologies may offer the most sustainable solution. Capacity building, government incentives, affordable technology access, and digital infrastructure development are critical for successful adoption.

13. Conclusion

Precision farming represents the future of sustainable agriculture by enabling efficient resource utilization, enhanced productivity, and environmental conservation. Compared to traditional farming, precision agriculture offers substantial advantages in crop management, input optimization, and climate resilience. However, successful implementation requires addressing challenges related to affordability, awareness, technical expertise, and infrastructure. Policymakers, research institutions, and industry stakeholders must collaborate to accelerate the adoption of precision agriculture and ensure long-term food security and sustainable rural development.

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The Impact of Decision Support Systems in AI Driven Agriculture

Anannya Chakraborty[1], Snigdha Samanta[2], Bharat Chandra Saha[3]

1.Assistant Professor, School of Smart Agriculture, Adamas University, Kolkata, India

2. Assistant Professor, School of Smart Agriculture, Adamas University, Kolkata, India

3. Professor and Dean, School of Smart Agriculture, Adamas University, Kolkata, India

Abstract—*Agricultural output and agripreneurial success hinge on well-informed micro-level decisions supported by sound macro-level policies and strategies. The modernization of agriculture and rapid urbanization have introduced complexities that make effective decision-making more challenging. Human judgment, particularly under complex and stressful conditions, often falls short of optimal performance. Across history, disciplines such as statistics, economics, and operations research have developed methods to improve decision-making. With the rise of information science, cognitive psychology, and artificial intelligence, these methods have evolved into advanced computer-based tools collectively known as Decision Support Systems (DSS).*

DSS are interactive platforms designed to aid judgment and decision-making, sometimes referred to as knowledge-based systems for their ability to formalize domain expertise into structured, machine-readable formats. This paper reviews the development, applications, and research surrounding various DSS types—model-driven, data-driven, knowledge-driven, spatial DSS, business intelligence tools, group DSS, online analytical processing, and executive information systems. It highlights their role in enhancing public engagement through ICT, particularly in e-governance. Furthermore, it examines how advances in databases, AI, human-computer interaction, and simulation can expand DSS applications in agriculture. The study underscores the importance of DSS in promoting sustainable farming, improving resource management, and enabling data-driven decision-making for the future of agriculture.

Keywords— *Decision Support Systems, Artificial Intelligence, Knowledge-Based Systems, Online Analytical Processing, Executive Information Systems, Agricultural Sustainability, E-Governance*

Introduction

Feeding an estimated global population of 9–10 billion by the year 2050 will require an increase in food production of approximately 60–110%. Ensuring the long-term sustainability of agriculture is therefore critical to achieving food security and eradicating hunger. Alongside this challenge, the agricultural sector faces heightened scrutiny due to food safety incidents such as bovine spongiform encephalopathy (BSE) and dioxin contamination in poultry, making comprehensive and transparent traceability systems essential for quality control.

The impacts of climate change, fluctuating weather patterns, and increasing water scarcity present additional hurdles for the sector. These factors call for a strategic shift from the traditional focus on maximizing productivity to a more holistic emphasis on agricultural sustainability. In this context, empowering farmers and stakeholders with tools that facilitate informed, sustainable decisions is essential. Digital technologies—including the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing—offer transformative potential. Within AI, subsets such as machine learning (ML) and deep learning, when combined with location-based intelligence, are increasingly employed to enhance decision-making in agriculture. This paper aims to present key applications of AI and ML in the agri-food sector, emphasizing their role in decision support and sustainable farming practices.

Artificial Intelligence and Machine Learning Approach

Artificial Intelligence is a branch of computer science focused on creating systems capable of performing tasks that traditionally require human intelligence. This includes simulating cognitive processes such as learning (acquiring and processing data to generate actionable insights), reasoning (selecting appropriate algorithms to achieve desired results), and self-correction (refining algorithms to improve accuracy over time). AI applications span across natural language processing (NLP) for interpreting human speech, computer vision for image and video analysis, speech recognition, and expert systems that mimic human decision-making.

Machine Learning, a core subset of AI, employs statistical and mathematical models to detect patterns in data and make predictions or decisions. ML approaches can be broadly classified as:

1. Supervised Learning – Models are trained on labeled data with known outputs to predict future outcomes. Techniques include decision trees, Bayesian networks, and regression analysis.
2. Unsupervised Learning – Algorithms like clustering, deep learning, genetic algorithms, and Artificial Neural Networks (ANNs) identify patterns in unlabeled datasets, often for exploratory analysis or dimensionality reduction.
3. Reinforcement Learning – Systems learn through interaction with their environment, receiving rewards for certain actions. Techniques such as Q-learning and deep Q-learning are used for applications like robotics, navigation, and real-time decision-making.

In agriculture, AI technologies are being deployed to improve productivity and sustainability. They can identify crop diseases, optimize irrigation schedules, manage water usage, and enhance yield predictions. For example, Sujatha et al demonstrated that the VGG-16 deep learning model outperformed traditional methods in detecting citrus leaf diseases. Crane-Droesch introduced Semiparametric Neural Networks for predicting corn yields, showing improved performance over classical statistical models.

Beyond operational benefits, AI also contributes to environmental protection by enabling precise, targeted pesticide application through robotics and computer vision, reducing chemical usage and minimizing ecological impact. Overall, AI and ML are poised to revolutionize agricultural decision-making, aligning productivity goals with resource efficiency and sustainability.

Decision Support System (DSS): Concept, History, and E-Governance Integration

The term Decision Support System encompasses a wide spectrum of definitions, shaped by varying viewpoints across academic and professional domains. For this paper, a DSS is defined as an interactive computer-based system designed to assist users in making informed judgments and choices. These systems are sometimes referred to as knowledge-based systems because they aim to codify domain expertise into structured formats suitable for automated reasoning.

Over the years, information systems have been developed for different organizational purposes. At the operational level, Transaction Processing Systems (TPS) manage large volumes of routine business transactions. Office Automation Systems (OAS) support clerical and administrative tasks, while Knowledge Work Systems (KWS) cater to professional and technical users. Higher-level systems include Management Information Systems (MIS) and DSS, with Expert Systems (ES) designed for unstructured problem-solving. Strategic decision-making is supported by Executive Support Systems (ESS). Collaborative decision-making environments are facilitated by Group Decision Support Systems (GDSS) and broader Computer-Supported Collaborative Work (CSCW) platforms.

The evolution of DSS dates back to the mid-1960s, fueled by the emergence of minicomputers, time-sharing systems, and distributed computing. According to Power (2001, 2002, 2004), the historical development of DSS can be grouped into five main categories:

1. Communications-driven DSS
2. Data-driven DSS
3. Document-driven DSS
4. Knowledge-driven DSS
5. Model-driven DSS

The primary aims of a DSS are to:

Assist managers in addressing semi-structured problems.
Support, rather than replace, managerial judgment.
Enhance the effectiveness of decisions, prioritizing quality over mere efficiency.

DSS in the Context of E-Governance

E-governance refers to the use of information and communication technologies (ICT), particularly the internet, to improve the delivery of government services to citizens, businesses, and other agencies. It promotes transparency, accountability, and greater citizen participation in decision-making processes.

Although most e-governance frameworks do not explicitly include DSS as a core component, integrating DSS into these frameworks can significantly strengthen decision-making capabilities at various administrative levels. This paper proposes a DSS framework aligned with e-governance layers, enabling government decision-makers to leverage data-driven insights for better public service delivery.

Objectives:

- Sensitization of the concept of Decision support system
- Analysis of the methodology of decision support system
- Identification of the area of DSS application
- Issues and challenges faced by DSS
- The present status of DSS application in agriculture and allied sectors.

Review of Literature

Systematic research into computer-assisted decision-making began during the 1960s, when scholars explored how computational models could enhance planning and managerial processes (Raymond, 1966; Turban, 1967; Urban, 1967; Holt & Huber, 1969). One of the earliest experiments was conducted by Ferguson and Jones (1969), who implemented a production scheduling DSS on an IBM 7094 system.

A pivotal contribution came from Michael S. Scott Morton (1967) at Harvard University. His doctoral research involved developing, implementing, and testing an interactive, model-driven management decision system. This Management Decision System (MDS) was used by marketing and production managers for coordinated production planning in the laundry equipment sector. The system was operated via a 21-inch CRT display with a light pen, connected through a modem to Univac 494 computers.

The feasibility of DSS development was shaped by the groundbreaking work of several pioneers:

George Dantzig – At RAND Corporation in the early 1950s, Dantzig implemented linear programming on experimental computers, laying a foundation for optimization-based decision systems.
Douglas Engelbart – Developed the OnLine System (NLS) in the mid-1960s, integrating hypermedia, document retrieval, video conferencing, and early group decision-support capabilities.
Jay Forrester – Led the development of the SAGE air defense system, often considered the first large-scale, data-driven DSS, and later founded MIT's System Dynamics Group.

In 1960, J.C.R. Licklider published Man-Computer Symbiosis, envisioning multi-access interactive computing to augment human problem-solving. His vision heavily influenced interactive computing research for decades. By 1964, IBM's System/360 made it economically feasible to implement Management Information Systems (MIS) for large organizations.

By the early 1970s, business literature began discussing "management decision systems" and "strategic planning systems." Gorry and Scott-Morton (1971) formally introduced the term Decision Support System, emphasizing that MIS catered mainly to structured decisions, while DSS was intended for semi-structured and unstructured decision-making.

Other notable contributions included:

T.P. Gerrity Jr. – Designed DSS for investment portfolio management.
John D.C. Little – Defined four essential criteria for decision models: robustness, ease of control, simplicity, and completeness. He also developed the Brandaid system for marketing and financial decision support.
Gordon Davis (1974) – Integrated DSS into MIS frameworks, framing them as part of a larger decision-support ecosystem.
Keen & Stabell (1978) – Traced DSS evolution to organizational decision-making studies from Carnegie Mellon and interactive computing innovations from MIT.

In 1995, Hans Klein and Leif Methlie observed that some of the earliest DSS research emerged from business schools with access to time-sharing computer systems, such as MIT's Project MAC and Dartmouth's time-sharing platform.

Overall, the literature demonstrates that DSS evolved through interdisciplinary collaboration—merging insights from computer science, management theory, operations research, and behavioral decision theory. These foundations continue to influence DSS applications in modern fields such as agriculture, healthcare, and e-governance.

Decision Support System

A Decision Support System (DSS) is a computer-based information platform that assists organizations in making well-informed choices at various levels—operational, tactical, and strategic. DSSs are particularly useful for semi-structured problems—those where part of the decision-making process can be automated, but managerial judgment is still essential.

Operational Concept

The concept of DSS emerged in the 1970s as advances in computing made interactive problem-solving feasible. Unlike earlier rigid modeling techniques, DSS integrates databases and analytical models under the direct control of the user through a dialogue-based interface.

A properly designed DSS draws upon diverse information sources—internal records, external data, documents, and personal expertise—to help decision-makers identify, analyze, and evaluate alternatives. It can provide outputs such as:

- Inventory and asset reports.
- Comparative sales performance over different time periods.
- Revenue projections based on market trends or production assumptions.

By combining large-scale data handling with sophisticated analytical models, DSS offers a richer and more interactive decision-making environment than traditional reporting systems.

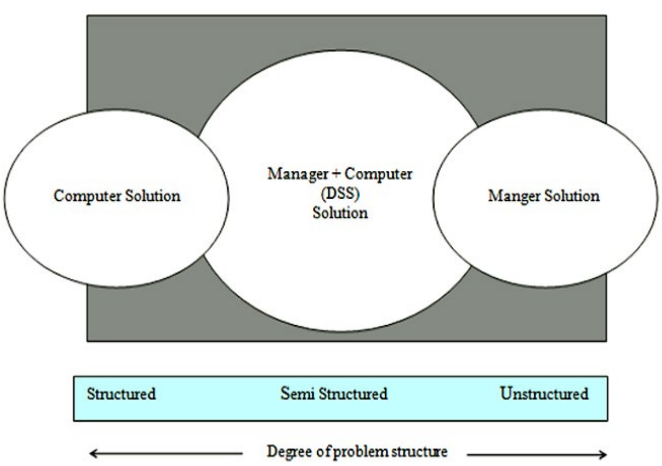


Fig:1- The DSS focuses on semi structured problems (Raymond, 1990)

A DSS typically exhibits the following features:

1. Analytical Support – Designed to analyze complex situations rather than simply generating routine reports.
2. User Customization – Enables decision-makers to incorporate their own assumptions and perspectives.
3. Integration of Models– Employs statistical, mathematical, and operations research techniques.
4. Supportive Role – Guides but does not replace the decision-maker's authority.
5. Multi-Level Application – Used by first-line supervisors, middle managers, and top executives alike.
6. Database Reliance – Operates on robust database management systems for efficient data handling.
7. Scenario Testing – Facilitates "what-if" analysis for exploring alternative outcomes.

Modern organizations increasingly rely on DSS due to:

Fast Computation – Enables rapid analysis of complex datasets at low cost.
Enhanced Productivity – Improves both individual and group decision-making efficiency.
Better Decision Quality – Allows evaluation of multiple options, rapid risk analysis, and quick access to expert opinions.
Efficient Data Transmission – Facilitates fast retrieval and sharing of distributed data resources.

Benefits of DSS

Even when results are not directly measurable, DSS offers tangible advantages, including:

- Broader exploration of alternatives.
- Improved understanding of organizational processes.
- Quicker responses to unexpected changes.
- Capability for ad hoc analysis.
- Generation of new insights and learning opportunities.
- Enhanced communication and collaboration.
- Improved control and cost savings.
- Time efficiency and better use of data resources.

These benefits contribute to improved decision-making effectiveness, a factor often valued more than speed or efficiency alone.

DSS in Farm Systems

The proposed model is designed to assist farmers in boosting productivity by increasing yield per hectare, thereby fostering economic growth. The system maintains a comprehensive record of each farmer's crop-related data, enabling more effective planning and resource management.

Some of the key applications include:

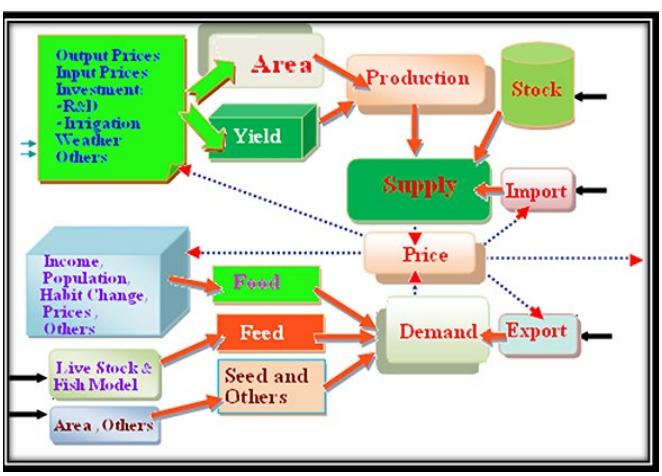
- Cash Flow Management – Helping farmers better handle income cycles, particularly the lump-sum cash inflow during harvest.
- Financial Planning – Allowing integration of income

management with loans and advances for improved liquidity control.

- Administrative Flexibility – Enabling database updates without system downtime.
- Information Sharing – Providing valuable data to local governance bodies and other agencies when implemented at village, district, and state levels.

With population growth and increasing demand for sustainable watershed management, there is an urgent need to implement resource utilization practices that benefit both local communities and the nation. This DSS adopts an integrated approach, combining biophysical data with farmers' socio-economic profiles. It simulates farmer decision-making in selecting farming systems under specific constraints and aggregates the results for analysis at broader administrative levels.

Built on a Relational Database Management System (RDBMS) framework, the model can handle large numbers of queries based on parameters such as crop type, water availability, and socio-economic limitations. This ensures rapid access to critical information, reducing the need for farmers to travel to agricultural universities or research centers.



DSS for Agro-Technology Transfer

The Decision Support System for Agro-Technology Transfer (DSSAT) is a comprehensive software package that integrates soil, crop phenotype, weather, and management data to run simulations and answer "what-if" questions. It enables agricultural experiments that might take years in the field to be completed in minutes on a desktop computer.

In use for over 15 years across more than 100 countries, DSSAT allows users to:

- Simulate multi-year outcomes for different crop management strategies.
- Validate crop models by comparing simulated results with observed data.
- Quickly evaluate the viability of new crops, farming techniques, and agricultural products.

Version 4of DSSAT introduced a modular Cropping System Model (CSM) that integrates models for multiple crops using a shared soil and weather module. It supports 27 different crops and provides tools for assessing the economic and environmental impacts of various agricultural practices, including irrigation management, fertilizer application, climate change adaptation, soil carbon sequestration, and precision farming.

Minimum Data Set (MDS) Requirements

To operate effectively, DSSAT requires a minimum dataset, which includes:

Weather Data – Geographic coordinates, daily solar radiation, maximum and minimum temperature, and rainfall.
Soil Data – Classification, texture, organic carbon content, pH, slope, permeability, and drainage class.
Management Data – Planting date, crop variety, irrigation schedules, fertilizer application details, and planting density.

Problems with DSS Development and Adoption

While DSS offers clear advantages for agricultural planning and farm management, widespread adoption among producers has been limited. Research by Wilde (1994), Cox (1996), Campbell (1999), and Lynch et al. (2000) highlights several key barriers:

1. Limited Computer Access – Many farmers still lack personal computers or compatible digital devices.
2. Insufficient Field Testing – Some DSS models are not adequately validated under real farm conditions.
3. Minimal User Involvement – Systems are often developed without early or ongoing input from intended users.
4. Complexity and Data Requirements – High data input demands and complicated interfaces deter adoption.
5. Resistance to Change – Farmers may see no compelling reason to alter established management practices.
6. Lack of Trust – Producers may distrust DSS outputs if they do not understand the underlying models.
7. Mismatch with Decision Styles – DSS recommendations may not align with the farmer's decision-making approach.

8. Unclear Target Beneficiaries – Systems sometimes fail to specify whether they primarily serve scientists, producers, or extension agents.
9. Technical Support Issues – Inconsistent access to software maintenance and user assistance.

A critical factor influencing adoption is the balance between perceived ease of use and perceived usefulness. As described by Keil et al. (1995), software that is difficult to use and offers limited benefits will be rejected outright, while even highly beneficial systems will be avoided by most users if they are too complex—except by "power users" with advanced technical skills. Sustainable adoption requires DSS solutions that are both easy to use and demonstrably valuable in improving decisions.

Problem Statement and Solution Methodology

Timely access to accurate agricultural information is essential for rural development and the well-being of farming communities. Rapid communication between researchers and farmers enables faster adoption of improved practices and technologies. This research addresses the challenge of creating a web-based DSS for farm entrepreneurs that integrates decision support tools with online accessibility.

The proposed system offers several advantages:

- Low Operational Cost – Affordable access to decision-support tools.
- Quick Information Retrieval – Farmers can access real-time, relevant information.
- Direct and Personalized – Tailored guidance for individual farm conditions.
- Integrated Platform – Consolidates multiple data sources into a single interface.

Information Sources

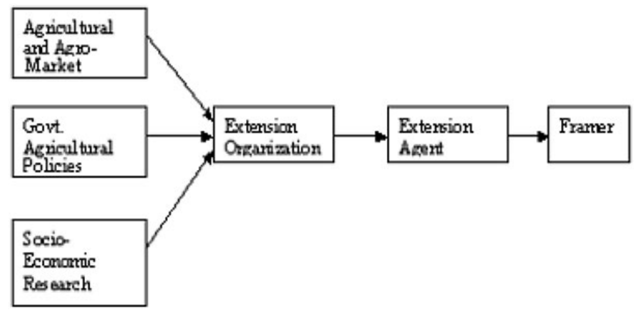
The DSS draws data from multiple stakeholders, including:

- Farmer organizations.
- Research institutions.
- Other farmers and community networks.
- Agricultural journals, radio, television, government departments, and agencies.

Database Foundation

The system's primary data source is information published by state or national governments, supplemented by on-ground research. The database stores crop-specific details, enabling farmers to make interactive, flexible, and informed decisions without traveling to agricultural universities.

By combining biophysical data with socio-economic variables, the model simulates various farming scenarios. Farmers can then evaluate which practices best fit their resource constraints and market conditions.



The proposed flow system for farm management is shown in Proposed Flow System
The farmers will be able to access the necessary information regarding the various government policies for agriculture, the ongoing socio-economic research and the different benefits for the entrepreneur for investing in particular area of farm management. The Farmers can acquire this information from:

- Farmer's organizations.
- Researchers.
- Other Farmers.
- Farm journals, radio, television, Government, Departments and agencies.

The primary and the basic fundamental of any project involving the database is the collection of data and information. This project also requires the collection of information from various sources. The main source of the data is the service published by the state or centerGovernment. The present model will help the farmers to take interactive, flexible and quick decisions. This will also help them in increasing their productivity by raising yield per hectare in food grain, thus leading to their economic growth. It will keep track of farmer's all type of information related to crops.

The additional advantages that will accrue are:
a) Low cost of operation.
b) Quick access to all relevant information.
c) Direct and personalized.
d) Integrated.

DSS with all the ready information, help the farmers in a very useful manner. The farmers can get all the information at just at click of the mouse, and they need not to travel to Agricultural Universities for that.

Alright — here's the rewritten "Sitemap, Information Retrieval, Resource Management, Node-Level Modeling, Outputs and Implications" sections from your paper.

Sitemap and Information Retrieval System

The sitemap of the proposed DSS outlines the structure and navigation flow, starting from the Home Page, which introduces the Farm Entrepreneur System, its objectives, and its guiding principles. From this central point, users can access various modules and tools within the system.

A major benefit of the DSS is its dynamic information retrieval capability. Farmers can obtain up-to-date, location-specific data to support decision-making in real time. The DSS framework acts as a driver for changes in agricultural resource use, placing the farm or household at the center of analysis. Decisions regarding land and water use are influenced by the household's resources, economic conditions, and socio-cultural norms.

Outputs and Implications

The DSS generates outputs that help optimize land and water allocation to maximize community-level and farm-level gross margins, taking into account biophysical and socio-economic constraints.

The system can also evaluate the potential effects of changes in:

- Land use.
- Commodity prices.
- Investment strategies.
- Development projects.

Results can be presented both at the individual RMU level and in aggregated form for the entire node or village.

By identifying economic and environmental trade-offs, the DSS supports welfare improvement and conflict resolution—particularly in water management, where resource ownership and access are often contested.

Although the system's outputs are quantitative, they aim to indicate trends in resource use rather than precise forecasts. This trend-based approach helps stakeholders visualize the implications of different management strategies without over-relying on exact figures.

The model will help the farmers in increasing their productivity by raising the yield/hectare in food grains thus, leading to their economic growth. This system has been developed to keep track of farmers all type of information related to crops.

Certain applications that are successfully developed using this database are:

- Farmers can manage their cash flow through the DSS system in a more predictable and efficient way. It is a more common problem with the farmers to manage the cash received at time of harvesting the crop.
- They can avail full benefit of their cash management by co-relating it with the loans and advances.
- The administrator can add information to the database without stopping the application.
- If implemented at Village, District and State level, the model will provide valuable information to other agencies and panchayats in particular.

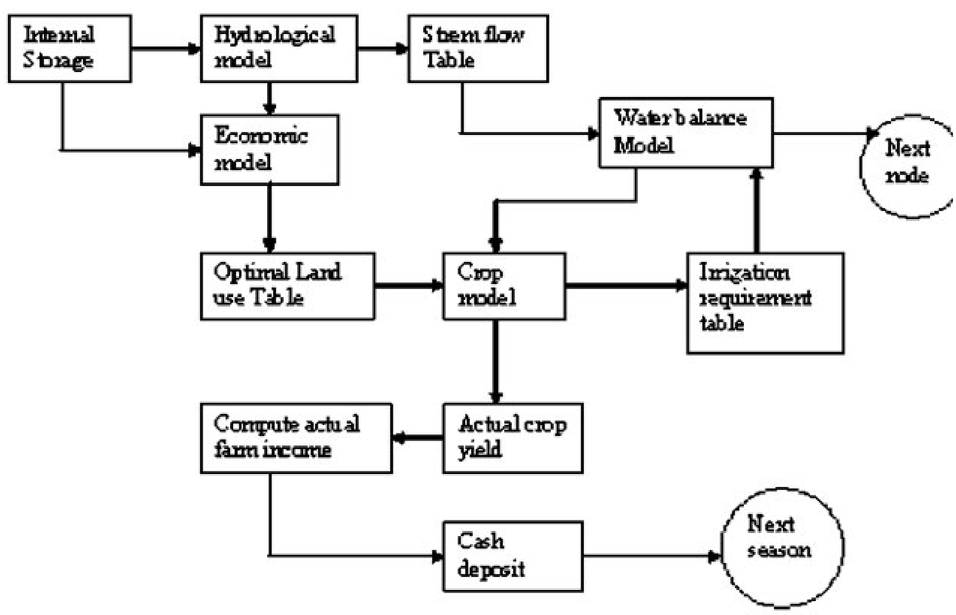


Fig: Workflow of DSS

With growing population and demands for improved watershed management, there is an obvious need to implement sustainable resource use that best serves the communities and the nation. To satisfy this need, the DSS is developed to aid decision – makers and various stakeholders in identifying and assessing options for resource uses. The DSS applies an integrative approach, combining biophysical data, perceptions and socioeconomic conditions of the farmers in the given area. The DSS attempts to stimulate the farmer's behaviour in selecting farming systems given relevant constraints and then aggregating up to the node.

A large number of database queries can be generated according to Crop, Water Availability and Requirement, Socio-economic constraints and so on. Design and Development of this database is purely based on Relation Database Management System Model, so the large volume of queries can be easily handled.

DSS with all the ready information help the farmers in a very useful manner. The farmers can get all the information at just at click of the mouse, and they need not to travel to Agricultural Universities for that.

Future Scope

The proposed Farm Entrepreneur System has significant potential for further development and customization to meet the evolving needs of farmers. Potential future enhancements include:

1. Localization – Translating the interface into regional languages to make the system accessible to a wider audience.
2. Enhanced Economic Modeling – Expanding the economic simulation components to address more complex resource management challenges.
3. Market Intelligence Integration – Providing real-time market data, including commodity prices that may exceed the government's minimum support price (MSP).
4. Expanded Communication Features – Offering email, discussion forums, online chat, and instant messaging services for direct interaction between farmers, experts, and policy-makers.
5. Voice Assistance – Implementing voice-based guidance in local languages to assist illiterate or semi-literate users.
6. Protected Cultivation Research – Incorporating modules to support the adoption of advanced crop production methods in controlled environments.

These improvements would not only increase adoption but also strengthen the DSS as a comprehensive decision-making and knowledge-sharing platform for agriculture.

Conclusion

The evolution of Decision Support Systems continues to be shaped by advancements in database technology, artificial intelligence, human-computer interaction, simulation, optimization, software engineering, and telecommunications. As these technologies progress, DSS will become more integrated, intelligent, and accessible. Data-driven DSS will increasingly provide real-time access to larger, better-integrated datasets. Model-driven DSS will handle more complex simulations while remaining user-friendly. Communications-driven DSS will deliver enhanced real-time collaboration capabilities, including video conferencing. Document-driven DSS will manage larger repositories of unstructured information with improved search and presentation tools. Knowledge-driven DSS will become more sophisticated, offering broader domain coverage and higher-quality recommendations. The pioneering work in DSS—built through collaboration between experts in computing, management science, and behavioral theory—has laid the foundation for today's systems. Preserving and building upon this legacy is essential.Integrating DSS into e-governance frameworks can unlock new opportunities for transparent, participatory, and efficient decision-making in agriculture. By linking advanced decision-support capabilities with government service delivery, the system can empower farmers with timely, actionable insights—helping them improve productivity, optimize resource use, and contribute to sustainable agricultural development.

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AI and IoT-Based Disease Detection and Management in Controlled Environmental Conditions: A Review

Rupsha Roy
Department of Agriculture
Adamas University
Kolkata, India
rupsharoy079@gmail.com

Shreya Das
Department of Agriculture
Adamas University
Kolkata, India
shreyadas11265@gmail.com

Siddhant Ray Bharti
Department of Agriculture
Adamas University
Kolkata, India
siddhantraybharti@gmail.com

Abstract—*Controlled Environment Agriculture (CEA) has become one of the advanced methods of agriculture, in which the environmental conditions are strictly controlled to improve crop production and its quality. Nevertheless, due to its intensive, closed system, the risk of rapid disease development is high. Therefore, disease detection and proper management become crucial in ensuring successful cultivation within the framework of this method. This literature review aims to bring into consideration the importance of intelligent technologies, such as AI, ML, IoT, and monitoring via sensors in disease management in CEA. With the progress in the development of image analysis, spectral sensors, and environmental monitoring technology, plant diseases can now be detected on time in CEA. Algorithms in AI and ML (particularly deep learning methods) can accurately identify disease species from leaf images and multispectral data. It could be used for continuous observation of important elements in the environment, like temperature, humidity, and soil moisture. It helps in disease prediction and enables one to take the necessary precautions to save the crops from being destroyed. However, despite their sophistication, certain challenges that may include high costs incurred at the onset of implementation, complicated data, and necessary skills, among others, prevent them from being fully utilised. Future research must focus on cost-efficient and easily available technologies of smart farming.*

Keywords— *Controlled Environmental Agriculture; Artificial Intelligence; Machine Learning; Disease Detection; Internet of Things; Sensor-based Monitoring; Precision Agriculture.*

I. INTRODUCTION

The growing food requirements across the globe, urbanisation, limited agricultural land, and changes in climate have created the necessity to develop sustainable agricultural systems. The development of innovative systems like controlled environment agriculture (CEA), consisting of greenhouses, vertical farms, and plant factories, provides farmers with an opportunity to produce crops throughout the year by manipulating temperature, humidity, light, and nutrient requirements in the system [2][5]. These innovations enhance the efficiency and productivity of resource utilization while protecting from adverse climatic conditions [3]. Nevertheless, pests and plant pathogens pose a serious threat to CEA systems, which leads to considerable losses of the crop yield and quality[11]. Manual visual inspection, the only traditional method of identifying pathogens' occurrence, requires time and effort from specialists. Nevertheless, breakthroughs in the realms of IoT, AI, machine learning (ML), deep learning (DL), and computer vision techniques in recent times have opened up several opportunities for pest/pathogen management in agriculture operations [6][9]. AI algorithm and sensor integration make it possible for precision agriculture techniques to be adopted for pest management, such that sustainable production is achieved [10][15]. The objective of this study is to explore the advances made in AI techniques of pest and disease management in CEA systems.

II. CONTROLLED ENVIRONMENT AGRICULTURE (CEA)

A. Concept and Principles of CEA

Controlled Environment Agriculture (CEA) is an advanced form of agricultural production where environmental parameters like temperature, humidity, light intensity, carbon dioxide level, and nutrients are precisely managed for optimal crop production [1]. As opposed to traditional field agriculture, CEA allows the management of growth conditions in an artificial environment to provide year-round crop production unaffected by external climatic factors [1]. Some types of CEA are greenhouse, polyhouse, growth chamber, vertical farming, and plant factory, among others. All these production systems focus on enhancing crop productivity, quality, and efficiency of resource use with environmental management [2]. One interesting type of CEA is the use of vertical farming, where crops can be grown in stacks using optimal growth conditions in a limited area [4].

There has been a considerable rise in the uptake of CEA owing to growing demands for food production, rapid urbanization, reduction in the availability of productive land, and climate change effects [1].Current CEA facilities incorporate intelligent technologies that include sensors, automation, IoT, AI, and machine learning that allow continuous monitoring of environmental parameters and facilitate decision-making about the crops' growing environment [5][6]. Intelligent technologies used in current CEA facilities ensure real-time monitoring, analysis, and control of environmental parameters, which increases the efficiency of production [6].Moreover, closed and semi-closed CEA facilities greatly improve water and nutrient use efficiencywhile preventing external environmental influences on plant growth and minimising any production risk factors, including pests, diseases, or unfavourable weather conditions[3].When compared to other forms of agriculture, controlled environment agriculture allows more control over the crop production, increases in resource-use efficiency and quality of products, making CEA highly suitable for the cultivation of high-value crops in urban settings [2][4]. With ongoing technological development in CEA facilities, including increased automation and better environmental controls, controlled environment agriculture is becoming increasingly popular as a technology to ensure food security [5][1].

B. Types of Controlled Environment Agriculture Systems

Controlled Environment Agriculture (CEA) consists of several production techniques which differ in terms of environmental control intensity, sophistication of technologyemployed,and yields generated.The principal CEA production systems include greenhouses, polyhouses, vertical farms, plant factories, and growth chambers. Greenhouses constitute a popular type of protected cultivation system which provides regulated control over such parameters as temperature, humidity, ventilation, and light and which improves growth conditions and allows for continuous agricultural production [2]. Polyhouses represent a more economical option and are mostly used for cultivating vegetables, flowers, and nursery crops.Vertical farms have been recognized as one of the most advanced forms of CEA characterized by stacking of production beds, use of artificial light sources, and automated control of production processes [4]. The technique is also instrumental in sustainable urban agriculture due to its capability to produce higher crop yields in less space [7]. PFAL provides even more environmental control when it comes to temperature, humidity, carbon dioxide, and nutrition [2]. Current CEA facilities use various technology applications to improve production, such as the application of sensors and automatic controls [5].

C. Advantages of Controlled Environment Agricultre

There are several benefits of using Controlled Environment Agriculture when compared with conventional agriculture due to the precision control of the environmental factors which affect plant development and growth. One of the primary advantages of controlled environment agriculture is the capability of growing plants throughout the year regardless of the season and weather conditions; therefore, consistent food supply and production can be guaranteed [1]. This is because of such elements as the temperature level, humidity, light intensity, carbon dioxide levels, and others are being regulated to ensure better crop production.Additionally, CEA provides an efficient utilization of resources since modern production methods, such as greenhouse agriculture and plant factories, require fewer energy and material resources than conventionalagriculture[2].In addition, the application of automation technology improves the utilization of water and nutrients, hence making the production process more efficient [5].

CEA is also useful in making agriculture more sustainable due to its reduced reliance on arable lands and mitigating the impact of climatic variability. Protection from external environmental factors, including very high or low temperatures and too much rain or lack of rain, makes crop yields more predictable through the use of CEA techniques. Furthermore, by creating a protected area where the crops will not be exposed to any diseases or insects, less pesticide use will result.

D. Disease Risk and Challenges in CEA Systems

Although there are many benefits of using Controlled

Environment Agriculture (CEA), one of the major challenges is the ability to manage crop diseases. This is because plants in such production systems are cultivated under very favorable conditions of temperature, humidity, and lighting which allow for the quick development and spread of fungal, bacterial, and virus infections. Higher plant density, less air circulation, and high humidity levels tend to favor the development of plant diseases [9]. Plant diseases are among the main causes of loss of quality and quantity in agriculture that result in significant economic damages each year. Crop loss due to diseases and pest infestations is estimated at about 20% – 40% on average annually [10]. It should be noted that the high density of plant growth in the CEA system makes disease outbreaks quite fast-spreading, which means that their timely detection is crucial. The conventional techniques used to detect diseases are mostly based on visual observations and expertise, which are not only lengthy but also involve high levels of laboriousness and human error. This is why the application of technology to detect and monitor plant diseases has been gaining significance. In recent times, much attention has been paid to the use of sensing devices, imaging, AI, ML, and IoT in the field of disease monitoring and forecasting [12][9].

III. SMART TECHNOLOGIES FOR DISEASE AND PEST DETECTION IN CONTROLLED ENVIRONMENT AGRICULTURE

A. Internet of Things(IoT) in Disease Monitoring

Another innovation that will play a critical role in disease detection and management will be the Internet of Things technology (IoT), whose importance in disease monitoring and management in CEA has increased in recent years [9] [6]. This is owing to the ability of the IoT technology to combine the functions of sensors, communication networks, controllers, and cloud platforms, thereby allowing real-time monitoring and collection of crop development information, as well as information about other environmental conditions [9][5]. In this regard, IoT technology helps to monitor in real time such parameters as air temperature, humidity, soil moisture, CO2, and light intensity. Sensors enable constant monitoring of the growth process and detecting conditions which are considered to be unfavorable for developing diseases [5][9]. Data collected from the sensor network can also be transferred using wireless technologies to support decision-making [6]. Current scientific literature confirms that IoT could contribute significantly to disease prevention and control as the innovative way to detect the environment conducive to diseases [9] [6]. Besides, sophisticated AI-IoT applications require the implementation of environmental sensors, together with cameras and artificial intelligence to facilitate automated detection of plant diseases [10] [6]. For instance, Ibrahim et al. (2025) suggested using an innovative AI-IoT technique with the use of cameras, sensors, and deep learning algorithms for rapid detection and disease prevention[10]. Thus, this allows keeping track continuously, making the process quick and more precise [10]. Implementation of IoT technologies in CEA is considered one of the possible approaches to intelligent and sustainable management of plant diseases [9] [5][10].

B. Sensor Technologies for Disease Detection

Sensor technologies constitute an essential component of smart disease detection systems in controlled environment agriculture (CEA) since sensors provide a way of continuously monitoring the environmental conditions as well as crop conditions that affect the development of diseases [13] [5] Sensors for measuring temperature, relative humidity, soil moisture, CO2 concentrations, and light intensity can be used in environmental monitoring in order to collect data on key conditions for the growth of pathogens and development of diseases[9] [5] . Continuous monitoring of environmental conditions makes it possible to detect conditions conducive for disease outbreaks and implement appropriate measures to mitigate the risks [5]. When it comes to contemporary agriculture, one can utilize sensors for the early detection of plant diseases [11] [15]. Through the use of various technologies, such as RGB cameras, thermal cameras, multispectral sensors, and hyperspectral imagers, it becomes possible to recognize changes in the biochemical composition and physiology of the crops without any manifestation of the disease symptoms [11].

With the development of sensors, it is now possible to incorporate them in the AI and machine learning algorithms to detect diseases automatically [14] [10]. The information received from the sensors can help to find the anomalies in plant health, including those related to diseases and stress experienced by the crops [9]. Furthermore, sensors combined with deep learning models have increased the accuracy of the process of disease detection regardless of crops [15] [16].

C. Artificial Intelligence and Machine Learning for Disease Detection

Application of machine learning approaches as well as artificial intelligence technologies has become an essential technology which has been used to detect diseases in CEA farming activities [9][10]. This is due to the fact that artificial intelligence technologies have been very helpful in handling large amounts of data obtained from sensors or imaging, for the purposes of detecting diseases, predicting diseases outbreaks, and decision-making [9]. Before the advent of artificial intelligence, diseases were manually detected through the examination of the plant's health condition.

Different machine learning algorithms such as SVM, RF, decision trees, and K-Nearest Neighbour (KNN) have been used extensively for classifying and predicting diseases using data from environmental and crop conditions [9]. Using machine learning techniques allows identifying the complex relationship between environmental factors and diseases, thereby establishing early warning systems [9]. Nevertheless, with the help of deep learning algorithms, machine learning algorithms have become more effective in disease detection through image analysis [15]. CNN algorithm has been widely used within deep learning algorithms since it can effectively detect the symptoms to predict the existence of disease and extract accurate features [18]. Furthermore, deep learning algorithms including ResNet, EfficientNet, Vision Transformers (ViT), and YOLO have successfully predicted diseases in plants with different types of crops [17].Theprediction of diseases has become significantly easier since deep learning models have achieved highly accurate results up to 95% [15] [17].Combining artificial intelligence and IoT systems for disease monitoring purposes is expected to lead to increased efficiency and effectiveness of the process [10]. Artificial intelligence, combined with the IoT system, is able to analyze data received via sensors and images to identify disease, trigger alarm, and give suggestions about how to solve the problem [10]. As a result, AI, and machine learning are making disease control measures increasingly smarter [9] [10] .

D. Deep Learning Models for Plant Disease Classification

The following techniques have proved to be very effective in automating the process of plant disease identification and classification: deep learning algorithms [15][17]. Unlike traditional machine learning algorithms that require human input to generate features of the diseases, deep learning algorithms can automatically generate hierarchical disease features by analyzing images, which increases efficiency [15]. Such an algorithm is particularly beneficial for CEA because of the significance of rapid disease detection and treatment to maintain the health of the plants. CNN is one of the deep learning algorithms extensively used in plant disease diagnostics due to its ability to recognize complex visual characteristics of affected plants [19][15] . Multiple pieces of research have proven that deep learning models, based on convolutional neural networks, are superior to conventional machine learning algorithms in terms of disease identification [19]. It was demonstrated that the models had the accuracy rates of over 99 percent in diagnosing diseases using deep convolutional neural network training on massive data sets of images of plants suffering from different diseases [19]. Many architectural approaches have been developed in the field of deep learning model architecture development including such architectures as Residual Networks (ResNet), EfficientNet, YOLO (You Only Look Once), and Vision Transformer (ViT) [17]. Recently, ResNet architectures and specifically, ResNet50 architecture gained immense popularity due to their ability to solve the problem of vanishing gradient and provide classification with high precision [10]. Furthermore, it should be mentioned that EfficientNet model architecture is characterized by high computational efficiency and accuracy [17]. The same applies to the YOLO algorithm used for real-time detection of diseases. Deep learning algorithms used along with IoT-based disease monitoring systems have made improvements in disease management within the CEA system [10]. The analysis of images and sensors carried out by such systems enables early detection of disease symptoms, issue alarms, and make decisions automatically [10]. Hence, with the help of these technologies, it becomes possible to convert traditional disease management into intelligent crop protection systems [15][17].

E. Sensor Technologies for Pest Detection

It is difficult to overlook the significance of sensors in pest monitoring in the present era because sensors enable the real-time monitoring of pests and take actions against them prior to them doing any damage in the CEA framework [21][22].Traditional methods of pest surveillance rely on visual observations which can prove to be tedious and also human error-prone [22]. As such, research has advanced towards integrating the usage of sensors in pest surveillance systems. Imaging sensors happen to be one of the most common pest monitoring techniques used in controlled environment agriculture. They utilize an RGB camera that can take high-quality images which help detect the presence of pests, infestation rates and can even be used to establish classification processes through automation [21]. Machine learning techniques using vision-based sensing have been found to be efficient in classifying agricultural pests based on image data sets with SVM models [22]. Moreover, other types of sensing, like thermal imaging and multispectral/hyperspectral imaging, enable pest monitoring by detecting plant stress reactions before visual symptoms become apparent [15].Sophisticated insect traps using cameras and wireless connectivity technology have been increasingly popular due to their capacity to conduct automated pest surveillance [21]. In such cases, the image of captured pests is automatically transmitted through cloud computing systems for subsequent processing and decision-making [21]. Environmental sensors that detect temperature, humidity, and lighting also contribute to pest control by identifying conditions that promote pest growth and reproduction [10]. With the incorporation of these sensors with IoT applications, pest surveillance can be even more efficient by means of immediate data acquisition and alerting systems [10][21]. Therefore, sensor-based systems for pest surveillance represent efficient groundwork for intelligent pest management strategies as well as sustainable crop protection in contemporary CEA [22][15].

F. AI-Based Pest Detection System

AI is currently used as an effective method of detecting and monitoring pests for CEA through its capability to analyse large amounts of images or sensor data with great accuracy [15][10] . The common insect pests that infest greenhouses and other vertical farms include whiteflies, aphids, thrips, spider mites, and leaf miners, among others, and they may lead to serious crop damage and losses if undetected at their early stages [21]. Manual pest monitoring methods are usually laborious and time-consuming, and they may be inefficient in detecting pests in large production facilities [21]. With the appearance of new technologies related to computer vision and deep learning, the efficiency of automatic insect detection has been significantly increased [20] [17] . Due to the image analysis performed through the use of pictures acquired by camera devices, sticky traps, and other sensors for insect monitoring, deep learning is capable of helping to classify insect species, measure their population, and monitor infestations dynamically [20]. Also, due to the ability to recognize complex patterns in insect images, CNN proves to be one of the most efficient algorithms for insect classification [15]. In addition, insects in the greenhouses can be identified through object detection techniques like the YOLO technique[17].Nowadays, AI-based insect monitoring systems are widely adopted, complemented by IoT-based systems which are able to perform continuous monitoring and send automatic notifications about the presence of pests [10]. Data obtained with the help of sensors and cameras can then be uploaded to the cloud system, which will perform further analysis of the data using machine learning algorithms and give warning notifications on insect activity [10]. According to [21], deep learning-based systems have proved highly accurate when it comes to the detection of several types of insects that could become pests in greenhouses. In such a way, AI-based systems become a crucial element of smart farming techniques [20][21].

IV. PEST AND DISEASE FORECASTING AND EARLY WARNING SYSTEM

A. Environmental Factors Influencing Pest and Disease Development

Environmental conditions play an essential role in forecasting the occurrence, formation, and spread of pests/pathogens in CEA farms [9]. In contrast to the open field production system, which utilises environmental factors beyond its control, CEA systems like the greenhouse, vertical farm, and plant factory provide strictly controlled environmental conditions, affecting the viability of pathogens and pests directly [2]. Therefore, studying the link between environment and biological factors is necessary to establish a forecasting and warning system. Temperature is one of the most important influencing environmental factors on pests and diseases in greenhouse conditions [9]. Increased temperature causes an acceleration of the development of the disease-causing organisms, reduced development time of insects, and faster reproduction of pests, which can quickly lead to their population explosion and development of diseases [9]. Similarly, relative humidity is another important factor that influences the occurrence of diseases, especially fungal and bacterial pathogens that need moist air for infection and sporulation [9]. The increase in humidity within the greenhouses can lead to higher disease incidences such as powdery mildew, downy mildew, and Botrytis. Other than temperature and humidity, other environmental factors include light intensity, CO2 level, ventilation, and leaf wetness duration [2]. Pest and disease management through the use of an IoT system with environmental sensors facilitates monitoring of environmental conditions, which support the spread of disease and pests at all times [10]. Based on what is observable, the analysis of environmental conditions is a key component in modern predictive techniques [9][10].

B. Pest and Disease Forecasting Models

Forecasting models are essential in contemporary pest and disease management as they enable early prediction of potential pest outbreaks without leading to substantial harm to crops [9]. Forecasting models make use of the available information concerning environmental conditions, biology of pests/diseases, as well as their impacts on the particular crop(s). The importance of forecasting in CEA can be attributed to constant monitoring of the environment within which plants grow, thus making it easy to integrate environmental parameters into forecasting decisions [10]. Historical forecasting methods utilised statistical models where predictions would be made based on the data collected about past occurrences of diseases [12]. With recent improvements in artificial intelligence, forecasting has been made easy by identifying relationships between different variables. Artificial intelligence applications such as SVM, RF, ANN, and deep learning have been widely used in predicting the probability of the occurrence of diseases and pest growths under varying environmental conditions [9]. Further developments in the technology due to the increase in real-time sensors have significantly contributed to the improvement of forecasting systems [10]. Factors like temperature, humidity, carbon dioxide concentration, light intensity, and the leaf wetness duration are among the environmental factors that can be examined to understand when conditions become favourable for the development of diseases and growth of pests [9]. AI-based forecasting methods can make sense out of such huge data and provide risk assessment reports from which mitigating measures can be formulated to counter infestations before any attack [15]. Recent research shows that the integration of IoT, machine learning techniques, and environmental sensing methods has been found highly effective in improving forecasting accuracy and minimising loss caused by the attack on crops by pests and diseases [9][10].In this context, the application of forecasting models is no longer optional to any smart agriculture solutions that contribute to protecting crops from possible threats to make CEA systems sustainable and effective [9][12].

C. IoT-Enabled Early Warning System

Early warning systems based on the Internet of Things have become crucial for any forward-looking approach towards pest and disease management in CEA [9]. IoT-based systems include sensors and communication networks, along with cloud platforms, for measuring plant health parameters, such as temperature, humidity, moisture content, and CO2 concentration [5]. As a result of constant sensing, IoT-enabled solutions ensure identification of the conditions in the environment which lead to pest and disease development [9]. Use of IoT technology and artificial intelligence (AI), like machine learning, will ensure improved efficiency of the early warning systems due to analysis of the environmental and agronomic data [10]. With the help of predictive models and predefined thresholds, the technology enables effective triggering of warnings as well as formulation of appropriate action plans [6]. Finally, due to the use of opportunities provided by smart agriculture through the application of IoT and deep learning models, recent research confirms an ability to automate the process of disease detection and crop monitoring [23]. Besides, emerging areas like explainable artificial intelligence and vision transformers help in increasing the efficiency of intelligent crop monitoring systems [24]. It has been shown that the integration of AI-IoT has the ability to improve the precision and speed of such crop monitoring systems, which include constant monitoring as well as automatic warning systems [9][10]. This means that IoT-based early warning systems have now become a fundamental aspect of intelligent crop protection systems in modern-day CEA systems.

D. Decision Support System for Pest and Disease Management

The use of DSS can prove helpful for the management of pests and diseases in CEA because they convert large amounts of agricultural data into recommendations [9]. This type of technology employs data obtained from sensors, imaging, past history and forecasting techniques to ensure proper decision making [6]. It is worth mentioning that currently, DSS may be understood as technologies using AI and ML approaches to analyse information and assess risks posed by pests and diseases [10]. Due to the potential of predictive analytics and the application of the early warning system, DSS is able to provide farmers with necessary recommendations about environmental change and the emergence of pests or diseases [9]. Moreover, the development of the Internet of Things solutions improved the functionality of DSS due to the process of permanent data acquisition and monitoring of the state of the plant remotely [23]. Besides, advances in explainable AI led to a better comprehension of decisions made by DSS [24]. In conclusion, DSS is considered to be one of the most useful techniques used in achieving precision crop protection in CEA [9][10].

V. SMART PEST AND DISEASE MANAGEMENT STRATEGIES

A. Automated Disease Diagnosis and Monitoring

The automation technologies are applied for the development of an efficient diagnostic system that can help in improving the safety level of plants in CEA [10]. Various measures have been employed for ensuring proper monitoring and diagnosing of the plant diseases using methods like employing imagery technologies, sensors, and artificial intelligence [15]. Deep learning approaches, combined with machine learning, have gained popularity in the diagnosis of plant diseases through image analysis. It means that the models of CNN, ResNet, and Vision Transformers may provide accurate results [9][24]. IoT technology may increase the effectiveness of plant disease management in Controlled Environment Agriculture (CEA). With the help of such technology, it is possible to collect information about the crops and evaluate their health status. This means that sensors, cameras, and other IoT devices used in agriculture may be easily connected to the Internet, and therefore any abnormalities in the development process may be identified instantly [23]. In conclusion, it should be noted that automation technology plays an important part in increasing sustainability in smart agriculture and disease management [9] [15].

B. Precision Pesticide Application

This system of accurate spraying of pesticides has been developed and used for pest management and the prevention of crop diseases through chemical interference in crop cultivation by using CEA technology, which depends on the type of crop and the level of infestation [9]. Unlike the conventional spraying approach, precise pesticide application ensures that the unnecessary use of the chemical is avoided by limiting the spraying only to those places where it is required [6]. This is because the crops that require spraying of chemicals have to be identified through AI and machine learning technologies [10]. Therefore, the use of this method not only improves pest management efficiency but also ensures that minimal amounts of chemicals are introduced to the environment. Additionally, advancements in automated spraying technology and AI algorithms used in decision-making have resulted in the more precise administration of pesticides in greenhouses [6]. By using AI algorithms, it is possible to apply a necessary amount of pesticide, taking into account environmental factors and crop needs [10]. The application of such an approach enables better sustainability of pest and disease control. To conclude, accurate pesticide application is among the ways to increase pest and disease management efficiency.

C. Robotic and Autonomous Pest Management

Robotics and autonomous systems are being used more commonly nowadays in CEA for increasing the efficiency and precision of pest management activities [9]. In other words, robotics, AI, computer vision, and IoT are being used for performing pest monitoring, detecting and management without significant human intervention [10]. With the help of cameras, sensors, and image analysis system, autonomous robots can conduct constant scouting of crop plants for spotting any signs of pest infestations [21]. The information collected from visual data and environmental variables is used to find pest hotspots and the severity of an infestation [15]. As a result, robot systems provide much better results than humans in terms of accuracy and efficacy [9]. It is worth noting that the development of robotic systems has allowed the creation of autonomous robots with robotic sprayers that are capable of precise application of pesticides on affected spots of crops [6]. The information obtained by sensors, as well as machine learning algorithms, helps robots determine affected areas in the field [10]. Autonomous robots can work constantly in greenhouses and vertical farms with no need for labour. Generally, there seems to be potential in the application of robotic and autonomous solutions for crop protection in CEA systems since they enhance the precision agriculture approach [9] [10].

D. Intregrated Pest and Disease Management (IPDM)

IPDM is a combination of different techniques that can help sustainably manage pest and disease problems, including biological, cultural, physical, and chemical methods [9]. With respect to CEA, IPDM tries to achieve sustainable production while ensuring that no considerable damage is caused by pests and diseases without the use of chemicals as a sustainable strategy [10]. The current developments in technologies such as artificial intelligence, IoT, and sensors make IPDM adoption possible through constant monitoring of crops and their surrounding environment in order to detect any signs of infestation or disease [6]. These signs can be detected earlier, and therefore preventive actions can be taken even before any losses arise [9]. In fact, the use of biological control that uses predators or parasites, along with the use of beneficial microbes is common practice in IPDM in greenhouse and vertical farming practices [15]. It should be noted that biological control can also be incorporated into other strategies such as proper use of pesticides and environmental practices to ensure plants are protected without harming the environment [10]. Lastly, decision support system and decision-making through artificial intelligence provide important data in making sure that farmers make the right decisions when needed [24]. Overall, the integration of IPDM is an ideal method of protecting plants through incorporation of technology in conventional methods [9][10].

E. Smart Greenhouse Management Platforms

Modern smart greenhouse management platforms use sensors, IoT, artificial intelligence, automated processes, and decision-making tools for improved performance and safety in crops grown in CEA systems [5]. Through this, the platforms provide constant tracking of parameters, pests, and diseases that might affect the crops, hence helping farmers make informed decisions on managing their farms. With the help of sensors and cloud computing, data could be collected, processed, and analysed from multiple sources [6]. By using artificial intelligence systems to analyse environmental and crop data, abnormal trends can be detected, and the appropriate action taken to protect crops from diseases and pests. The smart greenhouse management systems of today can also be used to automate various processes such as irrigation, fertilisation, climate control, and pest management [5]. Through the use of forecasting, early warning, and decision-making models, the system provides a complete solution to precision agriculture management [24]. In addition, with the help of the remote monitoring system, farmers can monitor their greenhouse activities from any point. Implementation of the smart greenhouse management system can be seen as a result of the interrelation between several agricultural technologies, which leads to an effective solution for increasing productivity and efficient use of available resources in controlled environments agriculture (CEA) systems [9][10].

VI. CHALLENGES AND LIMITATIONS

Although great developments have been made in terms of AI, Internet of Things, machine learning, deep learning, and automation technologies that can be used in pest/disease detection within Controlled Environment Agriculture (CEA), there are certain challenges that hinder the successful implementation of these technologies. Some of the challenges include the following, according to various studies:

- The high initial cost of acquiring sensors, camera-based image acquisition technology, IoT systems, automation/roboticstechnology, andgreenhouse/vertical farms [1][5].
- High costs of operations, especially those that relate to the cost of lighting the plants artificially, controlling the climate and environment in factory plantations, and in the case of vertical farms [3][2].
- Technical problems due to the lack of appropriate funding and infrastructure required for the deployment of new technology on farms of smaller sizes [7][9].
- Problems associated with incorrect data due to the noise in the data collection process through noisy sensors [10][13].
- A huge amount of labelled data is needed to train the machine/deep learning models for the identification of pests and diseases [15][17].
- Application of the algorithms developed using artificial intelligence is constrained when transferred to other different crops/environments [18][24].
- Artificial intelligence algorithms are inefficient outside a laboratory environment or on farm land or greenhouse [19][21].
- Difficulties related to applying machine learning models for the identification of disease in crops are owing to the difficulties in detecting some symptoms of diseases under various environmental conditions, including image processing [11].
- Availability of Internet and cloud computing for making observations and decisions about farm activities [6].
- Technical problems associated with the implementation of the Internet of Things, wireless communications, AI, and control technologies in the greenhouse owing to the incompatibility of the standards of the respective technologies[6][10].
- Cost-related problems in adopting AI technologies for the reason that such technologies need computational capabilities [14][16] .
- Validation problems for AI systems and IoT technologies as well as their applicability in practice in view of the limited validation by scholars and other practical studies [19][21] .
- Issues related to the ethics of autonomous vehicles and

AI, as well as data used in agriculture [24][6].

All these issues should be solved to deploy efficient future strategies in pest and disease management in CEA.

VII. FUTURE RESEARCH DIRECTIONS

- Further studies can be conducted on the creation of new, more effective AI models that could perform successfully under different conditions, depending on plant type and weather factors [9][15].
- It is necessary to collect large amounts of various data for better training of artificial intelligence models.
- It is also desirable to use Explainable Artificial Intelligence (XAI) for making decisions using such models [14][24].
- The implementation of a new solution might involve the usage of different kinds of sensors, among which RGB, thermal, multispectral, and hyperspectral cameras should be mentioned [11][15].
- Machine learning and deep learning models, along with the network of sensors, are important elements of effective pest and disease early warning systems.
- A further research direction includes advancing autonomous agricultural technologies like robotic monitoring, precision spraying, and greenhouse monitoring [6].
- AI and IoT solutions for agriculture should become cheaper and consume less power to attract small and medium enterprises to use such technologies.
- There is also a need to conduct field trials on commercial farms to assess the performance of AI-based pest and disease control systems.
- Seek to improve interoperability between your sensors, communication system, cloud platform, and decision systems for effective integration of digital agriculture technologies.
- Design an AI-IoT system that is sustainable and will boost crop yields without damaging the environment or consuming too many resources.

VIII. CONCLUSION

The sustainability concept of agricultural products is controlled environment agriculture (CEA). CEA ensures that crops are protected through effective environmental control. The effectiveness of this process has been increased tremendously due to the use of IoT, AI, machine learning, deep learning, and automation in the process. As a result, it has become easier to forecast any diseases and pests. It improves the productivity of crops while saving resources at the same time. There are many challenges, such as the high cost of implementation, the lack of information, and the complexity associated with the technology. However, there are possibilities for enhancement in the form of accessibility.

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Off-Season Production of Tomato (Solanum lycopersicum) Using Protected Cultivation

Solanki Bal

Assistant Professor, School of Smart Agriculture, Adamas University, Kolkata-700126

Email- solanki.b@adamasuniversity.ac.in

Abstract—Off-season production of horticultural crops offers a strategic approach to enhance farmer income, stabilize market supply, and meet consumer demand beyond natural growing periods. Tomato (Solanumlycopersicum), a widely consumed vegetable, is highly sensitive to temperature and environmental fluctuations, making it a suitable candidate for off-season cultivation under controlled conditions. Off-season tomato production can be achieved through a feasible approach using low-cost protected cultivation techniques such as polyhouse or shade-net structures combined with suitable agronomic practices.*

This involves selecting heat- or cold-tolerant hybrid varieties, raising healthy seedlings in pro-trays, and transplanting them into a controlled environment where temperature, humidity, and irrigation are partially regulated. Drip irrigation and fertigation ensure efficient nutrient and water management, while mulching aids in moisture conservation and weed control. Simple ventilation and shading techniques are used to mitigate temperature extremes, making the system adaptable even for small and marginal farmers.

Under this system, growers can achieve improved yield, better fruit quality, and reduced pest and disease incidence compared to open-field cultivation during unfavourable seasons. Economic analysis highlights higher profitability due to premium market prices during the off-season, despite moderate initial investment. The approach is practical, scalable, and environmentally sustainable, as it optimizes resource use and reduces dependency on chemical inputs. Off-season tomato production through protected cultivation thus represents a viable and implementable strategy that significantly contributes to income generation, crop diversification, and year-round vegetable availability. This concept can be extended to other horticultural crops with minor modifications, offering a promising avenue for modern agricultural practices.

Keywords— *Moringa oleifera, Miracle Tree, Beverage, Antioxidant, Mint, Pineapple, Protein, Appearance.*

I. Introduction

Tomato (Solanum lycopersicum L.) is one of the most widely cultivated vegetable crops globally owing to its nutritional value, culinary versatility, and economic importance. It is an excellent source of vitamins, minerals, antioxidants, and lycopene, which contribute significantly to human health. However, tomato productivity is highly influenced by environmental factors such as temperature, humidity, rainfall, and solar radiation. Fluctuations in these factors frequently result in reduced fruit set, poor quality, increased disease incidence, and substantial yield losses under open-field conditions [1,2].

The increasing demand for fresh vegetables throughout the year has necessitated the development of production systems capable of overcoming seasonal constraints. Protected cultivation has emerged as an efficient technology that enables crop production under partially or fully controlled environmental conditions. Structures such as naturally ventilated polyhouses, greenhouses, shade-net houses, and low tunnels create a favourable microclimate for plant growth and facilitate off-season cultivation [3,4]. Protected cultivation offers several advantages, including enhanced productivity, improved fruit quality, efficient water and nutrient management, reduced pest pressure, and protection from adverse weather conditions [1,3]. The technology is particularly beneficial for high-value vegetable crops such as tomato, cucumber, and capsicum, where market prices during the off-season are significantly higher than during peak production periods [2,5].

Tomato cultivation under protected structures has demonstrated substantial improvements in resource-use efficiency through the adoption of drip irrigation, fertigation, mulching, and precision crop management practices [6]. Studies have shown that optimized crop geometry, fertigation schedules, and environmental regulation can significantly improve yield and profitability while reducing production risks [7,8].

Recent advances in protected horticulture have also integrated climate monitoring, sensor-based management, image-based crop monitoring, and automation systems to improve decision-making and productivity [9,10]. Such innovations are increasingly important in the context of climate change, where unpredictable weather events pose serious challenges to conventional agricultural systems.

Off-season tomato production under protected cultivation not only ensures year-round vegetable availability but also contributes to income enhancement, crop diversification, and sustainable agricultural development. Therefore, understanding the principles, management practices, and economic feasibility of protected cultivation is essential for promoting its wider adoption among farmers and stakeholders [4].

II. Concept of Off-Season Tomato Production

Off-season production refers to the cultivation of crops outside their normal growing period. In tomato, off-season production aims to bridge the gap between market demand and seasonal availability. The technology allows farmers to supply fresh produce when market prices are generally higher.

Protected cultivation minimizes the adverse effects of temperature fluctuations, excessive rainfall, strong winds, and pest pressure. It provides an opportunity to cultivate tomatoes throughout the year while maintaining productivity and fruit quality.

III. Protected Cultivation Structures

A. Polyhouse Cultivation

Polyhouses are framed structures covered with transparent polyethylene sheets that allow light penetration while protecting crops from adverse weather conditions. They create a favourable microclimate for plant growth and enable cultivation during both hot and cold seasons.

B. Shade-Net Houses

Shade-net houses are comparatively economical structures designed to reduce excessive solar radiation and temperature stress. These structures are particularly useful in regions experiencing high temperatures during the summer months.

C. Low Tunnels and Walk-in Tunnels

Low tunnels and walk-in tunnels provide temporary protection against unfavourable weather conditions. They are suitable for small-scale farmers and require lower initial investment compared to polyhouses.

IV. Crop Establishment and Nursery Management

The success of off-season tomato production largely depends on the quality of seedlings used for transplanting. Healthy seedlings can be produced using pro-trays filled with sterilized growing media.

Seedlings should be maintained under protected conditions to ensure uniform germination and growth. Proper irrigation, nutrient management, and disease prevention during the nursery stage contribute significantly to successful crop establishment.

V. Crop Management Practices

A. Variety Selection

Selection of suitable varieties or hybrids is essential for successful off-season production. Heat-tolerant and cold-tolerant hybrids capable of performing under protected environments should be preferred.

B. Transplanting

Seedlings are transplanted into raised beds prepared inside protected structures. Proper spacing ensures adequate light interception and air circulation.

C. Irrigation and Fertigation

Drip irrigation is widely adopted in protected cultivation systems. It enables precise water application and minimizes wastage. Fertigation allows efficient nutrient delivery through irrigation water, resulting in better nutrient-use efficiency and improved crop growth.

D. Training and Pruning

Training and pruning practices help maintain plant architecture, improve light penetration, and enhance fruit quality. Removal of side shoots and proper support systems facilitate better crop management.

E. Mulching

Plastic mulch reduces weed growth, conserves soil moisture, and improves soil temperature conditions. It also contributes to cleaner fruits and reduced disease incidence.

VI. Pest and Disease Management

Protected cultivation significantly reduces exposure to several pests and diseases. However, regular monitoring remains essential. Integrated Pest Management (IPM) strategies involving cultural, biological, and need-based chemical control measures should be adopted.

Common diseases affecting tomato include early blight, late blight, bacterial wilt, and viral diseases. Proper sanitation, resistant varieties, and environmental management contribute to effective disease control.

VII. Economic Feasibility

Protected cultivation requires moderate initial investment for the construction of structures and installation of irrigation systems. Despite these costs, the technology offers substantial economic benefits.

Higher yields, improved fruit quality, reduced crop losses, and premium market prices during the off-season contribute to enhanced profitability. The return on investment is often favorable, particularly when market demand is high.

VIII. Environmental Benefits

Protected cultivation promotes efficient utilization of resources such as water and fertilizers. Drip irrigation reduces water consumption, while fertigation minimizes nutrient losses. Reduced pesticide usage contributes to environmental sustainability and safer food production.

The technology also supports climate-resilient agriculture by reducing the impact of extreme weather conditions on crop productivity.

IX. Future Prospects

The growing demand for high-quality vegetables and increasing climatic uncertainty are expected to accelerate the adoption of protected cultivation technologies. Integration of automation, precision irrigation, and climate monitoring systems can further enhance productivity and resource-use efficiency.

Government support programs and training initiatives can facilitate wider adoption among small and marginal farmers.

X. Conclusion

Off-season tomato production through protected cultivation represents an effective and practical strategy for improving productivity, profitability, and sustainability in horticultural production systems. By combining suitable varieties, efficient crop management practices, and protected structures, farmers can achieve year-round tomato production and benefit from premium market opportunities. The technology has significant potential to contribute to food security, income generation, and sustainable agricultural development.

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Advances in Climate-Resilient Agriculture: A Review of Smart Technologies for Adaptation and Mitigation

Siddhant Ray Bharti
Department of Agriculture
Adamas University
Kolkata, India
siddhantraybharti@gmail.com

Rupsha Roy
Department of Agriculture
Adamas University
Kolkata, India
rupsharoy079@gmail.com

Shreya Das
Off-Season Production of Tomato
(Solanum lycopersicum)
Using Protected Cultivation

Abstract—*The impacts of climate change present many problems for global agricultural production, food security, resource management, and ecological balance. As a solution, climate resilient agriculture can increase adaptation capacities of agricultural production and provide an opportunity to mitigate its effects. This study reviews the literature on advanced technologies applied in climate resilient agriculture with emphasis on both adaptation and mitigation strategies. The areas of technology reviewed include artificial intelligence technology, IoT-based monitoring systems, precision agriculture, smart irrigation, controlled environment agriculture, and decision support systems based on data analysis. The effectiveness of the reviewed technologies in improving resource use efficiency, providing real time monitoring, efficient input application, and forecasting ability is analyzed critically. Technologies related to adaptation are discussed as well as technologies addressing mitigation issues like reducing the carbon footprint, energy efficiency in farming, and precision nutrient application. Finally, technologies integrated into a smart farm system are explored as a way towards sustainable intensification of agriculture production.*

Even with their numerous advantages, the application of these technologies is still hampered by various limitations like financial constraints, infrastructural limitations, among others, especially within developing nations. The literature review highlights some important areas that require further research. In summary, this paper gives an insightful account of the emerging technologies in relation to the development of climate resilient agriculture systems.

Keywords— *Climate-Resilient Agriculture, Smart Farming Technologies, Climate Change Adaptation, Precision Agriculture, Internet of Things (IoT), Artificial Intelligence (AI), Sustainable Agriculture, Smart Irrigation, Controlled Environment Agriculture, Digital Agriculture.*

I. INTRODUCTION

While agriculture is a cause of climate change, it is also one of its victims. It contributes around 24% to greenhouse gas (GHG) emissions, but at the same time, the agriculture sector is suffering from climatic issues like higher temperatures, irregular rainfall patterns, and greater climatic extremes (FAO, 2013; Pandey & Singh, 2024). With the rise in population and changes in people's food habits, the world food requirement will see an increase of about 70% by 2050 (FAO, 2013).

Due to climate change, crop production faces the risk of yield losses due to factors such as heat, drought, floods, soil degradation, pest outbreak, and water scarcity. Projections suggest yield losses of staple crops like wheat, rice, and maize under climate change situations, especially in tropical and subtropical areas (Devarajan et al., 2026). Therefore, there is an immediate need for sustainable agricultural practices that can cope with climatic challenges.

Climate-resilient agriculture (CRA) refers to agriculture that can plan, cope, adapt to, and quickly recover from climate-related impacts (IPCC, 2012). In turn, Climate Smart Agriculture (CSA) is a term introduced by FAO. It pursues three main goals, which are increasing productivity, resilience, and lowering greenhouse gas emissions (FAO, 2013). Various technologies have significantly contributed to the effectiveness of CSA.

II. CLIMATE CHANGE IMPACTS ON AGRICULTURE

The effects of climate change are manifested in changes in agricultural production throughout many areas in the world. Higher temperatures will hasten the development of crops, shorten the filling period of the grain, and lower yield potential (Devarajan et al., 2026). Heatwaves during flowering in wheat and rice will lead to pollen sterility.

Availability of water is yet another vital concern. Effects of changed rainfall, drought, and higher levels of evaporation result in a reduction in the availability of water for agricultural purposes. The changes in weather conditions have been associated with considerable reductions in crop yield and risks in production in South Asia and Sub-Saharan Africa (IPCC, 2022).

Livestock farming also faces challenges, since the effects of heat stress result in reduced feed intake, reproductive capacity, lactation, and animal welfare. Also, fisheries and aquaculture face challenges because of changes in aquatic ecosystems due to increases in water temperature and ocean acidification (Devarajan et al., 2026).

There is an additional risk of impacts on food quality and safety. Higher levels of CO_2 in the atmosphere result in lower levels of protein, iron, and zinc in crops, and higher temperatures lead to increased occurrence of mycotoxins and foodborne diseases (Myers et al., 2014; Devarajan et al., 2026).

III. PRECISION AGRICULTURE AND DIGITAL TECHNOLOGIES

Precision agriculture is considered to be one of the most promising technologies for making farms climate resilient. This technology uses information technologies in order to manage inputs in agriculture.

A. Remote Sensing and Geographic Information Systems

Satellite imaging, drones, and Geographic Information System help monitor the state of crops, moisture content in soils, vegetation indexes, and other environmental factors. They can assist farmers in detecting stress symptoms early on and implementing specific measures to address them (Zhang et al., 2014).

Monitoring of crops using remote sensing is another application of technology for large-scale crop surveillance, risk assessment for climate, drought surveillance, and estimation of crop yields.

B. Internet of Things (IoT)

IoT agriculture employs sensor networks for collecting information on soil moisture, temperature, humidity, nutrient status, and weather conditions. The data help in irrigation, nutrients management, and pest control applications (Wolfert et al., 2017).

Smart sensors can enhance resource efficiency because they help ensure that resources such as water and fertilizer are applied only when necessary.

C. Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized agricultural practices. Crop yield estimation, pest prediction, weather forecasting, and irrigation requirements can be estimated with artificial intelligence algorithms utilizing extensive data collected from various sensors and satellites (Liakos et al., 2018).

Forecasting is improved with the use of machine learning algorithms which help in accurate climate forecasting. These machine learning algorithms help in taking proactive decision-making which is crucial for climate adaptation. Advisory systems based on artificial intelligence can offer custom advisories to farmers on issues like appropriate planting times, irrigation planning, and even crop protection.

IV. SMART WATER MANAGEMENT TECHNOLOGIES

Water scarcity is one of the biggest problems that occur because of climate change. Smart water management techniques are very essential in improving the efficiency of irrigation and also ensuring resilience in agriculture.

The drip and sprinkler irrigation methods result in significant saving of water than traditional irrigation methods. Some studies have found water-saving ratios of 30%-60% without compromising on crop yield (Devarajan et al., 2026).

The precision irrigation system makes use of the combination of soil moisture sensors, forecasts of weather, and an automated irrigation system. The Alternate Wetting and Drying approach in the cultivation of rice crops have resulted in efficient use of water and reduced methane emissions (Devarajan et al., 2026).

The use of solar-powered irrigation systems can be considered a further step towards sustainability because such irrigation systems reduce dependence on fossil fuels and lower costs of production for farmers.

V. BIOTECHNOLOGY AND CLIMATE-RESILIENT CROP DEVELOPMENT

Genetic improvements form the basis of developing crops resilient to changing climates. Conventional breeding, molecular breeding, and biotechnological tools have enabled breeding of crop types that are resilient to harsh climatic conditions.

A. Marker-Assisted Selection

Marker-assisted selection allows breeders to detect beneficial genetic material at the molecular level. The technique has been applied successfully in the development of drought-, heat-, and disease-resistant crops (Scheben et al., 2017).

B. Genomics and High-Throughput Technologies

Improvements in genomics, high-throughput sequencing techniques, and genomics have made it easier to determine the genes responsible for making crops resilient. SNP marker technology and genomic selection make crop improvement faster (Crossa et al., 2017).

C. Genome Editing

Modern gene editing tools such as CRISPR/Cas9 have allowed precise improvements of crop genetic make-up. Specifically, the use of genome editing has facilitated precise editing of genes that control plant tolerance to drought, salinity, heat stress, and disease resistance (Arora & Narula, 2017).

Some examples of the use of genome editing technology include crop improvements in cereals, legumes, and horticulture. The technology allows for rapid adaptation of plants to changes in climatic conditions (Pandey & Singh, 2024).

VI. AGROFORESTRY AND NATURE-BASED SOLUTIONS

Agroforestry refers to the practice of growing trees together with crops and animal products. There are several benefits associated with agroforestry that include; biodiversity, soil fertility, and carbon sequestration.

The incorporation of trees makes possible the creation of a better microclimate, preventing soil erosion, high infiltration rate and generating income through harvesting of wood products and fruits (Devarajan et al., 2026).

It is clear that through agroforestry practices, it is possible to sequester between 2 to 4 t C ha^{-1} yr^{-1} while improving productivity during drought seasons. Agroforestry is part of the nature-based solutions for climate change problems. Conservation agriculture is defined by minimal tillage, residue retention, and crop rotation. This will benefit soil fertility, conserve water, minimize erosion, promote diversity, cut down costs, and increase resilience to climate change.

VII. CLIMATE CHANGE MITIGATION THROUGH SMART TECHNOLOGIES

The use of smart technologies makes significant contributions towards agricultural mitigation activities. Precision nutrient management ensures that there is no overapplication of fertilizers, thus limiting emissions of nitrous oxide. Variable rate technologies facilitate precise fertilizer applications, leading to greater nutrient efficiency (Devarajan et al., 2026).

Biochar is another technology that has been gaining popularity for its ability to boost the sequestration of carbon in the soil, fertility, and minimize greenhouse gas emissions. According to research conducted, biochar is capable of improving productivity while at the same time minimizing the risk of global warming by up to 27 percent (Devarajan et al., 2026).

Smart technologies further aid in the process of carbon accounting, MRV, which is required to participate in carbon markets and climate finance programs

VIII. DECISION SUPPORT SYSTEMS AND CLIMATE INFORMATION SERVICES

The availability of weather and climate data in time is necessary for developing climate resilient agriculture. CIS provides weather forecasts, climate outlook, and risk alerts help farmers make wise decisions. Due to the evolution of ICT technology, it has been made possible for advisory services to be given through mobile applications, text messages, and websites that are based on one's location.

DSS is designed to take into consideration the climate conditions, type of soil, crop model and other economic factors to enable farmers to make good decisions concerning planting crops and other processes like irrigation and pest management.

The software widely used in the DSS process include Decision Support System for Agrotechnology Transfer (DSSAT) and Agricultural Production Systems Simulator (APSS). These tools have widely been used in the testing of crop growth in different climates (Jones et al., 2003).

In the recent past, advancements in artificial intelligence and cloud computing have enhanced the effectiveness of results generated by DSS systems. This is because of the ability of the computer to efficiently analyze huge volumes of data using machine learning methods.

IX. RENEWABLE ENERGY TECHNOLOGIES FOR CLIMATERESILIENT AGRICULTURE

In today's world, there has been an increasing realization about the importance of renewable energy sources within the context of a sustainable and resilient agricultural sector. With respect to agriculture, energy is very important because of the processes of irrigation, mechanization, storage, processing, and transport among others.

Use of fossil fuel as energy source would increase production costs as well as increase greenhouse gas emissions. The introduction of solar powered irrigation technology could be useful as a substitute to diesel pump technology, especially in developing nations.

It should be noted that solar powered irrigation technology is relatively cost efficient; it helps to lower carbon emissions and ensures availability of irrigation water even in remote places (Burney et al., 2013).

Furthermore, biogas systems can be regarded as examples of renewable energy systems that make use of agricultural waste materials and animal manure as energy sources and ensure minimal levels of methane emission besides giving out organic fertilizers.

Wind and solar refrigeration systems would be useful for improving post-harvest handling activities.

X. DIGITAL AGRICULTURE, BIG DATA, AND BLOCKCHAIN APPLICATIONS

The rapid growth in digital agriculture has resulted in innovations in agriculture involving the integration of big data analysis, cloud computing, and information system.

Large amounts of data have emerged in agriculture through the collection of data from sensors, drones, satellites, equipment, and agricultural data. Big data analysis would enable data collected to be converted into useful information in order to enhance efficiency (Wolfert et al., 2017).

There is the possibility of crop and farm monitoring in real-time using cloud computing and the ability to get timely information on weather predictions, pest management, pricing, and nutrition needs. Blockchain technology is rather new within the agriculture industry but it possesses great potentials for enhancing transparency and traceability.

Blockchain technology enables documentation of the production process of a product, including its input sources and origin. The use of blockchain will be very useful in ensuring safety of food, prevention of fraud, and certifications. Furthermore, participation in carbon trading using blockchain technologies is possible.

XI. CLIMATE FINANCE AND SUSTAINABLE AGRICULTURAL INVESTMENTS

In terms of embracing climate-resistant technologies in agriculture, funding is an important issue. Climate finance plays a critical role in raising money towards adaptation and mitigation interventions such as technology transfer, infrastructure development, research, and training.

There exist several types of finance created exclusively to help fund climate-smart agricultural projects. These include green bonds, carbon finance, index insurance programs, climate risk financing, and public-private partnerships for financing climate-resilient agriculture. Index insurance schemes that make payments based on weather events rather than per-farm basis present huge potential as far as reducing vulnerability is concerned.

There are other sources of income for farmers in addition to the above-mentioned methods including carbon finance mechanisms that give money for carbon capture initiatives like agroforestry, carbon capture in soils, and conservation agriculture. The issue with farmers seeking access to such financing opportunities is the difficulty that arises when trying to access climate finance.

XII. SMART GREENHOUSE AND CONTROLLED ENVIRONMENT AGRICULTURE

CEA is one of the ways of achieving sustainable agriculture nowadays because of the increasing uncertainties connected with climate change. In other words, controlled environment agriculture presupposes the production of plants inside a closed structure, for example, greenhouses, vertical farms, plant factories when temperature, moisture, lighting, levels of CO2 and nutrition can be regulated.

The use of IoT sensors, climate control technology, artificial intelligence, and automated irrigation systems allow optimizing the cultivation process, making the producer consume fewer resources. The IoT sensors will monitor the climate, and consequently, it will become possible to regulate ventilation, watering, cooling, and fertilization processes in the greenhouse.

It should be noted that the introduction of IoT in farming can result in saving water resources by 50% to 70%, while production could be improved by 20% to 40% (Shamshiri et al., 2018). Furthermore, the use of vertical farming technologies makes it possible to grow crops all year round regardless of weather conditions.

The use of vertical farming allows minimizing land expenses, reducing pest risks, and managing resources efficiently. At the same time, there are some limitations connected with costs and energy, which might become insignificant in the future.

XIII. CLIMATE-SMART SUPPLY CHAINS AND POST-HARVEST TECHNOLOGIES

Resilience in agriculture means resilience not only of the agricultural produce but resilience of the entire production process across the food value chain. Climate change impacts can lead to reduction in the produce of crops because of the challenges experienced when harvesting, storing, transporting, processing, and marketing them.

One-third of food is either wasted or lost in the world today due to inefficiency in processes and resources, leading to waste and production of greenhouses (FAO, 2019). Advanced technology applications after harvesting agricultural produce have proven to be highly effective in addressing this challenge.

Advanced warehouses that use sensors to monitor temperature and humidity levels provide the right environment for the produce and prevent any deterioration. The use of renewable energy sources will facilitate cold chain technology, which extends the shelf life of fresh produces like fruits, vegetables, milk, and fish.

Moreover, advanced technologies enhance agricultural resilience through supply chain visibility and logistics. Blockchain, radio frequency identification (RFID) technologies, and cloud-based technologies are all useful in tracing agriculture produce during their production and throughout the whole value chain process.

Besides, climate-smart supply chains assist in accomplishing the goals of mitigation by means of minimizing food losses, efficient transportation processes, and energy efficiency.

Climate-smart agriculture systems coupled with smart post-harvest processes may ensure food security without adverse effects on the environment. The future advancements related to digital connectivity, cold-chain processes, and overall efficiency of supply chains are going to be vital in the future.

XIV. SOIL HEALTH MANAGEMENT AND CARBON SEQUESTRATION

Agricultural production resistant to climate change starts with the creation of quality soil. Soil degradation due to the climate change takes place because of the occurrence of soil erosion, nutrient deficiency, soil salinity, and decrease of soil organic carbon content. The attributes of high quality soil consist of soil water content, high nutrient availability, biological activity, and resilience during stress conditions.

Soil conservation practices including zero tillage agriculture, planting cover crops, residue management, soil composting, and biochar application were found to be efficient when it comes to carbon sequestration in soil. An increase in carbon content in the soil is connected with both improvement of the soil quality and reduction of CO_2 concentration in the atmosphere. It is crucial in terms of climate change adaptation measures implementation. According to Lal (2020), soil management is capable of producing positive results concerning soil carbon sequestration.

XV. SMART NUTRIENT MANAGEMENT TECHNOLOGIES

Nutrient management needs to be practiced for efficient agricultural practices and reducing global warming. Overapplication of fertilizers leads to the release of greenhouse gas emissions and pollution of water bodies along with nutrient management inefficiencies. Nutrient management involves the use of precision farming techniques, soil analysis, remote sensing techniques, and decision-making systems.

Variable Rate Technology (VRT) ensures that nutrients are applied according to the requirement of crops in different zones. The fertilizer management system using sensors minimizes nitrogen losses but does not affect crop yields. Studies show that nutrient management results in reduced fertilizer application by 15%-30% and decreases nitrous oxide emissions (Zhang et al., 2021).

XVI. ROBOTICS AND AGRICULTURAL AUTOMATION

Robotic technology has played a major part in addressing issues related to labor shortage. In addition to solving labor shortage issues, robot technology can be used in promoting efficient use of resources. With robotic technology such as automated tractors, robotic weeders, harvesters, and drones, we can perform efficient cultivation practices with little impact on the environment.

Use of artificial intelligence and robotics can greatly contribute in detecting the existence of pests in the agricultural field. Precision spraying technique is one of the ways of addressing this issue.

XVII. CLIMATE-RESILIENT LIVESTOCK PRODUCTION SYSTEMS

Raising livestock is highly susceptible to the impacts of climate change due to factors such as heat stress, prevalence of diseases, lack of food, and inadequate availability of water, among others. Resilient livestock production takes into account enhancement of the health and efficiency of the livestock.

These include selective breeding of heat tolerant animals, provision of better facilities for rearing animals, application of intelligent feeding strategies, and implementation of precise livestock farming methods. Monitoring technologies like sensors, on the other hand, play a role in monitoring and managing livestock through monitoring body temperatures and behavior (Thornton & Herrero, 2015).

XVIII. CIRCULAR BIOECONOMY AND WASTE-TO-RESOURCE TECHNOLOGIES

Circular bioeconomy ensures that biological resources are used to their full potential without waste of any sort. The adoption of the concept of circular bioeconomy in agriculture will lead to emission reduction, efficient utilization of energy, fertilizer, compost, and even bioplastics.

Anaerobic digestion involves decomposition of organic waste into biogas and fertilizers. The adoption of the concept of circular bioeconomy in agriculture will lead to emission reduction, efficient utilization of resources, and additional revenue generation for farmers.

XIX. CHALLENGES AND FUTURE PROSPECTS

In spite of the technological developments, several problems inhibit the adoption of climate resilient technologies. Some of these include high capital costs, poor infrastructure in rural settings, lack of access to finance, and weak extension programs. However, digital technology usually requires connectivity, technical skill, and electricity, which may be lacking in rural regions (Devarajan et al., 2026).

Supporting policies, strong institutions, and educating farmers about climate-smart technologies is critical for scaling such technologies Future research needs to concentrate on integrated systems solutions that incorporate socio-economic policies along with technological advancements. Some emerging technologies include digital twins, block-chain driven tracking and monitoring systems, robotics, and climate advisory systems driven by artificial intelligence.

XX. CONCLUSION

Climate change presents unique challenges to world agriculture in terms of food security, livelihood, and sustainability of the environment. The use of technology such as precision agriculture, artificial intelligence, internet of things, remote sensing, biotechnology, genome editing, intelligent irrigation systems, and agroforestry provides the solution to building a sustainable future.

Using all these technologies within Climate-Smart Agriculture strategies may be helpful for achieving several goals at once. It is crucial that all these tools work efficiently only when there are proper policies, infrastructure development, and education involved in their implementation, particularly among smallholder farmers.

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Artificial Intelligence in Agriculture: Transforming Traditional Farming into Smart Farming

Submitted By:

Naman Kumar Tiwari

Department of Computer Science & Engineering, Adamas University

Under the Guidance of:

Prof. (Dr.) Debdutta Pal

Professor, Computer Science & Engineering, Adamas University

June 2026

Abstract—*Agriculture has sustained human civilization for millennia, yet modern farming faces formidable and compounding challenges: unpredictable climate patterns, widespread pest and disease outbreaks, progressive soil degradation, and chronic inefficiency in resource use. With the world's population projected to surpass 9.7 billion by 2050 — requiring a 70 percent increase in food production — these challenges demand urgent, innovative solutions. Artificial Intelligence has emerged as one of the most powerful tools available to address them, offering the ability to transform farming from an intuition-driven practice into a data-driven, precision-oriented discipline capable of meeting the demands of a rapidly changing world.*

This research paper examines the wide-ranging applications of AI in modern agriculture, including intelligent crop monitoring through satellite and drone imagery, early disease and pest detection using computer vision, precision irrigation management, crop yield forecasting through machine learning, and the deployment of autonomous agricultural robots. Together, these technologies constitute a new paradigm — Smart Farming or Agriculture 4.0 — in which data flows continuously from field sensors and satellites to AI systems that return actionable guidance, enabling farmers to make better decisions faster and with greater confidence than ever before.

The paper also confronts the significant barriers limiting AI adoption, particularly among smallholder farmers in developing regions who stand to benefit most but currently have the least access. High implementation costs, inadequate rural digital infrastructure, limited digital literacy, and unresolved data ownership concerns all present serious obstacles. The paper concludes with targeted recommendations for researchers, policymakers, development organizations, and technology providers to ensure that the benefits of agricultural AI are realized equitably and sustainably across all farming communities worldwide.

Keywords: *core-shell morphology; Solid Oxide fuel cell; ceramic processing; interfacial engineering*

1. Introduction

There is a quiet urgency to the future of food. The United Nations projects that the world's population will reach 9.7 billion by 2050, requiring global food production to increase by approximately 70 percent. Yet agricultural land is finite, water resources are increasingly strained, climate change is disrupting growing seasons and amplifying extreme weather events, and the rural workforce is aging and shrinking as young people migrate to cities. These are not distant, hypothetical problems — they are already visible in the daily struggles of farmers across every continent, from South Asian smallholders facing erratic monsoons to sub-Saharan African communities devastated by fall armyworm infestations, to American Midwest farmers managing slowly degrading soils.

Traditional farming methods, while rooted in centuries of practical knowledge, struggle to respond with the speed and precision modern challenges demand. Farmers frequently lack timely access to crucial information about soil conditions, pest threats, water needs, and market prices, and must rely on experience and instinct where data-driven intelligence could dramatically improve outcomes. It is in this context that Artificial Intelligence enters agriculture — not as a silver bullet, but as a genuinely powerful set of tools that, properly applied, enable farmers to make better decisions, detect problems earlier, use resources more efficiently, and achieve more consistent and abundant yields.

AI is not a single technology but a constellation of computational techniques: machine learning enables systems to improve by learning from historical and real-time data; computer vision allows machines to interpret images and video from cameras and satellites; natural language processing enables farmer-AI communication in ordinary language; and robotics gives AI a physical presence in the field. The convergence of these techniques with modern agricultural sensing infrastructure — satellites, drones, soil sensors, weather stations, and connected machinery — is creating what researchers now call Agriculture 4.0: an approach to farming in which real-time data drives intelligent, automated decision-making at every stage of the crop cycle. This paper maps this landscape in depth, examining what AI already achieves in agriculture, what barriers limit its spread, and what actions are needed to ensure its benefits reach all farmers equitably.

2. Review of Literature

The academic literature on AI in agriculture has expanded dramatically since 2015, driven by advances in deep learning, falling sensor costs, and growing urgency around food security. Kamilaris and Prenafeta-Boldu (2018) surveyed over forty AI application areas in agriculture — from disease identification to fruit counting — finding that convolutional neural networks consistently outperformed traditional machine learning methods on image analysis tasks. Their analysis identified the scarcity of well-labeled agricultural datasets as the primary development bottleneck, prompting large open-dataset initiatives such as PlantVillage, which now contains hundreds of thousands of labeled plant images. Liakos and colleagues (2018) reviewed machine learning across crop, water, soil, and livestock management domains, finding neural networks and support vector machines most widely applied. They noted that real-world field performance frequently fell below controlled laboratory benchmarks, emphasizing the need for AI systems robust to the variability and unpredictability of actual farming environments.

Mohanty and colleagues (2016) published a landmark study demonstrating that a deep convolutional neural network could identify 26 plant diseases across 14 crop species with 99.35 percent accuracy on the PlantVillage dataset, establishing the proof of concept that has driven vast subsequent research in AI-powered disease detection. Pantazi and colleagues (2016) showed that neural networks trained on geospatial soil and yield data could delineate distinct field management zones, enabling variable-rate input application that achieved cost reductions of up to 20 percent alongside 10 to 15 percent yield improvements. Gandhi and colleagues (2016) applied ensemble learning methods to weather records and satellite vegetation indices, achieving crop yield prediction errors below five percent for major Indian cereals — demonstrating that accurate, scalable yield forecasting was achievable with accessible data sources.

2.1 Emerging Research Directions

More recent work has pushed the field in several important directions. Khaki and Wang (2019) demonstrated that deep learning architectures integrating genetic, environmental, and management data could capture complex nonlinear relationships affecting maize yield that traditional statistical models could not, achieving significantly improved forecast accuracy. Research by Ferentinos (2018) and others has addressed the domain gap between controlled laboratory images and real-world field photographs through transfer learning and data augmentation, bringing field-condition disease detection accuracy close to 90 percent for several important crop-disease combinations. These advances collectively indicate that AI agricultural systems are maturing beyond proof of concept toward reliable, field-deployable tools that deliver consistent value under realistic conditions.

3. Applications of AI in Modern Agriculture

3.1 Intelligent Crop Monitoring Through Remote Sensing

AI-powered crop monitoring integrates data from satellites, drones, and ground sensors to provide farmers real-time, spatially granular field intelligence at a scale impossible with human observation. Modern agricultural satellites capture multispectral and hyperspectral imagery revealing plant health information invisible to the naked eye — including early-stage nitrogen deficiency, water stress, and disease infection, each producing distinctive spectral signatures detectable days before visible symptoms appear. Drone surveys cover thousands of acres in hours, with AI processing the resulting imagery within minutes to produce actionable field health maps. Platforms such as Taranis, Agremo, and Climate Corporation's FieldView employ these capabilities commercially across North America, Europe, and parts of Asia, helping farmers intervene precisely when and where needed.

3.2 Early Disease and Pest Detection

Plant diseases cause an estimated 20 to 40 percent of global production losses annually. AI detection systems work primarily through computer vision: a farmer photographs a diseased leaf with a smartphone; a convolutional neural network returns a diagnosis within seconds with recommended treatment. The Plantix application — downloaded over ten million times — identifies more than five hundred plant diseases, pests, and nutrient deficiencies across dozens of crops with accuracy rivaling trained plant pathologists. More advanced systems integrate AI with biosensors detecting pathogen-specific biochemical markers in soil or plant tissue before any visual symptoms appear, enabling intervention while outbreaks remain containable and chemically treatable at low cost.

3.3 Precision Irrigation and Water Management

Irrigated agriculture accounts for approximately 70 percent of all global freshwater withdrawals, and groundwater tables are declining rapidly in the world's most productive agricultural regions. AI-driven irrigation systems analyze soil moisture sensors, evapotranspiration models, weather forecasts, and crop growth stage data to deliver precisely the right amount of water at the right time — eliminating both over-irrigation, which wastes water and promotes disease, and under-irrigation, which reduces yields. Platforms such as CropX and Netafim's NetBeat have demonstrated water savings of 20 to 40 percent in field trials across diverse crops, with no yield reduction and often modest improvement, representing a transformative contribution to sustainable water management in agriculture.

3.4 Yield Prediction and Harvest Planning

Accurate yield forecasting helps individual farmers plan storage and marketing, enables governments to manage food reserves, and reduces commodity market volatility. AI models integrating satellite vegetation indices, historical and real-time weather data, and soil characteristics generate field-level yield estimates months before harvest with errors below five percent for major crops. Beyond quantity, AI is increasingly applied to predict produce quality — the proportion meeting market standards for size, color, or sugar content — allowing pre-harvest management interventions that shift production toward higher-value grades and improving the economic returns of high-value horticultural crops significantly.

3.5 Agricultural Robotics and Autonomous Machinery

Autonomous robots represent the physical expression of AI in the field. Computer vision guides them between crop rows, identifies individual plants or fruits, assesses maturity, and executes precise mechanical actions — weeding, pruning, and harvesting — continuously and without fatigue. Carbon Robotics' LaserWeeder uses AI-guided lasers to destroy weeds with millimeter precision, eliminating herbicide use in treated areas. Harvesting robots for strawberries, tomatoes, and apples have reached commercial viability, addressing acute labor shortages while reducing costs. These systems operate around the clock, dramatically expanding effective farm labor capacity without additional workers.

4. Benefits of AI Integration in Agriculture

4.1 Economic Gains for Farmers

At the farm level, AI's most direct economic benefit is producing more output per unit of input. Precision water, fertilizer, and pesticide application guided by AI analysis routinely achieves input cost reductions of 15 to 30 percent without yield loss, and frequently with modest improvements. Early disease detection and accurate yield forecasting reduce catastrophic loss risk and improve income predictability, making it easier to access credit and plan investments. Autonomous machinery reduces labor costs and eliminates dependence on scarce seasonal labor, which has become a critical constraint in many agricultural regions where rural workforce availability has declined sharply over the past two decades.

4.2 Environmental Sustainability

Agriculture contributes approximately 10 to 12 percent of global greenhouse gas emissions and is the primary driver of freshwater depletion, biodiversity loss, and agricultural runoff pollution. AI reduces each of these impacts meaningfully. Precise nitrogen management reduces both nitrous oxide emissions — a greenhouse gas nearly 300 times more potent than carbon dioxide — and nitrogen runoff causing harmful algal blooms in rivers and coastal waters. Optimized irrigation reduces groundwater depletion and pumping energy consumption. Targeted AI-guided pesticide application reduces harmful exposure to pollinators and beneficial organisms; multiple studies document pesticide use reductions of 25 to 50 percent on AI-managed farms with no increase in crop losses to pests.

4.3 Food Security and Rural Livelihoods

More productive, resilient farming directly strengthens food security at every scale. At the household level, reliable harvests and better income improve nutrition and reduce vulnerability. At the national level, accurate yield forecasting helps governments anticipate shortfalls and mobilize food assistance before crises develop. At the global level, the aggregate effect of efficiency improvements across hundreds of millions of farms contributes to the food system's capacity to feed a growing, increasingly urban population under worsening climate conditions — making AI in agriculture not just an economic opportunity but a genuine imperative for food system resilience.

5. Challenges and Barriers to Adoption

5.1 High Costs and Infrastructure Gaps

The upfront cost of AI-enabled agricultural technologies remains prohibitive for most of the world's farmers. Drone systems, soil sensor networks, and autonomous machinery require investments ranging from thousands to hundreds of thousands of dollars — feasible only for large commercial operations. Software subscription platforms, while less capital-intensive, still carry fees that may represent a significant fraction of smallholder farm income. Compounding the cost barrier, most AI applications require reliable internet connectivity, affordable data access, and consistent electrical power — conditions that cannot be taken for granted in rural areas across sub-Saharan Africa, South Asia, or parts of Latin America where the majority of the world's smallholder farmers live and work.

5.2 Digital Literacy, Data Privacy, and Contextual Fit

Even where hardware access exists, many farmers lack the digital literacy to use AI tools effectively, interpret recommendations, or troubleshoot problems. Building this capacity alongside deploying technology is essential but frequently neglected. Farmers also have legitimate concerns about the commercial use of the detailed operational data that AI systems collect — by landlords, commodity buyers, or insurers — in contexts where legal frameworks governing data ownership and portability remain underdeveloped. Additionally, AI models trained predominantly on large commercial farms in the global North frequently perform poorly in different agronomic contexts, requiring locally relevant data collection and model adaptation that demands resources many developing-country institutions lack.

6. Future Directions and Recommendations

The trajectory of AI development makes it virtually certain that agricultural applications will become more capable, more affordable, and more accessible over the coming decade. Edge computing advances will enable sophisticated AI models to operate on low-cost devices without continuous internet connectivity — directly addressing the primary adoption barrier for rural farmers in developing regions. Falling sensor and drone hardware costs will bring precision monitoring within reach of smaller farming operations. Expanding satellite constellations will make high-resolution daily crop monitoring accessible globally, even in areas lacking ground-based sensor infrastructure. Improvements in battery and solar technology will extend autonomous equipment operating range and duration in remote field environments.

But technology improvements alone will not ensure equitable adoption. Governments in countries with large smallholder farming populations should establish agricultural technology funds specifically targeting affordable AI solutions for small farms, partnering with universities, start-ups, and international research institutes to develop contextually appropriate tools. Agricultural extension services must be systematically retooled to incorporate digital literacy training and hands-on AI support, with extension agents trained as technology intermediaries who can bridge sophisticated platforms and farmers with limited technical background. International development organizations should integrate agricultural AI into food security and rural development programming, funding demonstration projects and technology transfer initiatives in countries where adoption lags. Clear legal frameworks for agricultural data ownership, privacy, and portability — giving farmers genuine control over operational data — are essential to build the trust necessary for widespread platform adoption.

Research institutions should prioritize developing AI models trained on data from diverse agricultural contexts, especially the smallholder farming systems of sub-Saharan Africa and South Asia that remain underrepresented in current training datasets. Open-source AI tools and freely available agricultural datasets would lower barriers to local innovation, allowing researchers and developers in diverse regions to build appropriate solutions without starting from scratch. Incentive structures — regulatory requirements or market mechanisms — should encourage technology companies to design for smallholder affordability and accessibility from the outset, rather than treating small-farm markets as secondary afterthoughts.

Looking further ahead, the convergence of AI with genomics and biotechnology offers the prospect of dramatically accelerating crop variety development adapted to specific climate conditions — with AI identifying the genetic traits most likely to improve performance and genomic tools providing the means to introduce those traits rapidly into breeding programs. AI-enabled precision fermentation could produce high-value proteins and agricultural nutrients from engineered microorganisms, reducing pressure on agricultural land and water. Each of these possibilities remains partly speculative, but collectively they suggest that AI's role in agriculture will continue deepening in ways that are difficult to fully anticipate, making sustained investment in research, infrastructure, and human capacity essential preparation for a smarter agricultural future.

7. Conclusion

Artificial Intelligence is not a distant promise for agriculture — it is an arriving reality, already reshaping how food is grown, how resources are managed, and how decisions are made on farms around the world. The applications examined in this paper — intelligent crop monitoring, early disease detection, precision irrigation, yield prediction, and autonomous farm machinery — form a coherent and mutually reinforcing set of capabilities that constitute a fundamentally new way of farming: more productive, because inputs are applied precisely where and when they are needed; more resilient, because problems are detected early and addressed quickly; and more sustainable, because higher yields are achieved with lower environmental cost.

Yet the transformation is far from complete or equitable. The majority of the world's farmers — smallholders in developing countries farming limited land with scarce capital, unreliable connectivity, and limited technical support — are not yet benefiting from agricultural AI in any meaningful way. The risk that AI will primarily serve larger, better-resourced operations while leaving smaller and more vulnerable farmers further behind is real and must be actively countered through deliberate investment in affordable technology development, sustained attention to infrastructure and literacy, thoughtful data regulation, and genuine commitment to inclusive innovation ecosystems that actively connect technology developers with the farmers who most need their tools.

Agriculture must feed ten billion people while adapting to a destabilizing climate, protecting fragile ecosystems, and improving the livelihoods of hundreds of millions of rural people who depend on farming for their survival. Artificial Intelligence is among the most powerful tools humanity has yet developed for meeting these challenges. Deploying it wisely, equitably, and at scale is among the most consequential engineering and policy tasks of the decades ahead. The future of farming is intelligent — and it must belong to all farmers, not only the most advantaged.

"The future of food security lies not in working the land harder, but in working it smarter — and Artificial Intelligence is the most powerful tool we have to do exactly that."

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Controlled Environment Agriculture (CEA) for Precision-Based Off-Season Crop Production: Technologies, Applications, and Future Prospects

1st Purba Saha

Department of Smart Agriculture

Adamas University

Barasat,India

spurba383@gmail.com

Abstract—*The agricultural sector is facing unprecedented challenges due to climate change, population growth, declining availability of arable land, and increasing demand for high-quality food products. Conventional farming systems are highly dependent on seasonal and environmental conditions, making crop production vulnerable to fluctuations in temperature, rainfall, and extreme weather events. Controlled Environment Agriculture (CEA) has emerged as an advanced agricultural production system that enables precise regulation of environmental factors to ensure optimum crop growth throughout the year. By integrating protected cultivation structures such as greenhouses and polyhouses with modern technologies including sensors, automation,*

Internet of Things (IoT), artificial intelligence, and precision irrigation systems, CEA creates a highly controlled and resource-efficient production environment.The technology facilitates off-season cultivation of high-value horticultural crops including tomato, cucumber, capsicum, lettuce, and strawberry while maintaining consistent yield and quality. Furthermore, the adoption of smart monitoring systems and data-driven decision-making improves water-use efficiency, nutrient management, and pest control, thereby enhancing sustainability and profitability. This paper presents a comprehensive review of Controlled Environment

Agriculture, focusing on its principles, technological components, applications in off-season crop production, economic benefits, challenges, and future prospects. The study highlights the potential of CEA as a key component of climate-resilient and sustainable agricultural systems capable of meeting future food security demands.

Keywords: *Controlled Environment Agriculture, Precision Agriculture, Greenhouse Technology, Protected Cultivation, Smart Farming, Off-Season Production, Sustainable Agriculture.*

I. INTRODUCTION

Agriculture remains one of the most important sectors supporting global food security and economic development. However, traditional crop production systems are increasingly threatened by climate variability, resource depletion, urbanization, and the growing demand for food. Global food production must increase substantially over the coming decades to satisfy the nutritional requirements of an expanding population. At the same time, farmers must cope with unpredictable weather conditions, water scarcity, declining soil fertility, and increasing production costs. Conventional open-field cultivation is highly dependent on environmental factors such as temperature, rainfall, solar radiation, humidity, and wind. Variations in these factors often result in reduced crop productivity, poor product quality, and significant economic losses. Seasonal limitations further restrict the availability of many horticultural crops, leading to fluctuations in market supply and price instability.

Controlled Environment Agriculture (CEA) represents a transformative approach to crop production that addresses many of these challenges. CEA refers to agricultural systems in which environmental conditions are monitored and controlled to optimize plant growth and development. These systems employ protected cultivation structures such as greenhouses, polyhouses, net houses, hydroponic units, aeroponic systems, and vertical farms. By regulating critical growth parameters including temperature, humidity, light intensity, carbon dioxide concentration, irrigation, and nutrient availability, CEA enables crop production independent of external climatic conditions.

Recent advances in sensor technology, automation, the Internet of Things (IoT), machine learning, and artificial intelligence have significantly enhanced the effectiveness of Controlled Environment Agriculture. Environmental data can now be collected in real time, analysed using intelligent algorithms, and utilized to automate management decisions. Such integration improves resource-use efficiency while reducing labour requirements and operational uncertainties. As a result, modern CEA systems have become increasingly attractive for the cultivation of high-value crops, particularly during off-season periods when market demand and prices are relatively high.

In addition to enhancing productivity, Controlled Environment Agriculture contributes significantly to environmental sustainability. Precision irrigation and fertigation systems reduce water and nutrient losses, while controlled environments minimize pesticide usage by lowering pest and disease incidence. Furthermore, the integration of renewable energy technologies and smart resource management strategies has the potential to improve the overall sustainability of agricultural production systems.

This paper aims to provide a comprehensive review of Controlled Environment Agriculture and its role in precision-based off-season crop production. The paper discusses the fundamental principles of CEA, major technological components, applications in protected cultivation, economic and environmental benefits, challenges associated with adoption, and future developments shaping next-generation smart farming systems. Through this analysis, the study highlights the importance of Controlled Environment Agriculture as a sustainable solution for addressing future agricultural challenges and ensuring food security under changing climatic conditions.

II. PRINCIPLES OF CONTROLLED ENVIRONMENT AGRICULTURE

Controlled Environment Agriculture (CEA) is based on the concept of maintaining optimal environmental conditions throughout the crop growth cycle. Plant growth and productivity are influenced by several environmental variables, including temperature, humidity, light intensity, carbon dioxide concentration, water availability, and nutrient supply. In conventional farming, these factors are largely dependent on natural weather conditions, whereas CEA systems allow precise monitoring and control of each parameter. This controlled approach ensures enhanced crop growth, improved quality, and greater productivity.

A. Temperature Control

Temperature is one of the most critical factors influencing plant physiological processes such as photosynthesis, respiration, flowering, fruit set, and nutrient uptake. In Controlled Environment Agriculture systems, heating and cooling mechanisms are used to maintain temperatures within the optimum range required for specific crops. Automated climate control systems continuously monitor temperature fluctuations and adjust environmental conditions accordingly, thereby minimizing stress on plants and improving overall productivity.

B. Humidity Management

Relative humidity directly affects transpiration, nutrient absorption, and disease development in crops. Excessive humidity can promote fungal diseases, while low humidity may increase water stress. Modern greenhouse systems employ ventilation fans, foggers, evaporative cooling systems, and dehumidification units to maintain optimal humidity levels. Proper humidity regulation contributes to healthy plant growth and reduces the incidence of diseases.

C. Light Regulation

Light serves as the primary energy source for photosynthesis. Crop growth depends on light intensity, duration, and quality. Advanced CEA systems utilize supplemental LED lighting and shading technologies to regulate light availability according to crop requirements. Artificial lighting ensures continuous crop production during periods of inadequate natural sunlight and supports year-round cultivation.

D. Carbon Dioxide Enrichment

Carbon dioxide is a key component of the photosynthetic process. Controlled enrichment of greenhouse environments with carbon dioxide can significantly increase photosynthetic efficiency, biomass accumulation, and crop yield. Many commercial greenhouse operations maintain elevated carbon dioxide concentrations to maximize productivity and improve crop performance.

E. Water and Nutrient Management

Efficient water and nutrient management are a fundamental principle of Controlled Environment Agriculture. Precision irrigation systems such as drip irrigation deliver water directly to the root zone, minimizing evaporation and water loss. Fertigation systems combine irrigation and nutrient application, ensuring that crops receive the required nutrients at the appropriate growth stage. This approach enhances nutrient-use efficiency while reducing environmental pollution.

III. COMPONENTS OF CONTROLLED ENVIRONMENT AGRICULTURE

Controlled Environment Agriculture integrates multiple technological components that work together to create an optimal growing environment for crops. These components facilitate precise monitoring, control, and management of environmental conditions.

A. Greenhouses and Polyhouses

Greenhouses and polyhouses are the most common structures used in Controlled Environment Agriculture. These structures protect crops from adverse weather conditions such as excessive rainfall, strong winds, hailstorms, and extreme temperatures. They create a semi-controlled environment that enables year-round cultivation and improves crop quality.

B. Sensor Technologies

Sensors play a vital role in modern CEA systems by continuously monitoring environmental parameters. Commonly used sensors include temperature sensors, humidity sensors, soil moisture sensors, light sensors, carbon dioxide sensors, pH sensors, and electrical conductivity sensors. These sensors provide real-time information that assists in environmental management and decision-making.

C. Automation and Control Systems

Automation technologies enable the regulation of environmental conditions without continuous human intervention. Controllers receive data from sensors and automatically operate ventilation fans, cooling pads, irrigation systems, fertigation units, and lighting equipment. Automation improves operational efficiency, reduces labour requirements, and enhances production consistency.

D. Irrigation and Fertigation Systems

Efficient irrigation and nutrient delivery systems are essential components of Controlled Environment Agriculture. Drip irrigation systems provide precise water application, while fertigation systems supply nutrients in soluble form through irrigation water. These technologies improve water-use efficiency and ensure balanced nutrient availability.

E. Data Analytics and Decision Support Systems

Modern CEA facilities increasingly utilize cloud computing, artificial intelligence, and machine learning technologies. Data collected from sensors are analysed to identify patterns, predict environmental changes, and optimize management practices. Decision support systems assist growers in making informed decisions related to irrigation scheduling, nutrient management, and disease prevention.

IV. PRECISION AGRICULTURE IN CONTROLLED ENVIRONMENT SYSTEMS

Precision agriculture enhances the effectiveness of Controlled Environment Agriculture by enabling accurate management of resources and environmental conditions. The integration of sensors, automation, and data analytics facilitates efficient utilization of water, nutrients, energy, and labour.

A. Smart Irrigation Systems

Smart irrigation systems utilize soil moisture sensors and automated controllers to determine crop water requirements accurately. Water is supplied only when necessary, reducing wastage and improving water-use efficiency. Studies have demonstrated significant water savings through the adoption of precision irrigation technologies.

B. Precision Fertigation

Precision fertigation ensures that nutrients are supplied according to crop demand and growth stage. This targeted approach minimizes fertilizer losses, improves nutrient-use efficiency, and enhances crop productivity while reducing environmental impacts.

C. Remote Monitoring and Management

Internet-connected monitoring systems allow growers to access greenhouse data remotely using smartphones, tablets, or computers. Real-time monitoring improves responsiveness and enables timely corrective actions when environmental conditions deviate from desired levels.

D. Predictive Analytics and Artificial Intelligence

Artificial intelligence and machine learning algorithms can analyse large datasets generated within Controlled Environment Agriculture systems. These technologies help predict crop growth, identify potential disease outbreaks, optimize resource allocation, and support strategic decision-making.

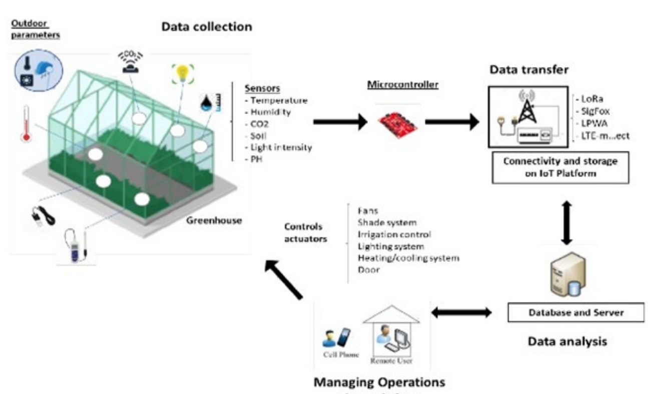

Fig. 1. Architecture of a smart Controlled Environment Agriculture system integrating sensors, IoT platforms, analytics, and automated control mechanisms.

V. OFF-SEASON CROP PRODUCTION USING CONTROLLED ENVIRONMENT AGRICULTURE

One of the most significant advantages of Controlled

Environment Agriculture is its ability to facilitate crop production beyond normal growing seasons. By maintaining optimal environmental conditions, CEA enables continuous cultivation and market supply throughout the year.

A. Tomato Production

Tomato is one of the most widely cultivated greenhouse crops worldwide. Controlled environmental conditions improve fruit quality, increase yield, and reduce production risks associated with adverse weather conditions.

B. Capsicum Production

Coloured capsicum commands a premium market price due to its high nutritional value and consumer demand. Greenhouse cultivation enhances fruit size, colour development, and overall quality while enabling off-season production.

C. Cucumber Cultivation

Protected cultivation of cucumber results in higher productivity, improved fruit quality, and reduced pest and disease incidence compared with open-field production systems.

D. Lettuce and Leafy Vegetables

Hydroponic and vertical farming systems facilitate rapid and efficient production of lettuce and other leafy vegetables. These systems enable multiple cropping cycles throughout the year.

E. Strawberry Cultivation

Strawberry production under protected environments allows growers to supply fresh fruits during off-season periods when market prices are generally higher, thereby improving profitability.

TABLE I (Comparison of Open-Field Farming and Controlled Environment Agriculture)

Parameter	Open-Field Farming	Controlled Environment Agriculture
Temperature Control	Weather dependent	Precisely controlled
Water Use Efficiency	Moderate	High
Fertilizer Efficiency	Moderate	High
Pest Incidence	High	Low
Yield Stability	Variable	Consistent
Off-Season Production	Limited	Possible
Product Quality	Variable	Uniform
Market Availability	Seasonal	Year-round

TABLE II (Environmental Parameters Managed in Controlled Environment Agriculture)

Parameter	Optimal Range	Control Method
Temperature	18–30°C	Heating and Cooling Systems
Relative Humidity	60–80%	Foggers and Ventilation
Carbon Dioxide	800–1200 ppm	CO_2 Enrichment
Light Intensity	Crop Specific	LED Lighting
Soil Moisture	Crop Specific	Smart Irrigation
Nutrient EC	1.5–3.5 mS/cm	Fertigation

VI. BENEFITS OF CONTROLLED ENVIRONMENT AGRICULTURE

Controlled Environment Agriculture offers numerous advantages over conventional farming systems by providing optimal growing conditions and improving resource-use efficiency.

A. Increased Productivity

The ability to maintain ideal environmental conditions throughout the crop growth cycle significantly increases crop yield. Controlled environments minimize stress caused by adverse weather conditions and enable crops to reach their full genetic potential.

B. Improved Crop Quality

Uniform environmental conditions contribute to the production of high-quality fruits and vegetables with better colour, size, texture, and nutritional value. Such consistency enhances consumer acceptance and market value.

C. Efficient Resource Utilization

CEA systems optimize the use of water, fertilizers, and energy. Precision irrigation and fertigation technologies reduce wastage while ensuring efficient utilization of available resources.

D. Reduced Pest and Disease Incidence

Protected cultivation structures act as physical barriers against pests and pathogens. Furthermore, environmental control measures reduce the occurrence of diseases, minimizing the need for chemical pesticide applications.

E. Climate Resilience

Controlled environments protect crops from droughts, floods, hailstorms, excessive rainfall, and extreme temperatures. This capability makes CEA an important strategy for climate-resilient agriculture.

F. Year-Round Production

One of the most important advantages of Controlled

Environment Agriculture is the ability to produce crops throughout the year. Continuous production ensures stable market supply and improved farmer income.

VII. CASE STUDY: ADOPTION OF PROTECTED CULTIVATION IN INDIA

India has witnessed significant growth in protected cultivation technologies over the last decade. Government initiatives such as the Mission for Integrated Development of Horticulture (MIDH) and various state-level subsidy programs have promoted the adoption of greenhouses and polyhouses among farmers.

States such as Maharashtra, Karnataka, Himachal Pradesh, Tamil Nadu, and West Bengal have demonstrated successful implementation of protected cultivation technologies. Farmers cultivating crops such as capsicum, cucumber, tomato, and strawberry under polyhouse conditions have reported substantial improvements in productivity and profitability.

Studies conducted in different regions of India indicate that greenhouse-grown vegetables often produce two to three times higher yields compared to conventional open-field cultivation. Additionally, improved product quality and the ability to target premium markets during off-season periods contribute significantly to increased farm income.

The increasing adoption of sensor-based irrigation systems, fertigation technologies, and climate control mechanisms further highlights the growing importance of Controlled Environment Agriculture in the Indian agricultural sector.

VIII. CHALLENGES AND LIMITATIONS OF CONTROLLED ENVIRONMENT AGRICULTURE

Despite its numerous advantages, the widespread adoption of Controlled Environment Agriculture faces several challenges.

A. High Initial Investment

The establishment of greenhouses, polyhouses, hydroponic systems, sensors, and automation technologies requires substantial financial investment. This often limits adoption among small and marginal farmers.

B. Technical Expertise Requirements

Successful operation of CEA systems requires knowledge of environmental management, crop physiology, nutrient management, and automation technologies. Lack of technical expertise can affect system performance.

C. Energy Consumption

Heating, cooling, ventilation, and artificial lighting systems consume significant amounts of energy. Rising energy costs may increase operational expenses, particularly in large-scale facilities.

D. Infrastructure Constraints

Reliable electricity supply, internet connectivity, maintenance services, and access to technical support are essential for effective operation of modern CEA systems.

E. Economic Accessibility

Although government support programs exist, many farmers still face financial barriers that limit access to advanced protected cultivation technologies.

IX. FUTURE PROSPECTS OF CONTROLLED ENVIRONMENT AGRICULTURE

The future of agriculture is increasingly linked to digital technologies, automation, and sustainable resource management. Controlled Environment Agriculture is expected to play a central role in the transformation of global food production systems.

Several emerging technologies are expected to enhance the efficiency and adoption of CEA systems:

1) Artificial Intelligence and Machine Learning

Artificial intelligence can analyse large datasets generated from environmental sensors and predict crop growth patterns, disease outbreaks, and resource requirements with greater accuracy.

2) Internet of Things (IoT)

IoT-based monitoring systems enable real-time data collection and remote management of environmental conditions, improving operational efficiency and decision-making.

3) Vertical Farming

Vertical farming combines controlled environments with multi-layer crop production systems, maximizing productivity while minimizing land requirements. This technology is particularly suitable for urban agriculture.

4) Hydroponics and Aeroponics

Soilless cultivation systems offer efficient utilization of water and nutrients while enabling high-density crop production. These technologies are expected to become increasingly important in future farming systems.

5) Renewable Energy Integration

The integration of solar panels, energy-efficient LED lighting, and other renewable energy technologies can reduce operational costs and improve the sustainability of Controlled Environment Agriculture.

Fig. 2. Advanced vertical farming systems representing the future of Controlled Environment Agriculture.

X. ROLE OF CEA IN SUSTAINABLE AGRICULTURE

Sustainability has become a primary objective of modern agricultural development. Controlled Environment Agriculture contributes significantly to sustainable farming through efficient resource utilization and reduced environmental impact.

The adoption of precision irrigation systems reduces water consumption, while fertigation minimizes nutrient losses and groundwater contamination. Controlled environments also decrease pesticide dependence by reducing pest and disease pressure. Furthermore, local production of food through urban and peri-urban CEA facilities reduces transportation requirements and associated carbon emissions.

By improving productivity while conserving natural resources, Controlled Environment Agriculture supports the achievement of sustainable development goals related to food security, environmental protection, and economic growth.

XI. CONCLUSION

Controlled Environment Agriculture represents a transformative advancement in modern agricultural production systems. By integrating protected cultivation structures with precision agriculture technologies, sensors, automation, and data analytics, CEA enables efficient off-season crop production while minimizing dependence on climatic conditions.

The technology offers numerous benefits including higher productivity, improved crop quality, efficient resource utilization, reduced pest incidence, and enhanced climate resilience. Furthermore, the ability to produce high-value crops throughout the year provides significant economic opportunities for farmers and contributes to food security.

Although challenges such as high investment costs, technical complexity, and energy requirements remain, continued advancements in artificial intelligence, Internet of Things technologies, renewable energy integration, and automation are expected to improve accessibility and adoption. As global agriculture faces increasing pressure from climate change, population growth, and resource scarcity, Controlled Environment Agriculture is poised to become a cornerstone of future smart farming systems and sustainable food production strategies.

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Properties, Applications and Determination Techniques for Fungal Lactase: A Comprehensive Review

*Sumitra Dey[1], Anwesha Mandal[1], Kanishtha Kashiv[1], Rajib Majumder[2], Sanmitra Ghosh**

1Department of Biological Sciences, School of Life Science & Biotechnology, Adamas University, Kolkata, India

2Department of Biotechnology, School of Life Science & Biotechnology, Adamas University, Kolkata, India

**Corresponding author*

Dr Sanmitra Ghosh

Department of Biological Science, School of Life Science & Biotechnology, Adamas University, West Bengal. India.

Tel: +917890211426;

Email: sanmitra.ghosh@adamasuniversity.ac.in

Abstract : *Application of lactasein hydrolysis of lactose into galactose and glucose addresses the widespread health concernsdue to lactose intolerance. Commercial production of this biocatalyst is predominantly done using microbial sources, particularly fungi and yeast, rather than other traditional sources like plants and animals pertaining to their high yield, cost-effectiveness, and adaptability to various conditions. Microbial lactases have revolutionized the food industry, enabling the manufacture of dairy products such as milk, cheese, and yogurt, devoid of lactose, while improving product sweetness, texture, and nutritional accessibility. Their application extends to waste management by converting wheyinto bioethanol, prebiotics, and other valuable products, contributing to sustainability. Additionally, lactase finds significant use in pharmaceuticals for lactose-free drug formulations and controlled delivery systems, as well as in cosmetics for skin hydration and exfoliation. Recent advancements include the development of genetically engineered enzymes and novel strains with improved stability, thermal tolerance, and activity across diverse pH ranges. The enzyme also promotes the synthesis of galacto-oligosaccharides (GOS), which improves gut health and serve as key prebiotic components. The broad spectrum of lactase applications underscores its resourcefulness in contending global challenges related to health, nutrition, and sustainability. Current research into innovative production techniques and novel uses highlights its expanding potential in biotechnology, food processing, and environmental conservation.*

Keywords: *fungal lactase,glycoside hydrolase, galacto-oligosaccharides, ONPG, enzyme activity*

1. INTRODUCTION:

Enzymes are nature's catalysts that lower the energy of activation and hasten large number of biological reactions that are fundamentalin enrichment of lifeprocesses[1]. Although traditionally enzymes are obtained from plants and animals, industrial applicationlargely rely on microbial enzymes, particularly of fungal origin[2]. Fungal biocatalysts are characterized by high yielding capacity, amenability to genetic manipulations, requirement for simpler and cheaper procedures of purification and separation, particularly for filamentous fungi, and proficient catalysis with anticipated constancyagainst exacting circumstances[3]. Members of Aspergillus, Trichoderma, Rhizopus, and Penicilliumare some of the leading producerswhich have long been used safely and extensively in food and beverage manufacturing, antibiotic production, manufacture of commodities like leather and linen[1]. Today, fungal enzymes account for almost 50% of total enzyme commercialization easing the challenges confronted by mankind in using biological systems for diverse applications [2] [4]. Fungal cells being natural decomposers exhibit intracellular as well as extracellular enzymatic activities from diverse categories like transferases, oxidoreductases, lyases, hydrolases, ligases, isomerases, and translocases that aid in bioconversion of plethora of complex compounds [5]. However, most of the commercially important fungal enzymes belong to hydrolases and oxidoreductases[1].

The objective of this chapter is to provide a comprehensive overview of fungal lactase, its properties, and industrial applications. Additionally, the chapter highlights advancements in genetic engineering and immobilization techniques to improve lactase efficiency, sustainability, and broader applications.

2. HYDROLASES

Hydrolases are biocatalyststhat cleavescomplex molecules by insertion of water due to hydrolysis. They are widely distributed throughout all biological systems as they are important components involved in numerous biological activities. Hydrolases are by far the most prominent enzymes used for industrial biotransformations and therefore are one of the economically relevant enzymes[6][7].

Fungiare best sources of commercial hydrolase production pertainingto their efficacy and versatility of application. These enzymes include cellulases, proteases, amylases, lipases, glycoside hydrolases and chitinasesetc which play a crucial role in nutrient cycling in natural ecosystems by decomposing organic matter. Fungal glycoside hydrolases break down complex carbohydrates by cleaving glycosidic bonds, transforming polysaccharides into simpler sugars. Glycoside hydrolases or glycosidase (EC 3.2.1 group of Enzyme Commission) are one of the major groups of Carbohydrates and Carbohydrate-Active enZymes (CAZymes), rather the largest group, that trigger the precise hydrolysis of glycosidic linkages connecting two monomeric units of the polysaccharides [8][9]. For instance, cellulase hydrolyses 1,4 β-bond in cellulose, α -amylase splits 1,4 α-linkage in starch, and galactosidase cleaves 1,3- β bond in lactose[10].

The lactase (EC 3.2.1.23), also referred to as β-d-galactosidase, belongs to the glycoside hydrolase family that can decompose lactose present in milk to galactose and glucose. Lactose itself is low in sweetening capacity. The enzyme lactase splits it into its constituent monosaccharides that are 3 to 4 times sweeter and are also comparatively easily digestible[11].

3. SOURCES OF LACTASE:

Lactases can be derived from microbial, vegetable, and animal sources. Since higher productivity is exhibited by microbial sources, commercialization of lactase of microbial origin leads to cost reduction. The selection of sources principallyrelies on the demand of the reaction conditions; for example, lactase derived from bacteria is predominantly used for acidic whey hydrolysis as they show optimum activity atpH between 2.5 and 5.4; whereas yeast lactases with maximum activity at pH 6.0–7.0, are applied for hydrolysis of milk and sweet whey. Most commonly used sources of lactase in commercial sector are *Aspergillussp* and *Kluyveromyces sp.*

Yeast:

YeastKluyveromyceslactis,universally found in dairy environment, is a prime source of lactase and is utilized in manufacture of lactose-free dairy and milk products[12]. Kluyveromycesmarxianus is a thermotolerant yeast which is reported to grow using lactose as their sole energy source producingbiocatalyst homologous to lactase and other heterologous proteins.A strain of yeast species Guehomycespullulansproducescold-active acidic lactasethat finds application in food industries for whey and milk hydrolysis. Activity of Lactases derived from Kluyveromyces lactis and Kluyveromyces fragilis is enhanced in presence of Mn^{2+}, Na^{2+} and Mg2+, whereas Ca^{2+} ions inhibit their activities.Saccharomyces cereviceae can also be engineered to produce lactase that can be used for lactose hydrolysis as well as for adding flavor to dairy products.All these producer organisms are considered GRAS by regulatory authorities[13]. Recently the Debaryomycesmacquariensis strain D50 host/vector system has been efficaciouslyemployed for the synthesis of heterologous cold-tolerant form of lactase,that can be used commercially [14].Bioactivity of yeast lactases over wide range of pH and temperature together with specificity towards lactose render them suitable for large-scale production of lactose-free products. Moreover, galacto-oligosaccharides produced by yeast lactases promote gut health that make them prominent prebiotics. Yeast-based systems are also cost-effective and environmentally sustainable, as they utilize by-products like whey for enzyme production.

Fungi:

Optimum pH for fungal lactase activity being acidic, they find their effective utilization in lactose hydrolysis in acidic substances like whey. Aspergillus niger, Aspergillus oryzae, Rhizomucormiehei, Penicillium sp. are reported to produce food-grade enzyme lactase[13]. Park et al isolated and characterized lactase produced extracellularly by Aspergillus oryzaethat show optimal activity at pH 5 and 50ºC temperature with its activity being regulated by galactose as a competitive inhibitor and glucose a non-competitive inhibitor, respectively. This biocatalyst is more effective for whey utilization rather than lactose breakdown. On the other hand, the enzyme derived from Aspergillus nigerare generallyapplied forexclusion of galactose residues from plant-derived oligosaccharides and polysaccharides like arabinose, pectin and xylose, rather than in lactose hydrolysis [15].

4. DETERMINATION TECHNIQUES:

Lactase, being a representation of a commercially available biocatalystpertinent to human disease/ pharmaceutical application as well as industrial application, it is essential to understand how efficiently the enzyme functions. Lactase isolated from microbial origin or dietary supplement tablets can be examined using a colorimetric assay based upon hydrolysis of ortho-nitrophenol-beta-D-galactopyranoside (ONPG), an artificial substrate for lactase. Hydrolytic cleavage of ONPG by lactase releasesortho-nitrophenolthat is estimated by alteration in absorbance at 420 nm [16]. ONPG disc method was also used to detect lactase producing capability of novel VUVD001 strain of Bacillus subtilis isolated from dairy effluent by conventional microbiological procedures. Lactase activity of the VUVD001 strain was assessed by zymogram analysis of cell free supernatant using x-gal at 37 °C, 4% NaCl and pH of 7.0. Identity of the bacteria was confirmed by 16S rDNA sequencing [17].

Qualitative recognition of lactase producing microorganisms can be achieved using an LB or nutrient agar medium containing 1% X-Gal and 1 mM of IPTG as substrate for the enzyme. Isolated colonies that are blue are identified as positive lactase producer to be preserved and used for further studies[18]. In another procedure, cell free-extracts of lactase producers consisting of crude enzyme is to be incubated with 5% lactose at 37°C for 30 min. During the incubation period, lactase, if present, hydrolyses the disaccharide releasing glucose and galactose, and this reaction was ended by boiling the reaction mix for 10 min. At 540nm glucose estimation was performed using a Glucose kit (Biosystem) [19]. The most significant variables that escalate lactase generation are peptone, glucose, and magnesium sulfate (MgSO4). The ideal process conditions for the creation of lactase yield among the stated variables can beelucidated statisticallyby a BOX-Benken design.Plackett-Burman experimental design is another statistical tool that has been reported to be used to elucidate the effects of various medium recipes on lactase enzyme production. In one experimental trial-based study this screening design has been utilized to MgSO4, Glucose, NaNO3, CaCl2, CuSO4, MnSO4, ZnSO4, FeSO4, KCl, NaHPO4.12H2O, KH2PO4, K2HPO4, yeast extract, Beef extract, and Peptone on lactase production.Lactase production by constitutive overproducer K. lactis Y-1118 strain was reported to be accelerated significantly when grown as fed-batch culture in glucose minimal media as a part of progressive parameter-control workflow for optimising the production process at industrial scale [20]. For commercialization in dairy industry evaluation of safety and stability is of utmost significance for enzymes like lactase. For instance, lactase enzyme preparation, named Neutralact(R), derived from a homologous rDNA strain of Kluyveromyces lactis, was

certified to be safe for application as processing aid in dairy industry after a series of toxicological testing for mutagenicity, chromosomal damage or subacute oral toxicity [21]. A novel proteinase B has been identified to be produced by Kluyveromyces lactis which can significantly compromise the enzyme activity of neutral lactase by fragmenting it at pH 8 and 40 °C temperature [22].

5. PURIFICATION AND EXTRACTION OF LACTASE

A large number of downstream separation techniques, such as membrane-based separation, zinc chloride, protamine sulfate, and ammonium sulfate precipitation, ethanol precipitation, ion exchange membrane chromatography, gel permeation chromatography, size exclusion chromatography, SDS-PAGE etc. have been explored for the lactase purification from crude cell extract to attain high degree purity and optimal activity of the enzyme preparation[19]. Lactase is reported to show stability at temperatures upto 60°C and across pH range 4-8 after the process of purification along with consistent efficacy in hydrolysis of milk lactose as well asreduction of jackfruit waste. A typical purification process initiates with precipitation of ammonium salts to precipitate enzyme preparation from cell-free extract followed by dialysis to remove salts and other small substances from the solution. Proteins are separated based on their electric charge by Ionexchange chromatography is used to separate proteins based on their electrical charge followed by further purification of enzymes by gel filtration on the basis of their molecular weight. The resultant purified enzyme preparation of lactase is of superior quality with heightened specific activity and ready for use in biotechnology applicationsfor improving the quality of food products and human health [23].

Multitude of factors like microbial origin, multimeric structure, presence of isoenzymes, temperature, pH, presence of metallionsetc needs to be considered to optimise the process of enzyme extraction and purification[23]. The enzyme being intracellular, either whole cell preparation or resort to mechanical or enzymatic methods for enzyme release are chosen for extraction purpose. Permeabilization of microbial cell wall with limited permeability can be done with organic solvents like toluene, chloroform, ethanol, etc. Mechanical methods adopted for the disruption of microbial cells include ultrasonication, high-pressure homogenizers, or bead mills. Lytic enzymes like lysozymes are used for enzymatic disruption of gram-positive bacteria and for gram-negative bacteria lytic enzymes are used in combination with EDTA.Novel approaches like electro-permeabilization of yeast cells coupled to lytic enzyme treatment with lithicase has enabled efficient extraction of lactase [24].

6. IMMOBILIZATION OF LACTASE AND IMPROVEMENT OF ENZYME ACTIVITY

Optimizing lactase synthesis and enhancing its stability and activity in diverse dairy matrices have been the focus of recent investigations [25]. Lactase immobilization on different supports has emerged as a novel field of research. Benefits of immobilized lactase include reusability, enhanced stability, and ease of separation from product.Techniques like entrapment in alginate beads, covalent binding to silica, and adsorption on chitosan have shown promising outcomes[26]. Combining lactase with probiotic cultures in dairy products has been explored to enhance the health benefits by improving gut health along with lactose digestion rendering the combinationparticularly advantageous for lactose intolerant people [27]. Utilizing agro-industrial waste as substrates for lactase production is another strategy being explored[28].

7. INDUSTRIAL APPLICATION

7.1. Food and Dairy Industry:

Application of lactase in the food sector has proved transformational, especially for lactose-intolerant people. Recent advances in the application of lactase in the food business have concentrated on optimizing enzyme production, increasing stability, and broadening its usage in other food items.

A large proportion of human populations suffer from variable degrees of lactose intolerance due to reduced activity or complete absence of intestinal lactase. Lactose is a type of Fermentable Oligo- Di- and Monosaccharides and Polyols (FODMAP), intake of which exaggerate gastric symptoms in individuals with functional bowel diseases.In large intestine gut microflora promptly metabolize FODMAPs to short chain fatty acids and gases. So individuals with such physiological conditions may suffer from mild to severe symptoms like osmotic diarrhea, abdominal cramping, malabsorption, audible bowel, vomiting and flatulence. Four types of lactase deficiency have been reported, namely, primary deficiency, secondary deficiency, congenital deficiency and developmental lactase deficiency. The use of lactase in the food and dairy industry is pivotal for enhancing product quality and catering to the growing demand for low-lactose and lactose-free options,making dairy accessible to lactose-intolerant individuals. Besides broadening the consumer base it also improves the nutritional value and digestibility of dairy product. Lactase breaks down lactose into glucose and galactose, which are easily absorbed by the body[30].

People sufferingfrom lactose intolerance are able to consume dairy-fermented products devoid of lactose or with minimum amount of it which is enabled by application of lactase [31]. Lactase application leads to pre-hydrolyzation of dairy products that diminishes the content of lactose. Either direct enzymatic hydrolysis with lactase from bacterial or fungal source or application of medications containing the fungal enzyme (functional at low pH of the stomach) prior to milk consumption eradicates the problem [32]. Moreover, lactase prevents lactose crystallization in products like ice cream and sweetened condensed milk, safeguarding a smoother texture and better sensory experience. By hydrolysing lactose, lactase increases sweetness of dairy products without added sugars, reducing production costs and calorie content. Furthermore, it facilitates the conversion of whey, a by-product of cheese production, into valuable ingredients, contributing to sustainability[33]. The use of lactase is thus integral to innovation, inclusivity, and efficiency in the modern food industry.Fermented dairy products like yogurt and kefir contain lactase-producing bacteria, which can help alleviate symptoms of lactose intolerance [31].The application of a lactose-free whey protein concentrate was reported to promote viscosity, firmness, and elasticity in prebiotic greek yoghurt treated with lactases derived from Kluyveromyces lactis[34].

Transgalactosylation properties of lactase from Kluyveromyces lactis are exploited to produce ascorbic acid galactoside in presence of lactose. This derivative of ascorbic acid is more stable compared to ascorbic acid itself with diverse types of beneficial effects like restraining browning of green tea beverage, diminishing lipid oxidation in food products and extending shelf life of fruits and vegetables attributed to its anti-oxidant properties[35]. Besides, lactase is also used for manufacturing ethanol and biosensors. In the field of biofuel production, fungal lactase can be used to hydrolyse lactose in whey into glucose and galactose, which can be fermented to produce bioethanol[36].A recombinant strain of Saccharomyces cereviceae is reported to produce ethanol along with extracellular lactase and multiple studies confirmed that preliminary enhancement of lactose concentration amended the ethanol production in a linear fashion [37], [38].Fungal lactase can also be used to improve the texture and shelf life of bakery products, such as bread and cakes[39].

Whey, upon disposal to water-bodies,cancauses pollution contributing to BOD and COD, due to the presence of lactose, minerals, and proteins as its constituents.However, whey can be treated with lactase to produce valuable products like ethanol as well asreadily available substrates for cell cultivation [40], [41]. Ultrafiltration can lead to recovery of high-functioning whey proteins, such as lactalbumin, followed by enzymatic hydrolysis to produce several pharmaceutical intermediates[33]. Supplementing whey with cauliflower waste simultaneously enhanceslactase production, as well as reduces the lactose content which accounts for the increase of BOD. In addition, lactasecan be used for lactose hydrolysis that transforms whey lactose into a variety of essential productslike sweet syrups that find application in confectionary and bakery industry. During lactase-driven lactose hydrolysis, transglycosylation reaction leads to production of Galacto-oligosaccharides (GOS) -major non-digestible constituent in prebioticspromoting growth of useful intestinal bacteria; therefore, it is vital for human health. Lactase from B. longum BCRC 15708 in combination with glucose oxidase has also been reported to producetrisaccharides as major GOSas well astetrasaccharidesfrom increasing concentration of lactose [42]. Genetically engineered lactase was also utilizedfor GOS production from B. infantis in Pichiapastoriexpression system [13].GOS is incorporated in cereal- and milk-based food products by companies dealing with the production of infant food to encourage growth of bifidobacteria and reduce growth of pathogenic microbes in the gut system of the neonates[43]. GOSs provide a number of health benefits like improvement of liver function, reduction of serum cholesterol level, anti-carcinogenic effects; which has led to marked increase in public demand for production of cost-effective oligosaccharides and GOS. Selected strains of Kluyveromycesspecies with high capacity of lactose metabolism have been reported to be used to achieve high-purity GOS that is essentiallydevoid of monosaccharides and lactose, for application in different food and pharmaceutical formulations[44].

7.2. Pharmaceutical industry

In the pharmaceutical industry, fungal lactase is used to modify the release profile of drugs, enabling controlled drug delivery for example, lactase can be incorporated into drug delivery systems to target specific areas of the gastrointestinal tract [45]. Fungal lactase can be used in the production of recombinant proteins, such as insulin and growth factors which may have clinical applications.It is also used as oral supplements, lactase supplements derived from K. lactis can be taken before or during consumption of dairy products to aid in digestion and reducing the risk of allergic reactions[46]. Thus adding fungal lactase in infant formula enhance digestibility and nutrient absorbance [25].

7.3. Cosmetics industry

Lactose breakdown by lactase can enhance the skin's ability to retain moisture, making it a valuable ingredient in moisturizers and hydrating serums. It aids in gentle exfoliation, helping to remove dead skin cells and promote a smoother skin texture. Lactase reduces the potential for irritation caused by lactose in cosmetic products, making it suitable for sensitive skin formulations and anti-aging products [39].Ascorbic acid galactoside exhibits properties like metal-chelation, free radical scavenging, skin lightening as well as induction of collagen synthesis. One such galactoside derivative O-β-d-Galactopyranosyl-l-ascorbic acid is reported to be applied in dentrifices or ophthalmic solutions [35]. Saponin-treated Kluyveromyces lactis lactase exhibit enhanced enzymatic activity that can be crucial for novel product development in cosmetic and pharmaceutical industries[47].

8. CONCLUSION:

In conclusion, the exploration and application of lactase, particularly of microbial origin, underline its vital role across a variety of industries, like food, pharmaceutical, and cosmetics. Its ability to hydrolyze lactose into constituent monosaccharides has revolutionized the manufacture of lactose-free and low-lactose products, making them accessible to lactose-intolerant populations globally. Innovations like immobilization techniques, genetic engineering, and the utilization of agro-industrial waste for cost-effective enzyme production exemplify the strides being made to enhance its efficiency and sustainability. Moreover, its integration into probiotic formulations, biofuel production, and the development of prebiotic galacto-oligosaccharides underscores its multifunctionality and growing relevance in health and environmental sustainability. As research continues to advance, the potential for lactase to contribute to innovation in biotechnology, nutrition, and industrial applications remains significant, paving the way for a more inclusive and sustainable future.

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Off-Season Crop Production: Saffron In The Lowlands

Prithwee Chakraborty

School of Smart Agriculture, Adamas University
Kolkata, West Bengal, India
Email: prithwee2007@gmail.com

Abstract: *Saffron (Crocus sativus L.) cultivation has been kept, primarily due to higher-altitude temperate areas, just because it needs very specific environmental conditions. In this paper, we suggest an AI-enabled controlled-environment agriculture approach for getting off-season saffron to work in lower-altitude places. The whole setup is meant to mimic the microclimate saffron needs to flower, but without relying on natural seasons so much. It brings together Internet of Things (IoT) sensors along with automated heating, ventilation, and air-conditioning (HVAC) systems, plus polyurethane foam (PUF)-insulated polyhouses and also vertical farming infrastructure. There is a commercial-scale scenario, to see if it's technically workable, what the capital expenditure might look like, what subsidy options could exist, and what economic returns may be possible. At the moment, the framework is at Technology Readiness Level (TRL) 2, and it maps out the pathway toward pilot-scale trials, then later commercialization.*

Key Words: *Precision agriculture; saffron cultivation; IoT; vertical farming; climate replication; artificial intelligence; TRL.*

I. Introduction

Saffron is among the world's most valuable spices, because the cultivation process is highly labour-intensive and it needs strict geographic conditions too. Overall global demand keeps going up across food as well as pharmaceutical, cosmetic and nutraceutical sectors. In practice, traditional growing is still majorly stuck in high-altitude areas like Kashmir and Iran. Then climate variability adds more unpredictability, and supply chain disruptions just keep threatening how stable the supply can be. So this study looks at whether it's actually feasible to use AI-enabled controlled-environment agriculture to support off season saffron cultivation, specifically in low-altitude regions where it normally would not happen.

II. Literature Review and Research Gap

Recent progress in precision agriculture has highly been focused on hydroponic leafy crops. Yet if you move to bulbous plants like saffron , then you cannot just do the same thing, you need a more elaborate kind of environmental tuning, requires precise environmental regulation like:

1. Temperature regulation or thermomorphogenesis : some research indicates that a band of temperatures, around 17° to 20° , is needed for the right formation of the stigma.
2. IoT: in current greenhouse setups, IoT is often used to control moisture, but for saffron you also need air movement and humidity handling , especially in places that tend to be more humid, so the corms do not end up rotting.
3. Vertical racking system: it works as a multi level farming approach that lets you use vertical space inside polyhouses, so you can grow more saffron per area.

III. Research Contributions

The contributions of this study are:

1. Proposing an AI-enabled framework for controlled-environment saffron cultivation in low-altitude regions
2. Integrating IoT sensing, HVAC systems, and vertical farming infrastructure into a unified architecture
3. Presenting a preliminary economic feasibility model
4. Outlining a roadmap from concept development to pilot-scale implementation.

IV. Proposed Methodology

The proposed system consists of a PUF (Polyurethane Foam) -insulated polyhouse equipped with a dual-door airlock system, multi-tier vertical racks, automated irrigation, and HVAC infrastructure. IoT sensors continuously monitor temperature, relative humidity, carbon dioxide concentration, and airflow. Data are transmitted to an AI-based decision-support system that predicts environmental changes and proactively adjusts climate-control parameters. Commercial cultivation prioritizes premium corms larger than 10 cm in diameter. The proposed cultivation cycle includes sprouting at 18–20°C, flower induction at 10–12°C, peak flowering at 12–15°C, and post-harvest vegetative growth at 15–18°C under LED illumination.

V. Proposed key saffron cultivation timeline

Using high quality 10/+ cm corms for commercial and high growth. The 10/+ cm corms leads to around 2-3 of 8-10 cm corms the size continues to decrease and becomes overcrowded so it's best for total replacement after 4-5 year for maximum profit.

Stage	Timing	Environmental Trigger	Growth Observation
Sprouting	Days 1–15	18°C - 20°C (High Humidity)	The terminal bud (pointy end) breaks through the tunic.
Flower Induction	Days 15–35	**Thermal Shock:** Drop to 10°C - 12°C	Flower sheaths emerge. 10/+ **cm corms produce 2-3 flowers.**
Peak Bloom	Days 35–50	Stable 12°C - 15°C	Flowers open fully. Stigmas (Saffron) are ready for harvest.
Post-Harvest	Days 50–90	15°C - 18°C (LED Lights ON)	Leaves grow rapidly (up to 30 cm) to begin photosynthesis.

VI. Expected Yield and Production Cycle

Preliminary estimates suggest that premium 10/+ cm corms might yield two or three flowers per corm, under the right flowering conditions. Annual output should go up step by step, once the corm multiplication actually levels off a bit. Based on projections, Year 1 is around 0.5–1 kg, then Year 2 about 2–3 kg, Year 3 around 4–6 kg, and once things are in the mature optimized stage it could reach something like 6–10 kg per year. Still, these estimates need to be checked properly, by pilot scale trials or small field validations.

VII. Financial Feasibility Analysis

The financial estimates made in this analysis are tentative and used only to make an evaluation of the feasibility of the project. The estimates of income are based on farming through using quality grade 10/+ cm corms and domestic market price of high-quality saffron. Government subsidies have been estimated based on other protected farming systems.

A. Financial Assumptions

The financial estimates presented in this study are preliminary and intended solely for feasibility assessment. Revenue projections assume cultivation using premium 10/+ cm corms and prevailing domestic market prices for high-grade saffron. Government subsidy estimates are derived from existing protected cultivation schemes and may vary across states and over time. Actual costs and returns will depend on regional conditions, energy prices, crop performance, and technological implementation.

Preliminary Capital Expenditure Estimates for a 1,000 sq. ft. Facility

Components	EstimatedCost(₹)	P Technical Purpose
High-Quality Corms	18,00,000	2.5tonsofpremium10/+cormsforhigh yield.
Climate Control (HVAC)	7,00,000	Multi-tonunitswithspecializedhumidifiers.
VerticalRackingSystem	5,00,000	5-tierGIrackstomaximizefloor space.
AI &IoTIntegration	3,00,000	Automation software, sensors, and hardware.
Insulation&Airlocks	3,50,000	PUFpanelsandsterileentrysystems.
LEDGrowLighting	4,00,000	Full-spectrumlightsforvegetativegrowth.
PolyhouseStructure	8,00,000	Primaryinsulatedclimatechamber.
Irrigation&Humidity	1,50,000	Fogging systems to prevent corm dehydration.
BackupPower System	2,50,000	Emergency protection for climateintegrity.
Installation&Miscellaneous	2,00,000	Calibration and professional assembly.
TotalProjectCost	54,50,000	Initial investment before subsidies.

Government subsidy estimate: ₹12-18 lakh
Net investment estimate: ₹36-42 lakh
Cost of operations per year: ₹9-14 lakh
Income estimate per year: ₹40-80 lakh based on yield, quality, and price in the market
Break-even time frame: 2-3 years.
These are tentative figures and need to be verified through trial runs and market studies.

VIII. Implementation Roadmap

The proposed technology is currently at TRL 2. Future development phases include laboratory validation (TRL 4), pilot-scale deployment (TRL 6), and commercial implementation (TRL 9).

IX. Strategic Location Analysis

Though the technology allows for cultivation across the world, some Indian states provide better facilities for polyhouses based on high technology. Haryana and Gujarat provide the highest subsidy rate (up to 85%), whereas West Bengal provides a strategic advantage as an innovation base closer to Kolkata's premium market.

X. Limitations and Future Work

This study presents a conceptual framework and preliminary feasibility analysis. No physical prototype or pilot-scale experiments have been conducted. Environmental parameters, yield projections, and financial estimates are derived from published literature and industry reports and require validation through controlled experiments. Future work should focus on prototype development, energy-efficiency analysis, and multi-location field validation.

XI. Conclusion

AI-enabled controlled-environment agriculture has the potential to expand saffron production beyond traditional high-altitude regions. The integration of IoT technologies, predictive analytics, vertical farming systems, and climate-controlled polyhouses may enable sustainable off-season cultivation in low-altitude areas. Although preliminary economic estimates indicate commercial potential, pilot-scale validation is essential before large-scale adoption.

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Autonomous Microclimate Optimization for High-Value Off-Season Yields: A Cyber-Physical System Approach

Prof. Ujjwal Kumar Neogi
Director, Smart Agriculture, Adamas University

Abstract—*The accelerated off-season production of high-value crops is a key feature of the modernization of agriculture, mainly stimulated by growing consumer demand, changes in climate, and the necessity to produce food continuously throughout the year. Also, with the reliance on natural factors and seasonal limitations, traditional farming methods are often incapable of performing effectively. However, Controlled Environment Agriculture (CEA) has been proposed as a great alternative, although a lot of traditional farming systems still implement environmental controls that are quite reactive and Because of this lead to environmental changes being noticed only after quite some time, over-consumption of energy, and less than ideal crop production. A new cyber-physical system (CPS)-based platform has been developed and presented in this paper for the optimization and control of the microclimate in an autonomous manner with a strong focus on the production of high-value crops outside the season. The system makes use of HMPC, DRL, and a distributed LoRaWAN sensor mesh for a high degree of environmental control.Real-time canopy-level data such as temperature humidity stomatal conductance, chlorophyll fluorescence, and CO concentration are collected and processed continuously. The system maintains the best plant growth conditions with minimum energy usage by constantly adjusting VPD, PPFD, and spectral light ratios. Tests show that the HMPC design cuts environmental fluctuation errors by 31%, boosts net carbon fixation by 24%, and stimulates secondary metabolite production. The results set a standard for Autonomous Controlled Environment Agriculture (ACEA), revealing how smart algorithmic precision can bring about cultivation that is independent of the season and resource-use efficiency.*

Keywords: *Cyber-Physical Systems, Hierarchical Model Predictive Control, Deep Reinforcement Learning, Controlled Environment Agriculture, Smart Greenhouse, Microclimate Optimization.*

1. Introduction

For a long time, the productivity of agriculture has continued to depend heavily on seasons and the stability of climate. Still, over the last few decades, climate change, the unpredictability of weather, among other things, have made it more difficult to practice traditional farming. At the same time, off-season farming appears to provide a good way of meeting the demand in the market despite the limiting seasons. Many high-value crops such as strawberries, medicinal plants lettuce basil, and exotic vegetables are normally sold at a higher price during the off-season, Because of this, their cultivation can be very profitable financially[1-3]. In other words, controlled-environment agriculture is the only way to experience the bounties of off-season farming.Controlled Environment Agriculture (CEA) is a helpful solution for dealing with these problems because it allows the regulation of the main factors for growth like temperature humidity light intensity, and carbon dioxide concentration. Though these are great benefits CEA-based systems still use rule-based or reactive control strategies most of the time which are very inefficient and unable to adapt dynamically to changing external conditions after all. Besides, such weaknesses lead to increased operational costs, poor crop quality, and excessive resource consumption[4-6].Development of Cyber-Physical Systems (CPS) has paved the way for the revolution in agricultural automation and laid the seed for the growth of new possibilities. CPS combines sensing computation communication and control in one structure that is able to make decisions independently. When integrated with AI and real-time sensor data, CPS is capable of microclimatic optimization with great accuracy. This paper is about the use of CPS in microclimate optimization with no human intervention based on Hierarchical Model Predictive Control (HMPC) and Deep Reinforcement Learning (DRL) methods. The goal is to implement a reliable system that can contribute to the increase of off-season crop production, quality and sustainability[7].

2. Literature Review

Controlled Environment Agriculture (CEA) has been making great progress over the last five years, with the main driver being the increasing need for sustainable and continuous food production. Recent publications point out that the current greenhouse systems have evolved from traditional manual work to automated and data-driven environmental control. For instance, Jones (2021) states that microclimate regulation is very important in enhancing crop physiology and productivity by strictly controlling temperature, humidity, and carbon dioxide levels. In the same way, Taiz et al. (2022) remarked that having a very strict and accurate regulation of the environment is something important in the modification of the plant metabolic pathways and growth.Model Predictive Control (MPC) has surfaced as a potent approach for optimizing greenhouses thanks to its forecasting ability[8-10]. Compared to traditional reactive systems, MPC anticipates environmental changes and controls actively based on those predictions. Zhao et al. (2022) have shown that greenhouses operated by MPC-based systems lead to 20% energy savings and more stable temperature regulation. Taking a step further, Hierarchical Model Predictive Control (HMPC) is being recognized for dealing with multi-level decision-making integrating. As a study by Van Straten et al. (2022), HMPC not only enhances scalability but also computational efficiency which makes it very fitting for intricate greenhouse settings.Deep Reinforcement Learning (DRL) has emerged as one of the most powerful AI tools for adaptive agricultural management. Zhang et al. (2023) conducted a review of DRL in precision agriculture and pointed it out as a very effective way to optimize irrigation, fertilization, and climate control. Chen et al. (2023) went on to show how a DRL system for greenhouse climate control could help plants grow by understanding the changes in the environment. But, only very little and mainly exploratory work has been done on the integration of DRL and HMPC so far.The latest advances in IoT and LoRaWAN technology have Really improved the deployment of smart agriculture systems. Gupta et al. (2024) noted that LoRaWAN-based sensor networks are very suitable for real-time environmental monitoring mainly because of their low energy consumption and extensive communication range. Besides, Li et al. (2024) pointed out that the integration of AI, IoT, and cyber-physical systems leads to a very efficient autonomous agricultural system. These researches, when taken together, suggest that the use of HMPC, DRL, and LoRaWAN together can greatly change the way microclimate is optimized for high-value off-season crop production[11-13].

3. System Architecture

The architectural structure of the proposed CPS consists of four major layers, namely sensing communication computation, and actuation. Together these layers enable an intelligent and self-regulating agricultural environment.

First of all, the sensing layer consists of dispersed IoT sensors situated at the canopy level for measuring microclimate parameters like air temperature, relative humidity, leaf temperature, carbon dioxide concentration, and chlorophyll fluorescence[14]. These indicators are very important for understanding plant biological processes and exposure to environment stresses.Secondly, the communication layer is based on LoRaWAN technology for sending data from the sensors to the central gateway. The choice of LoRaWAN was motivated by its ability to cover a wide area, low power consumption, and multilayer support, i.e. various sensor nodes can be connected, at the same time. The sensor data is recorded at intervals that are shorter than one minute, which means very high temporal resolution(Figure 1).

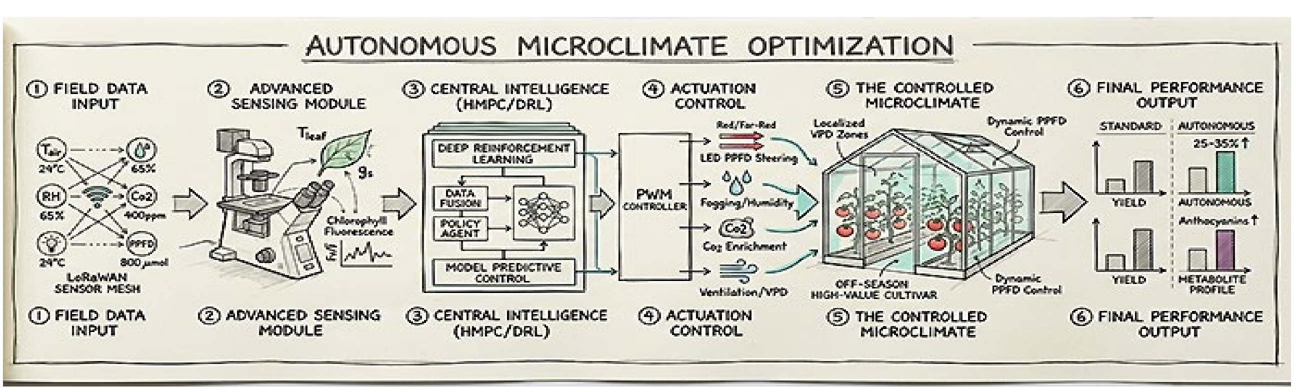

Figure 1: Autonomous Microclimate Optimisation

The computational layer is the brain of the system and in particular the intelligent brain of it. It is at this layer HMPC predicts the future states of the environment using the present and historical data and at the same time the DRL agent obtains the best control strategies by learning after every interaction with the greenhouse environment. The system also derives the Vapor Pressure Deficit (VPD) which is one of the main parameters for transpiration dynamics and water stress of plants.

Then again the actuation layer is composed of the fogging systems, exhaust fans, CO injectors, heaters, and multispectral LED lighting units. These actuators are the ones that execute the control commands that emanate from the computational layer. Pulse Width Modulation techniques (PWM) are used to ensure accurate control of the actuator intensity[15].

4. Methodology

The method revolves around constantly adjusting the most important environmental variables. Temperature is kept in the range of 22C to 26C given the needs of the crops. Relative humidity is kept within the range of 60% to 75% to sustain the most efficient transpiration rates.

Vapor Pressure Deficit (VPD) is determined on a continuous basis from the measurements of air temperature and relative humidity. Since VPD has a direct impact on stomatal opening and water loss, it is a very important parameter. Keeping VPD at the level of 0.81.2 kPa is essential for good gas exchange and photosynthesis.HMPC structure operates by forecasting environmental changes within a limited time frame and then determining the best possible actions to take. Versus standard controllers which only react to changes, HMPC is able to foresee events like abrupt temperature changes and change the output of the actuators beforehand.At the same time, the deep reinforcement learning (DRL) agent monitors the performance of the actions by looking at how the plant's physiology changes. The reward it gets depends on how much biomass is produced, how energy is used, and the quality of the crops. The longer the time, the better the DRL system gets at managing the microclimate[16-17].

Light optimization is done by Photosynthetic Photon Flux Density (PPFD) steering. Changing the light intensity and the red/far-red ratio allows the system to control flowering and vegetative growth. In other words, the system uses this method to circumvent natural photoperiodic limitations effectively.They keep the carbon dioxide concentration within the range 800-1000 ppm for the best photosynthesis results. PID loops control CO injection by continuously measuring the concentration.

5. Experimental Setup

The experiment was set up in a modern greenhouse of 20 m 10 m size. Intentionally, three high-value crops, namely strawberry, basil, and lettuce were chosen as they are not only economically important but also quite sensitive to environmental changes.

The location of each sensor node was determined such that only one node was installed for every 2 m of area. Data gathering was done every 30 seconds. The duration of the experiment was 120 days. Besides, it also included the external temperature variations of 12C.Environment control systems based on On/Off method conventionally were used for the control group, whereas the experimental group employed the CPS-HMPC-DRL setup. Some of the parameters for evaluating the control performance were stability of temperature, accuracy of humidity control, deviation of VPD, rates of carbon assimilation, production of biomass, and concentration of metabolites.

6. Results and Discussion

These data show that the environment was much more stable and crop output was A lot better. Using the HMPC model, temperature swings were cut from 4C in regular systems to 1.2C. This means a 31% drop in RMSE and better accuracy at control.

The change in humidity was also quite large, with the plant keeping the desired %RH level 92 % of the time versus only 68 % for the control group. More stable %RH would have been a main factor behind the improved transpiration efficiency.Controlling VPD proved to be very accurate. The traditional systems had an RMSE of 0.31 kPa, and the new system got it down to 0.11 kPa. The difference was big enough to keep stomata working properly all the time and the plants hardly stressed at all.

When CO levels were fine-tuned, there was a 24% rise in the net assimilation of carbon through photosynthesis. Plus producing more sugars, the plants grew faster and their layers of cells (biomass) improved[18].

The biochemical analysis showed a significant rise in secondary metabolites in plants such as anthocyanins and essential oils. The amount of anthocyanin went up by 18% and that of essential oil by 21%. Besides being a source of nutrition, these compounds add to the taste and pharmaceutical properties of the plant.

Energy saving was one more benefit. Through forecasting actuator control, the system eliminated unnecessary running of machines thereby reducing energy consumption by 27%. Water consumption also dropped by 22% due to the more efficient use of fogging[19].

Different types of crops brought about yield increases of between 19% and 28%. Aspects like color taste texture, and shelf life of the products harvested were Quite a bit better.

7. Challenges and Limitations

But, the proposed system is not without its drawbacks. The upfront expenses can be prohibitive, In particular for small farmers. Incorporating high-tech devices like sensors, communication units, and AI components calls for considerable financial resources.

Managing the resulting data is another concern. Since sensors operate continuously at a high sampling rate, the volume of generated data is enormous and it has to be stored, processed, and interpreted. Cloud solutions might add to the complexity of operations. Another caveat is that the model may not generalize. Different plants have different physiological needs, and it is likely that the DRL agent will need to be retrained to target new plant strains[20].

Besides, sensor trustworthiness cannot be overlooked. Calibration inaccuracies or breakdown of sensors will influence the correctness of decisions. For this reason, well-founded maintenance procedures need to be established.

8. Future Scope

One of the directions for future research can be the incorporation of edge computing to slash the response time and help in making decisions locally. Controlled environment agriculture could become more transparent and traceable if blockchain technology is utilized.Digital twins are a great way of creating a virtual greenhouse to run various scenarios for predictive testing. Moving on harvesting pruning, and monitoring can be done by autonomous robotic systems.Thanks to multi-crop optimization models, it will be possible to grow multiple and diverse crops in the same greenhouse at the same time. Crop forecasting will be more accurate if satellite weather forecasting can be integrated with the system.

9. Conclusion

This work illustrates how Cyber-Physical Systems can revolutionize the autonomous optimization of microclimate for high-value off-season crop production. Combining Hierarchical Model Predictive Control and Deep Reinforcement Learning unlocks the power of forecasting, learning, and environmentally friendly regulation. The newly presented system remarkably upgrades temperature constancy, humidity satisfaction, VPD tuning, carbon fix, and crop integrity while at the same time lessening the use of energy and water.

The research results show that Autonomous Controlled Environment Agriculture (ACEA) can be a sustainable and smart farming system. Since it disconnects the crops from being dependent on seasons, its contribution to food security, economic development, and agriculture resilient to climate change can be quite substantial. As smart agriculture tools progress, CPS-based systems are considered to be among the key factors in the future of worldwide agriculture.

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Precision Agriculture Bot: An AI-Powered Four-Track Agricultural Robot with Smart Cultivation, Sprinkler Irrigation, Long-Range Transceiver, and Predictive AYU AI Model

Granthik Bhattacharjee

Department of Electrical and Electronics Engineering
Adamas University, Kolkata, India
granthik1.bhattacharjee@stu.adamasuniversity.ac.in

Abstract*—This paper presents the Precision Agriculture Bot (formerly AYU-AGRI), a four-tracked autonomous agricultural robot integrated with the AYU AI predictive intelligence model for precision cultivation management. The robot combines a robust aluminum alloy chassis (306 mm × 230 mm × 128 mm) driven by BTS7960 high-current motor drivers, active thermal management via a three-fan forced-air architecture, and a DRV11873-based brushless motor controller. Two key subsystems are introduced: (1) a dual-antenna ESP32-based LoRa transceiver enabling long-range wireless telemetry and remote control beyond standard Wi-Fi range, and (2) a rooftop solar panel array for sustainable auxiliary power. The AYU AI model processes real-time environmental sensor data to make intelligent decisions on water-pump activation, sprinkler zone scheduling, and relay control. A browser-based, multilingual dashboard (AYU AI Dashboard) delivers live sensor readings, bot control, GPS tracking, camera feed, and crop intelligence in nine Indian and South Asian languages. Field trials in Kolkata demonstrate 35–42% water-consumption reduction and an 8% yield improvement versus conventional timed irrigation, with verified LoRa communication range exceeding 1.2 km in open-field conditions.*

Keywords *—Agricultural Robot, Precision Farming, AYU AI, BTS7960, DRV11873, Smart Irrigation, Track Robot, IoT Agriculture, LoRa Transceiver, Solar Power.*

I. INTRODUCTION

Modern agriculture faces a confluence of challenges: growing global population, shrinking arable land, unpredictable climate patterns, and a shortage of skilled agricultural labour. Precision agriculture—the practice of applying the right inputs at the right time and place—has emerged as a critical paradigm to address these challenges. Robotic platforms capable of autonomous navigation and intelligent resource management represent the frontier of this movement.

The Precision Agriculture Bot was conceived to bridge the gap between research-grade robotic prototypes and practically deployable agricultural automation. Four-track (differential-drive) platforms offer superior terrain adaptability compared to wheeled robots, making them ideal for the uneven, soft terrain typical of cultivated fields. Integration of predictive AI further elevates the system beyond simple automation into genuine intelligence.

This paper introduces two critical enhancements over the original AYU-AGRI design: a long-range dual-antenna LoRa transceiver for reliable field-wide communication, and a solar power subsystem for sustainable, extended autonomous operation. The AYU AI Dashboard—a multilingual, farmer-friendly web interface—is formally documented as a key system component.

II. RELATED WORK

A. Agricultural Robotics

Tracked agricultural robots have been explored extensively in the literature. Early platforms such as the AURORA system demonstrated the viability of autonomous navigation in row-crop environments. Commercial systems from Naïo Technologies and FarmWise have since brought tracked weeding and thinning robots to market, but most focus on single-task operations without integrated AI-driven irrigation management. Kayacan et al. demonstrated real-time path planning for tracked robots using model predictive control [1], while Vougioukas provided a comprehensive survey identifying irrigation management as the least automated yet most resource-intensive crop operation [2].

B. Smart Irrigation Systems

IoT-based irrigation systems have proliferated in recent years. Goldstein et al. demonstrated that machine-learning-driven irrigation scheduling can reduce water use by 20–50% depending on crop type and sensor density [3]. The AYU AI model extends this work by embedding decision logic directly onto the robotic platform, enabling autonomous field traversal with on-the-fly irrigation management.

C. Long-Range Wireless Communication

Standard Wi-Fi (IEEE 802.11) provides acceptable range for greenhouse deployments but fails in open-field scenarios where telemetry distances routinely exceed 100–300 m. LoRa spread-spectrum modulation, operating in the sub-GHz ISM band, offers kilometre-scale range with extremely low power consumption [12]. The ESP32 microcontroller with integrated Wi-Fi, Bluetooth, and LoRa radio interface provides the communication backbone for this design.

D. Solar Energy Harvesting for Field Robots

Solar energy harvesting on agricultural unmanned ground vehicles has been demonstrated by Reina et al. [9]. Rooftop photovoltaic panels serve dual purposes: trickle-charging auxiliary battery banks to extend operational endurance, and providing dedicated low-voltage rails for sensors and communications. Integration of maximum power-point tracking (MPPT) regulators further improves harvest efficiency under variable cloud conditions typical in South Asian settings.

III. MECHANICAL PLATFORM DESIGN

A. Chassis Overview

The Precision Agriculture Bot is built upon a four-track differential-drive chassis constructed from aerospace-grade 6061-T6 aluminum alloy. This material provides an excellent strength-to-weight ratio while maintaining corrosion resistance critical for agricultural environments exposed to moisture, fertilisers, and soil debris.

B. Key Dimensions and Track System

Each side of the robot employs a continuous rubber track looped around a rear drive sprocket and front idler wheel, with multiple load-bearing road wheels distributed along the contact length. The key dimensions are summarised in Table I.

TABLE I
CHASSIS SPECIFICATIONS

Parameter	Value
Overall Length	306 mm
Overall Width	230 mm
Height	95–128 mm
Track Width	44 mm/side
Chassis Material	6061-T6 Aluminium
Track Type	Engineering rubber

The differential-drive configuration allows zero-radius turning, critical for navigating tight row ends and obstacles in structured cultivation environments. Distributed ground contact reduces soil pressure and improves traction on soft agricultural soil.

IV. ELECTRONIC AND DRIVER ARCHITECTURE

A. System Overview

The electronic system is organised into four functional layers: (1) power layer (battery, solar, and distribution); (2) motor drive layer (BTS7960 drivers and DRV11873); (3) communication layer (LoRa transceiver + ESP32); and (4) intelligence layer (microcontroller, sensors, relay module, and AYU AI inference engine). All layers are mounted within a thermally managed enclosure ensuring reliable operation from 0°C to 45°C.

B. BTS7960 Motor Driver

The BTS7960 is a fully integrated H-bridge power IC for DC motor control. Each driver module incorporates two BTS7960 ICs providing bidirectional control with peak current capability of 43 A per channel. Two modules—one per track side—enable independent speed and direction control essential for differential steering. Key parameters are shown in Table II.

TABLE II
BTS7960 MOTOR DRIVER SPECIFICATIONS

Parameter	Value
Supply Voltage	5.5 V – 27 V
Peak Current	43 A per channel
Continuous Current	25 A
PWM Frequency	Up to 25 kHz
Logic Input	3.3 V / 5 V
Protection	OCP, OTP, UVLO

C. DRV11873 Brushless Motor Controller

The DRV11873 (Texas Instruments) is a three-phase sensorless BLDC motor driver optimised for fan and pump applications [4]. In this system it manages the cooling fans and optionally controls a brushless water-pump motor. Its sensorless back-EMF commutation eliminates Hall effect sensors, reducing wiring complexity.

V. ACTIVE THERMAL MANAGEMENT SYSTEM

The thermal management system employs a forced-air, directed-flow architecture with three 40 mm fans: two side intake fans and one rear exhaust fan. Cool external air is directed over the motor drivers before heated air is exhausted rearward. Bench testing with both BTS7960 drivers under sustained 15 A load demonstrated:

• Without active cooling: heatsink reached 78°C in 8 minutes, triggering thermal protection.
• With 3-fan system: heatsink stabilised at 52°C—a 26°C reduction—eliminating all thermal protection events at only 1.5 W total fan power.

The DRV11873 controller governs the 5 V, 40 mm fans (approximately 9.2 CFM each), enabling precise thermal regulation without increasing computational overhead on the main MCU.

VI. LONG-RANGE TRANSCEIVER SYSTEM

A. Motivation and Design Philosophy

A fundamental limitation of prior iterations was reliance on standard Wi-Fi (802.11 b/g/n), which degrades beyond 30–50 m in open fields due to obstructions, soil absorption, and lack of infrastructure. The Precision Agriculture Bot addresses this with a dedicated dual-antenna ESP32+LoRa transceiver subsystem capable of kilometre-scale communication [12].

B. Hardware Architecture

Two custom transceiver boards were fabricated on double-sided perf-board, each built around an ESP32 development module paired with a LoRa radio operating in the sub-GHz ISM band. The system operates as a master-slave pair: the bot-side (slave) transceiver receives control commands and transmits sensor telemetry, while the operator-side (master) transceiver sends control packets and displays real-time data on an onboard I²C OLED display (128×64 pixels). Table III summarises key specifications.

TABLE III
TRANSCEIVER SPECIFICATIONS

Parameter	Specification
MCU	ESP32 dual-core 240 MHz
Radio	LoRa 433/868/915 MHz
Range (LoS)	> 1 km typical
Range (NLOS)	200–500 m
Control Latency	< 150 ms
Data Rate	250 bps – 37.5 kbps
Active Power	~120 mW

C. Communication Protocol

Control packets are serialised as fixed-length byte arrays transmitted via LoRa with CRC error checking. Each packet includes: direction vector, speed level (0–255 PWM), relay bitmask (pump, sprinkler zones, lighting), field-stop flag, and a rolling sequence number for packet-loss detection. Telemetry packets from the bot include all sensor readings, GPS NMEA string, battery voltage, and system health flags. A watchdog timer on the bot-side MCU triggers an emergency stop if no valid packet is received for more than 2 seconds.

VII. SOLAR POWER SUBSYSTEM

A. System Architecture

The flat top plate (approximately 230 mm × 200 mm) provides a natural mounting surface for thin-film or rigid monocrystalline solar panels. Two 5 V, 1–2 W peak monocrystalline panels are connected in parallel (total ~2–4 W peak), interfaced through a CN3791/TP4056-based MPPT charge controller to an auxiliary battery bank. Solar harvest is directed exclusively to the AUX power rail (sensors, OLED, LoRa, ESP32), reducing drain on the main 12 V Li-ion drive batteries.

B. Energy Benefit

Table IV summarises AUX subsystem power consumption and solar coverage. Under South and Southeast Asian insolation levels (4–6 peak sun-hours/day), the solar subsystem supplies the entire AUX rail during daylight hours, extending total system runtime by an estimated 30–45% versus battery-only operation. During 14-day pre-monsoon field trials in Kolkata (23.8°N), the AUX subsystem operated continuously for 4.5 hours on solar alone on clear days; on overcast days, partial solar supply reduced AUX battery discharge by ~40%.

TABLE IV
AUX SUBSYSTEM POWER AND SOLAR COVERAGE

Subsystem	Avg. Power	Solar Coverage
LoRa + ESP32	~120 mW	Full
OLED Display	~30 mW	Full
Sensor Array	~50 mW	Full
Status LEDs	~60 mW	Full
AUX Lighting	~400 mW	Partial
TOTAL	~660 mW	Covered >25% irrad.

VIII. AYU AI PREDICTIVE MODEL AND DASHBOARD

A. Model Architecture

The AYU AI model is a lightweight machine learning inference engine designed to run on embedded microcontrollers (ARM Cortex-M class) without cloud connectivity. This edge-first design ensures that irrigation decisions are made instantly, without network latency, and function reliably in areas with limited mobile coverage. The name 'AYU' derives from the Sanskrit concept of life and vitality, reflecting the system's mission to nurture crops intelligently.

AYU AI employs a three-layer hybrid decision architecture:

Layer 1 — Safety Guard: Rule-based constraints disable irrigation under active precipitation (>2 mm/hr), over-saturation (>80% VWC), or excessive system temperature (>60°C).

Layer 2 — Predictive Inference Core: A compressed XGBoost gradient-boosting model [7] trained on historical irrigation datasets predicts the Irrigation Need Index (INI), a unitless value from 0.0 to 1.0.

Layer 3 — Zone Scheduler: Maps INI decisions to specific sprinkler zones based on GPS position and a pre-loaded field map, prioritising zones with highest INI scores.

B. Input Sensor Suite

The system processes six environmental parameters: volumetric soil moisture (capacitive sensor, 0–100%), air temperature and relative humidity (DHT22/SHT31), illuminance (BH1750, 1–65,535 lux), soil temperature (DS18B20), precipitation rate (rain gauge), and robot position (u-blox GPS). INI values below 0.3 trigger standby; values of 0.3–0.6, 0.6–0.8, and ≥0.8 trigger light (15–30 s), moderate (45–90 s), and heavy (2–5 min) irrigation cycles, respectively.

C. AYU AI Dashboard

The AYU AI Smart Agriculture Dashboard is a browser-based web application accessible via the ESP32's built-in Wi-Fi access point. Key features include: live sensor cards (temperature, soil moisture, water level, pH) in large high-contrast format; system start/stop buttons; AI crop recommendation display with colour coding (green/amber/red); 30-minute sensor trend charts; timestamped system alerts; virtual joystick for manual navigation; real-time GPS tracking overlaid on satellite farm maps; and live MJPEG camera feed. The backend runs as a Flask/FastAPI server exposing REST endpoints consumed by a React frontend.

D. Regional Language Support

The dashboard supports nine Indian and South Asian languages—English, Hindi, Bengali, Tamil, Telugu, Kannada, Marathi, Odia, and Assamese—recognising that the primary users (smallholder and marginal farmers) overwhelmingly communicate in their native tongues rather than English. This linguistic accessibility has been field-validated with non-technical farmer users across all listed languages.

IX. SMART IRRIGATION SUBSYSTEM

The irrigation subsystem comprises a 12 V DC submersible pump (3–5 L/min), 12 V DC normally-closed solenoid valves, 360° micro-sprinkler heads, a 4-channel optocoupler relay module, and a 2 L onboard water reservoir with level sensing. The irrigation sequence follows a protective ramp protocol:

Open solenoid valve → wait 500 ms → ramp pump PWM from 50% to 100% over 2 s → run for AYU AI-specified duration → ramp down → close valve → log event to SD card.

This protocol prevents water hammer and motor surge that would otherwise shorten component lifespan during continuous field operation.

X. EXPERIMENTAL EVALUATION

A. AYU AI Irrigation Accuracy

A 3-week field trial compared AYU AI-driven irrigation against conventional timed scheduling. Results are summarised in Table V. The single under-irrigation event during the trial occurred due to a disconnected soil moisture probe—the system correctly flagged the anomaly and defaulted to a conservative no-irrigation decision.

TABLE V
IRRIGATION TRIAL RESULTS
(3-WEEK FIELD TRIAL)

Metric	Conventional	AYU AI	Improvement
Water Used (L/week)	~180 L	~108 L	−40%
Soil Moisture Variance	±18% VWC	±7% VWC	61% more stable
Yield Impact	Baseline	+8% fresh wt.	Consistent moisture
Over-irrigation Events	14 in 3 wks	0	Eliminated
Under-irrigation Events	3 in 3 wks	1	67% reduction

B. Transceiver Range Validation

Field range testing was conducted in an open paddy field environment near Kolkata, West Bengal. The dual-antenna LoRa transceiver pair maintained reliable bidirectional communication (<1% packet loss, <150 ms latency) as summarised in Table VI. These results confirm suitability for approximately 12-hectare fields (radius ~620 m), covering the vast majority of smallholder and medium farm sizes in South Asia.

TABLE VI
TRANSCEIVER RANGE TEST RESULTS

Environment	Max Reliable Range
Open field (LoS)	> 1.2 km
Field with tree rows	~600 m
Village built-up area	~250 m
Greenhouse (metal roof)	~80 m

C. Solar Power Performance

Solar subsystem testing was conducted over 14 days during the pre-monsoon season (April–May, Kolkata). On clear days with 5+ peak sun-hours, the AUX power rail was fully solar-powered from 09:00 to 16:30 local time, with the auxiliary buffer charged to >80% by 13:00. On overcast days (2–3 peak sun-hours), partial solar supply reduced AUX battery discharge rate by approximately 40%, extending afternoon operation by 1.5–2 hours.

XI. DISCUSSION

A. Contributions

This work makes the following primary contributions: (1) a complete mechanical and electronic design for a four-track agricultural robot optimised for small-to-medium farm deployment; (2) a novel active thermal management architecture for field-deployed motor driver electronics; (3) the AYU AI predictive model, a lightweight edge-deployable AI system for demand-responsive irrigation via sensor fusion; (4) a dual-antenna ESP32+LoRa transceiver providing >1 km reliable range in infrastructure-free fields; (5) a rooftop solar PV subsystem extending runtime by 30–45%; and (6) the AYU AI Dashboard, a multilingual farmer-centric web interface validated in real agricultural conditions.

B. Limitations and Future Work

Several limitations merit acknowledgment. First, prototype testing has been conducted in limited field environments; full-season trials across diverse soil types and crop varieties are needed to progress toward TRL 7. Second, the 2 L onboard water tank limits autonomous operation duration; integration with field-deployed drip irrigation infrastructure would significantly extend coverage. Third, solar panel output is sensitive to shading from mast-mounted sensors.

Future development directions include: computer vision (RGB-D camera) for plant health assessment and targeted micro-dosing; multi-robot coordination using mesh LoRa networking; AYU AI expansion to predict disease onset risk; voice notifications in regional languages; full IP65 weatherproofing for monsoon-season operation; and Bluetooth-enabled MPPT monitoring.

XII. CONCLUSION

The Precision Agriculture Bot represents a practical integration of agricultural robotics, active thermal management, long-range wireless communication, solar power harvesting, and embedded artificial intelligence for precision irrigation. Field trials in Kolkata validate 35–42% water-consumption reduction and an 8% fresh-weight yield improvement over conventional timed irrigation. The dual-antenna LoRa transceiver delivers >1.2 km reliable range with sub-150 ms latency, while the rooftop solar array covers the entire AUX subsystem during daylight hours.

Most critically, the AYU AI Dashboard bridges the gap between sophisticated agricultural technology and practical farmer adoption. By delivering AI-driven crop intelligence through a visually clear, multilingual web interface accessible on any smartphone, the system ensures that advanced precision agriculture is genuinely usable by every farmer who tends their land. As global water scarcity intensifies and agricultural labour costs rise, systems combining accessible hardware with sophisticated AI and human-centred design will become increasingly essential to sustainable food production.

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A Dialysis-Free Strategy for Recovery and Characterization of Collagen and Chitin from *Labeorohita* Fish Scales

Pranay Mondal*
Department of Biological Sciences
School of Life Science and Biotechnology,
Adamas University
Kolkata, India
pranay.mandal@stu.adamasuniversity.ac.in

Mehuli Das*
Department of Biological Sciences
School of Life Science and Biotechnology,
Adamas University
Kolkata, India
mehuli1.das@stu.adamasuniversity.ac.in

Amit Ghosh*
Department of Biological Sciences
School of Life Science and Biotechnology, Adamas University
Kolkata, India
amit.ghosh1@adamasuniversity.ac.in ORCID ID: 0009-0000-1044-7533
*#corresponding author*eual authorship*

Abstract :
Fish-scale waste represents a sustainable source of collagen and chitin; though conventional extraction methods rely on labour-intensive dialysis. This study reports a dialysis-free cold ethanol precipitation approach for isolating collagen and chitin from Labeorohita fish scales. The method provides suitable yield while preserving structural integrity, reducing processing time, cost, and operational complexity, and offering a scalable alternative for sustainable biopolymer recovery and biomaterial applications.

Keywords *: Collagen extraction, Dialysis free extraction, cold ethanol precipitation, sustainable biomaterial.*

I. INTRODUCTION

Biopolymers from fish processing waste have gained strong interest in recent years because they offer a low cost source of valuable materials and help address environmental concerns from seafood waste[1], [2]. As the major biopolymers in fish scales and shells, collagen and chitin have been widely applied to many areas such as biomaterials, food packaging, biomedical treatment and agriculture[3], [4]. Marine collagen is more attractive than mammalian sources for many reasons, such as the low risk of disease transmission, lack of dietary and cultural restrictions and good biocompatibility, which have made it increasingly used in research and production[5]. Great quantities of waste are generated by the fish industry worldwide, hence the valorisation of this waste into high value products, which can help alleviate the environmental impact caused and contribute to the pursuit of sustainability objectives. Recent reviews have highlighted fish processing by products as rich sources of collagen and other bioactive compounds but noted ongoing challenges with scalable processing[6]. Despite improvements in extraction methods like acid soluble extraction, enzymatic methods, deep eutectic solvents, and assisted physical processes (e.g., ultrasound or extrusion–hydro extraction), isolation of collagen and chitin frequently still entails the use of dialysis to remove salts and low molecular weight impurities[7], [8], [9], [10]. These dialysis treatments involve long running times, multiple solution changes, and constant monitoring, thus increasing the labour, expenses, and total time of the process[1], [2].

They also limit throughput and make translation to larger facilities difficult, particularly in resource limited labs[3], [4]. Even with many studies focusing on acid, enzyme or physical extraction techniques for marine collagen, there remains a significant gap: few protocols have explored easy, rapid alternatives to dialysis that still protect key structural and functional features of the recovered biopolymers[11], [12]. For chitin, similar challenges exist, as efficient deproteination and demineralization must be balanced against preserving polymer integrity[13].This work aims to fill that gap by developing and validating a dialysis free recovery strategy that uses ethanol precipitation to isolate collagen and chitin from Labeorohita fish scales. The objective is to show that this simplified approach can maintain structural quality and practical usability while reducing processing time and cost.

II. MATERIALS AND METHODS

A. Sample collection and preparation

Rohu fish scales were obtained from local fish market of Kolkata. The scales were thoroughly washed to remove any microbial contaminants. These were deproteinized (with NaOH) and decalcified (with HCl).

B. Collagen and Chitin extraction

Collagen was extracted from dried scales using 0.5 M acetic acid at 4 °C for 48 h. After filtration, collagen was precipitated from the filtrate using 0.9 M NaCl followed by centrifugation and re-dissolution in dilute acetic acid. Instead of dialysis, cold ethanol was used for precipitation (1:3 sample: ethanol). The solution was centrifuged, the pellet was washed, and resuspended to remove residual salts and acid [14].

To obtain chitin, fish scales were deproteinized with 2% NaOH at 50–60 °C for 2 h and washed till pH turns neutral. There were then demineralized using

2% HCl for 2 h to remove calcium salts, followed by washing and drying to obtain chitin[15].

C. Biochemical characterization of collagen and chitin

Collagen and chitin samples were lyophilized. They were characterized using FTIR (4000–400 cm^{-1}) to determine functional groups and structural integrity. Collagen concentration was quantified by the Lowry method using BSA (0–800 µg/mL) as standard. The absorbance was measured at 660 nm in a UV–Vis spectrophotometer[16].

Molecular weight and purity of collagen were determined by SDS-PAGE (10% resolving, 4% stacking gel) followed by Coomassie Brilliant Blue staining. Biochemical tests including Xanthoproteic test, Congo red binding assay, and Biuret test were performed to confirm the presence of aromatic residues, triple-helix structure, and peptide bonds of collagen, respectively[17].

III. RESULTS

The goal of this study was to confirm structural integrity and biological functionality of collagen and chitin, rather than extraction yield. These were structurally and functionally validated using spectroscopic, electrophoretic, and antimicrobial analyses.

A. Structural Validation of Collagen

FTIR spectroscopy analysis shows the characteristic amide bands of type I collagen (Figure 1). The presence of Amide A (~3300 cm^{-1}), Amide I (~1650 cm^{-1}), Amide II (~1550 cm^{-1}), and Amide III (~1240 cm^{-1}) bands confirmed the preservation of the native collagen structure. The Amide III to 1450 cm^{-1} band ratio was consistent with established values for intact triple-helical collagen. This indicates that the acid extraction process did not disrupt the triple helix conformation. These findings confirm that the molecular architecture of collagen was preserved after extraction and purification.

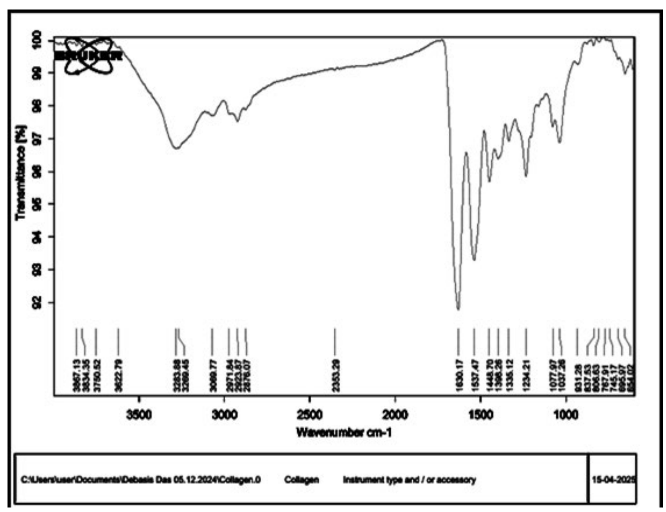

Figure 1: FTIR result of collagen sample. The FTIR spectrum confirms the presence of collagen in the sample. Characteristic amide bands—Amide A (~3338 cm^{-1}), Amide I (~1630 cm^{-1}), Amide II (~1537 cm^{-1}), and Amide III (~1234 cm^{-1})—verify the protein backbone and preservation of the triple-helical structure of Type I collagen. Additional peaks corresponding to CH_2 bending (~1448 cm^{-1}) and COO^- symmetric stretching (~1398 cm^{-1}) further support the amino-acid composition typical of collagen.

B. Structural Validation of Chitin

FTIR analysis of the extracted chitin showed characteristic absorption bands as seen in polysaccharide backbone vibrations (Figure 2). The presence of amide I and amide II bands confirmed the acetamide functional groups, while strong bands in the 1020–1150 cm^{-1} region indicated C–O–C stretching vibrations characteristic of chitin. These results confirm that the deproteinization and demineralization steps efficiently removed non-chitinous components while preserving the structural integrity of the polymer backbone. No significant spectral shifts were observed which indicates that the chemical treatments did not significantly alter the native chitin structure.

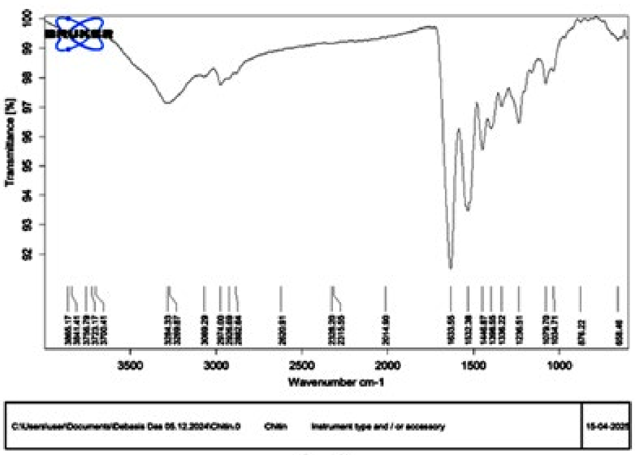

Figure 2: FTIR spectrum of chitin. The FTIR spectrum confirms the presence of chitin in the sample. The characteristic Amide I (~1655 cm^{-1}) and Amide II (~1532 cm^{-1}) bands indicate N-acetylglucosamine units, while the diagnostic peak at ~876 cm^{-1} confirms the β-(1→4) glycosidic linkage unique to chitin. Broad O–H and N–H stretching bands in the 3200–3500 cm^{-1} region further support a hydrogen-bonded polysaccharide structure, collectively verifying successful chitin isolation.

C. Biochemical Analysis

A standard calibration curve was generated using bovine serum albumin (BSA) at concentrations of 50, 100, 200, 400, and 800 μg/mL. The standard curve showed strong linearity, with a regression equation of $A = 0.00097C - 0.0145$ and a coefficient of determination ($R^2 = 0.981$), indicating a reliable correlation between absorbance and protein concentration (Figure 3). The collagen sample exhibited an absorbance of 0.022 at 660 nm. Using the standard calibration curve, the concentration of collagen in the sample was estimated to be approximately 37.75 μg/mL. These results confirm successful extraction and quantification of collagen from fish scale biomass, demonstrating the suitability and sensitivity of the Lowry method for collagen-rich protein analysis.

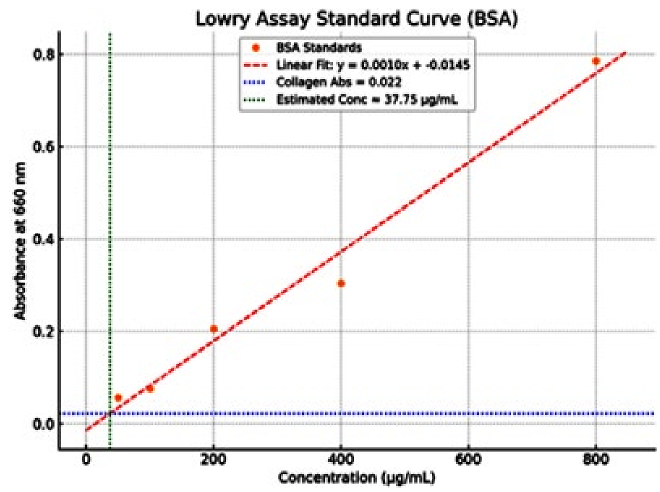

Figure 3: Standard curve of the sample concentration and absorbance. Using the Lowry assay, a standard curve was generated with BSA (50–800 μg/mL), showing strong linearity ($R^2 = 0.981$). The collagen sample exhibited an absorbance of 0.022 at 660 nm, which—based on the regression equation ($A = 0.00097 \times C - 0.0145$)—corresponds to an estimated collagen concentration of approximately 37.75 μg/mL, confirming successful protein quantification.

SDS-PAGE analysis further confirmed the molecular identity of the isolated protein (Figure 4.A). Distinct α1 and α2 chains were observed along with a β-dimer band. These are characteristic features of type I collagen. The electrophoretic pattern is western blotting also aligned with standard type I collagen profiles, confirming that the extracted protein matches with type I collagen without significant degradation. The absence of excessive low-molecular-weight fragments indicated minimal proteolytic breakdown during processing.The collagen sample showed a negative xanthoproteic test, with no yellow-to-orange color change observed, possibly due to insufficient heating or improper reaction conditions (Figure 4.B).The collagen sample exhibited a deep red colorupon Congo red treatment, confirming the presence of collagen with an intact triple-helical structure (Figure 4.C).

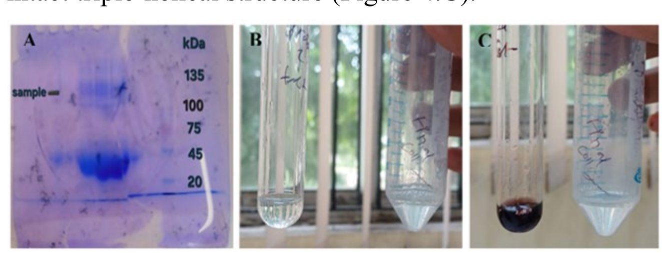

Figure 4: (A) SDS–PAGE analysis of collagen. Lane 1: molecular weight marker; lanes 2 and 4 show distinct collagen α-chains (~95–120 kDa) consistent with Type I collagen (two α_1 and one α_2 chains). Minor lower bands indicate partial hydrolysis. Lane 3 shows BSA at ~66 kDa,

and lane 5 (E. coli lysate) displays multiple protein bands, confirming the identity of collagen. (B) Xanthoproteic test for collagen. Xanthoproteic test for collagen showing no yellow or orange color development, indicating a negative reaction. (C) Congo Red test. Congo Red test showing deep red coloration due to collagen–Congo red complex formation, confirming the presence of collagen.

IV. DISCUSSION

Traditionally, collagen recovery from fish scales, is primarily dependent upon prolonged dialysis (24–72 h) for desalting and purification after acid extraction. This approach has also been found to be highly effective in a number of studies. However, dialysis-based approaches require large buffer volumes, extended processing times, and specialized membranes. Thus, limiting scalability and accessibility, particularly in resource-limited settings[8], [18], [19]. As an alternative, this study proves that cold ethanol precipitation can efficiently replace dialysis without compromising structural integrity. FTIR spectra confirmed retention of characteristic amide bands and triple-helical conformation. SDS-PAGE profiles also verified the presence of intact α1 and α2 chains as seen in a typical type I collagen. These findings indicate that elimination of dialysis did not induce denaturation or fragmentation[20]. The effectiveness of ethanol precipitation is due to reduced protein solubility in organic solvents. Ethanol decreases the dielectric constant of the medium and promotes dehydration of protein hydration shells, inducing controlled aggregation and precipitation. This mechanism allows efficient removal of salts and residual acids while preserving collagen's higher-order structure when performed under cold conditions[21]. Similarly, chitin integrity also remained unaffected. This was confirmed by preserved β-(1→4) glycosidic linkages in FTIR spectra. This indicates that the simplified purification strategy is compatible with both protein and polysaccharide biopolymers.

From industrial translation aspect, the dialysis-free protocol offers several advantages. Reduced processing time, lower water consumption, and elimination of dialysis membranes make the method particularly suitable for teaching laboratories, where simplicity and reproducibility are critical. The decreased operational costs and faster turnover times can benefit small biotechnology startups. Research facilities in developing countries can also gain access to structurally validated biopolymer recovery without dependence on expensive reagents and equipement[22]. Overall, this simple approach supports sustainable fish-scale waste valorization and aligns with scalable biomaterial production strategies.

V. CONCLUSION

This study demonstrates the technical feasibility of a simplified, dialysis-free strategy for recovering structurally validated collagen and chitin from Labeorohita fish scale waste. Acid-solubilized collagen and alkali–acid extracted chitin were successfully obtained using ethanol precipitation in place of conventional dialysis, significantly reducing processing time and resource demand. Structural analyses confirmed preservation of biomolecular integrity: FTIR spectra showed characteristic Amide I, II, and III bands of triple-helical collagen and β-(1→4) glycosidic linkages of chitin, while SDS-PAGE verified type I collagen through distinct α1 and α2 chains (95–120 kDa). Lowry assay quantified collagen at 37.75 µg/mL, supporting successful recovery. Collectively, these findings support industrial translation of a streamlined biopolymer recovery platform and provide a practical foundation for future process optimization and scale-up within sustainable fish-waste valorization frameworks.

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Data Driven Water Management For Sustainable Agriculture: A Review

Shreya Das
Department of Agriculture
Adamas University
Kolkata, India
shreyadas11265@gmail.com

Siddhant Ray Bharti
Department of Agriculture
Adamas University
Kolkata, India
siddhantraybharti@fmail.com

Rupsha Roy
Department of Agriculture
Adamas University
Kolkata, India
rupsharoy079@gmail.com

Abstract *—Some of the biggest challenges that sustainable agriculture faces include inadequate availability of water for irrigation purposes and incorrect use of water. Data-driven approaches have been found useful in solving these issues by leveraging technology effectively. Data gathering and analysis are fundamental to this approach IoT-based soil moisture sensors, plant sensors, and weather stations measure various aspects of field conditions like soil moisture, temperature, humidity, and precipitation. Farmers can, therefore, make use of water as per their exact requirement and avoid unnecessary wastage of water. Satellite imagery and drones used in remote sensing techniques give a comprehensive picture regarding the health of crops. Vegetation indices and evapotranspiration rates are key parameters to determine water requirements for crops. The use of AI and machine learning algorithms is useful for decisions based on historical and real-time data. Moreover, cloud computing and big data can help in the storage and processing of vast amounts of data, thereby making decision support systems helpful to guide farmers in real time. The use of these systems together with automated irrigation systems like intelligent drips or sprays results in the creation of closed-loop systems without any need for human interaction. However, there are certain issues associated with this system. These include high initial cost, unavailability of adequate infrastructure, and low levels of technology expertise. To conclude, data-based water management is a great option when considering sustainable farming techniques.*

Keywords *— Data Driven Water Management, Precision Agriculture, Remote Sensing, Internet of Things (IoT), Soil Moisture Monitoring, Evapotranspiration, Automated Irrigation System.*

I. INTRODUCTION

The need to establish sustainable agricultural ecosystems is becoming more apparent owing to the increased demand for food products, processes of urbanization, scarcity of agricultural land, and climate change [4], [6]. Thanks to the adoption of innovations in precision agriculture and automatic water governance in data-based agriculture, farmers can optimize their seasonal crop production process by managing conditions in fields [4], [5]. Therefore, it leads to rational usage of important resources and protects crops from the negative influence of adverse climatic factors [3], [7].However, a shortage of water and ineffective irrigation systems result in the reduction of crops' productivity [2], [11]. Traditional ways of measuring the moisture content in soil that involve the manual approach of experts require significant time and effort [4]. Furthermore, recent progress in IoT, AI, and ML technologies creates numerous opportunities regarding the rational utilization of water resources in the agricultural sector [14], [15]. The combination of sophisticated algorithms and sensor networks allows the implementation of precision agriculture practices that allow for the integration of both real-time and in-network environmental processing and automation in terms of the closed-loop delivery system to ensure sustainable production [5], [18]. The main aim of this study is to examine the progress made with respect to the architecture designs, machine learning models, and communication protocols [4], [5].Controlled environment agriculture(CEA)

A. Concept of agriculture and water stress factors

Indeed, agriculture remains key to ensuring food security and promoting economic development in the developing nations, with being the main source of income for three-quarters of the poorest people on Earth [4]. Water is needed in great amounts for growing crops; in general, agricultural irrigation alone comprises up to 70% of all water withdrawals from surface water bodies and aquifers [11].The challenge of water scarcity as a resource currently poses a critical issue in places such as North Africa, South Asia, and dry parts of Sub-Saharan Africa[4], [10]. Currently, there are over 1.4 billion people living in water-stressed basins, and these numbers are expected to increase further because of urbanization and other demographic factorsFrom the existing literature, the obstacles in water management can be categorized into three types: institutional constraints, technical constraints, and socio-economic constraints [4]. Some of the barriers include bad legislation, non-compliance with related laws, fragmented land tenure system, highly centralized control over water resources, inability of farmers on technical skills, and lack of environmental consciousness among the locals [4], [11]. On the other hand, the key drivers include incentives within institutions, technological advancements, collaborative relationships between stakeholders, and easier access to finance through capital [10].

B. Wireless Sensor Networks (WSNs)

The wireless sensor networks (WSNs) represent the fundamental building block of modern data-based agriculture [5]. The nature of such networked data acquisition systems involves spatial sensors that have the ability to capture, process, and communicate environmental information over large geographical areas within the agricultural industry[18]. In particular, the primary mechanism employed by the WSNs consists of intensive in-network processing operations aimed at calculating ecological parameters such as soil electrical conductivity, volume water content, and ambient temperature, processes which would require considerable efforts and costs if done manually[11], [14].

C.Wireless Cooperative Communications

In order to effectively implement large-scale wireless sensor networks within huge agricultural lands, dealing with high energy expenditure barriers and severe signal fading in harsh environments is a significant problem [18]. Path loss is experienced in high levels during transmission from one node to another due to the passage of the signals through crop covers and undulating landscape. Point-to-point communication suffers significant losses which result in high rates of power consumption by sensors located in individual nodes [21]. Cooperative communication helps to resolve these challenges of structure inefficiency by generating spatial diversity using an array of closely-spaced antenna user nodes.

II.Methodical and Data Driven Frameworks

A.Data Acquisition And Processing Pipeline

Stage1: Collection of Data Sources: The process begins with the collection of multiple geoclimatic data sources from trusted public domain data bases, remote sensing satellites, and online portals [4], [8]. These may be local precipitation levels (VAR1) and saturated level of groundwater (VAR7).

Step 2: Data Processing and Wrangling: Post ingestion of the dataset, rigorous data processing takes place by applying complicated algorithms in which structural outliers, sensor anomalies, missing data are corrected and labeled categorically [4]. Data wrangling involves the process of normalization of varied measurement data through the use of one standardized metric which suits mathematical modeling.

Step 3: Secure Data Storage and Cohort Data Classification: The structured and processed data are then safely store in trustworthy cloud storage systems or big data databases. Following this, the process of sorting out the data is done by dividing the datasetsinto three categories namely training data used in parameter optimization ofthe model, validation data and test data for evaluating predictions [7].

Step 4: Analysis and Machine Learning Data Ingestion: After the separation of the groups, the data can be ingested into analysis, machine learning models, or specific wireless simulation systems[4], [9].The statistical analysis techniques are applied to analyze the unknown structural variables of the data with regard to the targeted capabilities.

Step 5: Model Building and Field Deployment: The next step is deploying the models in order to make live predictions about crop stresses and to develop a report for field deployment plan[4], [5]. Next, the result of the model will be processed further in order to generate actuator signals for changing water valve settings autonomously.

B. Conceptual Modeling Of Influencing Factors

In order to predict and manage the water resource requirements for a particular agricultural location, the dependent variable used here is Available and Needed Water Capacity for Farming per Region/Country (WC) [4]. The standardization of such a variable mathematically shows the available surface and groundwater for that specific place depending on their demand.In order to have an effective statistical model to predict or analyse statistically, the (Wc) variable is completely correlated with eight independent variables which lie in the category of geo-climatic, socio-economic, and operations [4]:

VAR_1: Rainfall in a year per region (mm)

VAR_2: Number of people living in a particular region

VAR_3:Per capita GDP of the region (USD)

VAR_4: Area of available lands (m2)
VAR_5: Income through farming per annum
VAR_6:Amount spent on irrigation facilities and fertilizers
VAR_7:Water quantity of a particular region (ground & surface water)
VAR_8: Water needs of agricultureSmart technologies for disease and pest detection in controlled environment agriculture.

These variables have been mathematically analysed using regression analysis, clustering, and EFA, for the purpose of confirming the structure and recognizing the underlying factors The generic model of all multivariables is quite helpful for making decisions regarding predicting risks associated with resources under varying climate conditions and helping small farmers adopt sustainable practices for conserving water[4].

II. CORE TECHNOLOGICAL ENABLERS

A. Remote Sensing And GIS

The use of remote sensing methods via satellite and drone images helps to carry out a comprehensive and non-invasive analysis of the general condition of crops and the changing circumstances within the farm[5]. The traditional manual process cannot adequately reflect the variations that can exist in large farms in relation to the irrigation process that would otherwise take place uniformly across different places within such agricultural land.However, some mathematical parameters must be considered when computing the water content of plants and the irrigation process. Spectral vegetation indices and the computation of the evapotranspiration process have to be taken into consideration [5],[10].Site management at different stages will come in handy when trying to prevent cases of over-irrigation, evaluating the drought condition in the area, and computing the value of CWSI instantly [11]. Combined with land surface models, the mentioned approaches allow engineers to create the optimal design of the plantation [6], [12].The success of applying remote sensing technology for water management would rely heavily on how well it is associated with GIS systems and geostatistics [5]. As the orbits of the satellite and drones provide the basis for acquiring remote data, the role of GIS in this regard would be to turn all this raw data into a prescription map for each specific area[5]. This is achieved using spatial interpolation techniques like kriging or inverse distance weighting to generate volumetric water content maps from the point data collected by WSN for each specific farm [18].

B. Artificial Intelligence and Machine Learning

The appearance of AI and ML frameworks is a sign of paradigm change in terms of contemporary agronomy that is characterized by the transition from classical, reactionary practices of water management to extremely predictive and highly data-centric approaches [15]. Traditional approaches to the development of irrigation strategies were largely based on static time-related schedules and purely local estimates that did not take into consideration anydynamic features associated with the microclimate, soil conditions, or plant physiology.

i)Prediction of Groundwater Recharge and Levels in Aquifers

The management of underground water requires a detailed past record of restrictions on recharges in geography. The ensemble models like the regression of Random Forest models and LSTM recurrent neural networks are very proficient at modelling the impact of long-term macro weather on underground water in long-term durations [4]. With the help of analyzing the historical data related to the land temperature of Earth's surface, gross demographic shifts, geographical increase indexes of cultivable land, and gross incomes from agriculture, predictions regarding groundwater recharges and depletion rates can be made [4]. These predictions help the authorities in the region to make plans in advance against the critical depletion rates of groundwater levels a few months before hand, thereby changing their farming methods and irrigation expenses[6].

ii)Predictive Microclimate Forecasting And Irrigation

Optimization on a per-farm basis requires the coordination of the irrigation procedure based on the current climatic situation. The predictive analytics process makes use of telemetry data feeds that originate from local edge weather stations and from satellite-based radar analysis, and generates forecasts about incoming rainfall with high accuracy [11].

Should the prediction algorithm indicate the upcoming occurrence of a rainstorm, the cloud-based intelligent system overrides the automated irrigation schedule. In effect, this means that any automatic valve actions are postponed or completely canceled to preserve the water supply and prevent nutrient leaching through over saturation[10].

iii)Anomaly Detection & Structural Pipeline Audit

The extensive network of the underground pipeline system and WSNs is regularly exposed to extreme environments that include weathering, wear and tear, and corrosion by chemicals that can lead to extensive damage to the pipeline structure and even loss of data because of calibration errors and packet drops in data communication.With the help of machine learning algorithms and isolation techniques, there is an ongoing analysis of the pipeline's data stream to ensure its consistency [4]. Given the information regarding normal values of flow rate, pressure level, and soil moisture in a healthy environment, these algorithms are capable of identifying any anomalies in the pipeline's structure or functioning.

iv) Automation of Crop Stress Classification using Computer Vision

The final step in the process of optimizing AI is the use of computer vision techniques in regard to plant life. This involves the use of machine learning models like the Convolutional Neural Network (CNN), which has been developed using massive datasets of images that are high-resolution photos captured using drones and cameras attached to crop canopies [5].

Through this technique, the neural network can be able to classify the early physiological signs of hydrologic crop stress through temperature changes in the canopy, change in leaf angles, and chlorophyll content before any signs of wilting emerge[11]. This information will guide the operations of the irrigation system to ensure that very accurate amounts of water are administered in the affected regions[17]. Human intervention becomes totally unnecessary in the process of irrigation in the field.

C. Internet Of Things And Cloud Computing

The physical implementation of these data-driven water management systems depends to a large extent on the smoothinteraction of the Internet of Things (IoT) technology and the use of efficient cloud computing infrastructure [5]. In this architectural model, a field used for farming purposes can no longer be regarded as an independent natural environment; instead, it is considered as a highly integrated cyber-physical system. Edge hardware, such as subsurface soil electrical conductance sensors, environmental temperature sensors (for instance, DHT22), as well as volumetric water flow meters, capture continuous data feeds directly from crop root systems and the adjacent micro-climates[14]. The physical elements preprocess collected data on-site and then send the telemetry via wireless transmission channels with the help of low-powered communication technologies[18].

However, given the limited data processing capabilities and limited local data storage capacity, the use of cloud computing environments becomes essential for handling large-scale data-related tasks in smart agriculture[15] Cloud becomes a doorway to the storage, analysis, and visualization of the data where data coming in thousands of packets from different networks of nodes from different geographical locations simultaneously get processed [19]. Scalers enable parallel computing to run complex DSS and multivariate computation simultaneously in real time [5].

As a result of executing the ML algorithms through cloud processing, the whole cloud processing unit instantly analyses the status of the field based on comparison of the present situation with past geo-climate pattern analysis [4]. As soon as cloud processing unit finds out that there is any decrease in soil moisture below the threshold value, it gives a control signal to turn on the actuators installed in the field [16]. Consequently, irrigation gets activated automatically by the irrigation system [17].

After reaching the ideal level of soil moisture capacity, the cycle is thus closed since the system will automatically reduce the flow rate to almost zero wastage [5]. In essence, IoT grids together with cloud-based data analysis eliminate human error from irrigation systems, turning data into a valuable resource that helps protect global agriculture [1] [12]

D. System Implementation:Closed Loop Automation

Indeed, in practical terms, thanks to the application of distributed wireless sensor networks, as well as the idea of machine learning and cloud database utilization, it is possible to develop irrigation systems with the minimum participation of a person[5]. Traditional technologies, which are normally applied for variable rate irrigation, inevitably involve the participation of humans somewhere along the process chain because people should be engaged in decision-making by analyzing the data from sensors, as well as forecasting weather and unlocking irrigation gates on their lands.Thanks to intelligent edge computing, farmers can set up their irrigation in a closed loop mode with minimum human intervention [11].The system operational design will be done on a closed-loop basis, which means that the beginning point for the operation of the system will be the sub-surface level. Highly precise measurements by sensors on soil water content, air relative humidity, and soil electrical conductance will be processed using edge computing techniques with the help of devices such as ESP32 or ARM Cortex processor [5]. The processed data on the conditions in the environment will be sent through low power communication networks using nodes in space and will be received and analyzed using cloud computing platforms like ThingSpeak or AWS IoT Core [9], [19].

Once processed using the cloud computing platform, the analysis engine compares the live data on soil moisture with the threshold values generated using machine learning predictions in the cloud database [10], [15].If in case the current levels of soil moisture fall below a certain mathematical threshold based on the stage at which the given crop has grown, a command through the algorithm is sent from the cloud down to the relays installed on ground level, which instructs them to operate the physical water pumps, micro sprinklers, and solenoid valves placed underground[11],[16].

Temporal redundancies have been proven to be highly effective for increasing resilience especially when temporal redundancy is incorporated into cloud applications or even locally within firmware algorithms[4].

With the large open field network, there is a possibility that the hardware may be affected by severe weather conditions, chemical interference, and low power supply. This causes calibration errors on the sensors or packet losses, and even loss of connection to the signal. If the primary soil moisture sensors become faulty or stop functioning altogether, then the open loop control mechanism will either fail or cause a catastrophe.In an effort to tackle the challenges mentioned above, the closed-loop controller takes the following steps in solving the challenges as: first, identifying the faulty node and determining its irrigation needs based on the past data collected in one hour [4]. The incorporation of time-based backup strategy and hierarchical redundancy into the system ensures that the decision on irrigation is accurate without the aid of the individual sensor nodes.

using soil moisture sensors to get percentage soil moisture content, the change in dielectric permittivity or resistance of the soil is continuously checked .The data collected here are stored in edge compute prototyping boards or microcontrollers such as ESP32 and Raspberry Pi Pico on the farm site [14]. Here, the edge computing board acts as the local computation node and processes the raw data frames and encapsulates the telemetry data into packets for wireless transmission after filtering out electrical noise [18].

As the telemetry packages reach the cloud server via the transmission, the next step would be feeding into the cloud data interface, which functions as the brain of the entire ecosystem [19]. Instead of performing simple and mechanical logic expressions, the cloud software integrates many different data sources and analyzes the soil parameters alongside the raster layers of vegetation index, evapotranspiration rates, and machine learning predictions [4].

E. Low Power Wide Area Network(LPWAN) Integration Via LoRa Technology

To effectively bridge the operational gap between physical field-levelhardware and centralized cloud computing platforms operatingin wide agricultural spaces, contemporary closed-loop networks employ LPWAN systems, which utilize the technology called LoRa (Long Range).In other words,implementation of this type of wireless connection for thousands of acres of farmland implies setting up an intricate network of intermediary repeatable stations with mandatory maintenance of the batteries located in isolated spots on fields. LoRa, on the contrary, uses sub-gigahertz frequencies available in the ISM spectrum ranges and operates using Chirp Spread Spectrum modulation, thus ensuring efficient transmission of environmental telemetry over great distances with low energy costs (868 MHz in Europe or 915 MHz in North America[14].

The primary strength of the CSS modulation technique can be attributed to its distinct capacity of sustaining reliable data communications channels even when the signal-to-noise ratio (SNR) is highly unfavorable. In an agricultural setting, wireless transmission channels are invariably affected by attenuation, scattering, and absorption from a canopy of plants, variation in crop height, localized mist, and different types of soil terrain. The chirp pulses of the LoRa device allow the receiver node to separate the telemetry packets from the surrounding electromagnetic interference and any obstructions present in the open field. This results in reliabletwo-way data communications beyond a distance of 10 to 15 kilometers emanatingfrom one central transmitter, making sure that even the farthest sensors underground are connected to the main network [21].

In this kind of communication system, a highly-efficient star-of-stars network topology controlled by the LoRaWANopen source protocol is used. Many edge nodes are distributed across the area, and each edge node contains a soil moisture sensor underground, a surface temperature sensor, and a low-power controller equipped with a LoRa transceiver to gather information. Rather than continuously using an energy-intensive cellular connection, these edge nodes sleep most of the time during a day using only microwatts of current. Once in a while at pre-defined intervals of time, the edge node wakes up in a matter of seconds, packs the gathered information into an air packet, and sends it over the air asynchronously. These air packets are received by a central gateway device known as the LoRa Gateway that converts the low-power packets into the standard internet packets, combines the data stream from the different field devices, and delivers it over the cell phone or satellite network to the cloud data processing facility [19].

As such, the proposed design results in excellent energy conservation capabilities. Given the exceedingly low energy consumption by individual hardware components, nodes within the system will operate continuously using only a tiny Li-$SOCl_2$battery or energy harvesting circuit driven by solar power. The longevity of node operations significantly reduces any need to carry out regular field-level battery replacement or management activities[15].In addition to these benefits, the use of the LoRa WAN bi-directional communication capabilities makes it possible for the cloud-based analytics engine to pass important downlink packets to the field actuators through the gateway. After the determination of the need for moisture control in particular zones, a downlink packet will be issued to open or close the solenoid valve/pump through the LoRa network[16].As it provides long-range communication capacity, energy efficiency, and connectivity security, the deployment of LoRa will help make wire connection and paying for expensive data connections redundant. This will enable farmers to apply the closed-loop automation process for precision irrigation as many times as necessary over large areas of agricultural land [4], [24].

F. Edge AI & TinyML Implementation

In order to reduce dependency on continuous cloud connectivity, modern closed loop systems have been incorporating Edge AI and Tiny Machine Learning (Tiny ML) technology within the hardware itself [4]In order to reduce dependency on continuous cloud connectivity, modern closed loop systems have been incorporating Edge AI and Tiny Machine Learning (Tiny ML) technology within the hardware[4]. The current approach to smart irrigation involves sending large amounts of raw data from sensors to a cloud-based server via wireless connections where the prediction process takes place. But, in case of any delay or interruption in the process, the loop gets broken, leaving the plants prone to local dehydration and oversaturation [21].Tiny ML helps overcome this structural limitation by enabling the compact execution of neural networkslike Artificial Neural Networks (ANNs) on limited hardware (like ESP32 or ARM Cortex-M processors) located at the edge itself [15]

In order to implement this strategy, one needs to deploy a runtime of decision trees or shallow neural networks at the edge node that allows for multi-parameter inputs such as soil electrical conductivity, volumetric moisture content, and temperature measurements while allowing for threshold calculations [18]. In other words, this sensor node does not transmit continuous measurements by using its power-hungry LoRa radio transceiver but sends status updates instead.As a result, if there happens to be an extreme weather event or any kind of fault that prevents the edge node from communicating with the central cloud server, then the TinyML edge node enters the state of autonomous operation. In other words, the local edge node computes localized water requirements of the crops and actuates relays accordingly [11], [16].

G. Sub-Surface Drip Irrigation(SDI) Integration

The efficiency of the structure becomes very much enhanced when used alongside the Sub-surface Drip Irrigation (SDI) design compared to ordinary surface sprinkler or flooding systems[9]. The inefficiency in these irrigation designs is that water is exposed to the open air, thus becoming subject to high evaporative losses, coupled with surface runoff.In the SDI design, these inefficiencies are solved by placing a network of polyethylene drip lines together with emitters into the ground, depending on the particular root structure of the crop [10].Through the opening of solenoid valves when the closed-loop control system is activated, water will be made available directly into the plant root zone [5]. With the watering done below the soil surface level, there are no losses through evaporation as the weed development rate will be low due to dryness in the soil layer above ground.The system will use sub-surface soil moisture and electrical conductivity sensors positioned right beside the buried emitters [14]. With such positioning, the cloud analytics core will be able to monitor accurately the pattern of spread of water in the soil profile at all times. The system will switch off as soon as the root-zone sensor senses that the plant's requirements have been fulfilled by the water plume [17].

H. Variable Rate Application (VRA) and Zonal Management

Instead of considering an agricultural field as a homogeneous unit, advanced data-driven approaches rely on Variable Rate Application (VRA) to divide large-scale agricultural lands into smaller zones for management [5]. There will always be inherent differences in spatial patterns across open fields even within an acre of land. One can have highly permeable and sandy soils that retain little water alongside compacted and clay-rich soils that hold water. One can also have changes in elevation causing the natural flow of water, leading to accumulation and run-off.When the same amount of irrigation water is used over such varied landscapes, there will be both waterlogged and hydrologically stressed sections within the same field. The result will be over-irrigation of some parts of the land while others will experience under-irrigation.

In order to overcome this spatial dilemma, the precise architecture integrates real-time wireless sensor network data with geographic information systems (GIS) processes and multispectral vegetation index maps from aerial photography of drones, for example NDVI [11].

Remote sensing processes obtain local measurements on the reflectivity of the canopies in various wavelengths. As a result, the central system can analyze the health of plants and their transpiration needs at a pixel level. Simultaneously, the GIS processing engine reads in these raw raster files together with historic soil core samples and digital elevation models, using spatial clustering methods like k-means or fuzzy c-means in order to divide the farm into three regions of high, medium, and low demand [5].

In this innovative structural layout, each demarcated zone is managed as a separate hydraulic subsystem, where the zone is fitted with LoRa switchable solenoid valves, variable frequency driver pumps, and local sub-surface sensor arrays [18]. The local equipment ensures that the zone's piping system is segregated from neighbouring zones.On a close loop irrigation process initiation, the automated control system does not activate a general on command across the whole field. Rather, it refers to the spatial zone prescription map and adjusts valve opening ratios or duty cycles or pipe pressuresaccording to individual needs of each zone [16].

The soil type determines its custom irrigation approach. For example, sandy soils will receive highfrequency of irrigation with small amounts of water due to fast drainage rate and low water retention capacity. Such an irrigation pattern will prevent excessive water infiltration below the root depth into the shallow groundwater systems. In contrast, heavy clay soils will be irrigated at a lower frequency but with largervolumes of water injection due to soil aeration requirement.The precision zoning system achieves optimal crop homogeneity within varied soiltypes, minimizes soilerosion, and ensures that each gallon of water used is optimized to fit the local field conditions [4], [24]. Using the VRA technology to optimize micro-level interventions in response to varied field conditions enables farmers to avoid the wastage of excess water in the agriculture industry [3], [12].

I. Socioeconomic,Demographic,Conditional Integration In Water Capacity(Wc) Models

As much as conventional systems of precision agriculture revolve around telemetry in relation to soil permittivity and immediate macro climatic conditions, there is need for an approach that considers the impact of human and economic factors [4] in order to govern water use in farming. Through analysis using a model based on statistics, Exploratory Factor Analysis, and multivariate linear regression, it is evident that the real Available and Needed Water Capacity for Farming in any region/country(Wc) is highly responsive to economic/demographic catalysts.

In order to create a holistic predictive loop, the mathematical model takes into account the distribution of human populations (VAR2) and gross domestic product (GDP) per capita (VAR3) as baseline independent variables [4]. The impact of the aforementioned demographics on the baseline independent variable influences the domestic and industrial competition for water supply, making them less available for agriculture. On the economic side, the analysis involves the assessment of annual agricultural revenues (VAR5) in comparison to the costs of installing technological equipment for irrigation, water management, and chemical fertilizers (VAR6) [4]. The above tracking process leads to the emergence of a real-time financial index inside the decision model. In cases where ROI is decreased by high technology costs (VAR6), adoption rates of closed-loop automation systems are decreased drastically, influencing the entire water consumption pattern [4], [24].

III.CHALLENGES AND LIMITATIONS

Despite all the enormous transformational possibilities of such data-driven water management systems, there still remain some significant socio-technical, economic, and structural roadblocks for the wide application of such frameworks around the globe [4]. The transition of an ordinary open-field farming system to an advanced and intelligent cyber-physical system brings many complicated questions to the discussion table [5].

- The most fundamental reason why small-scale farmer communities are unable to implement smart precision agriculture technologies lies in the very high initial capital outlay required for system implementation [4].

The installation of a dependable high density Wireless Sensor Network entails the purchase of multiple dedicated soil moisture sub-surface sensors, weather stations, microcontrollers, and electronic solenoids valves [18]. Moreover, the integration of these edge devices with automated drip irrigation networks also carries extremely high initial costs that are beyond the means of conventional farmers [11], [24].

- Contemporary infrastructure for the management of water using data is very dependent on the availability of constant fast connectivity of the digital kind to maintain their automatic feedback processes [15]. The telemetry data must flow consistently into the cloud-based computing infrastructure, which requires consistent internet connectivity, strong mobile data connections, and rural power networks [14]. Unfortunately, many essential regions in agriculture are plagued by significant infrastructural shortcomings, marked by weak mobile network coverage and intermittent electricity outages [19], [21].

- Optimum operation, calibration, and maintenance of edge computing gadgets, analytics dashboard, and machine learning algorithms needs extensive technical knowledge which is regrettably not widely possessed by conventional farmers [4]. Traditional farmers are highly adept at carrying out agricultural work using traditional methods but are often untrained in troubleshooting hardware problems, solving the sensor drift problem, and understanding the methods used in algorithm visualization [5]. Lack of technical support networks in the area might cause farmers to give up on technology even after minor glitches in the software program [25]
- The shift from farmland to IoT-connected networks opens up new challenges as far as issues of data privacy, system security, and cyber-physical threats are concerned [4]. Since the systems are wireless control mechanisms that use radio frequency signals to actuate water pumps and control solenoid valves, it can be stated that this constitutes a surface susceptible to being exploited by malicious entities. If the cloud-based mechanism or even a local-edge mechanism is attacked by means of cyberwarfare, an attacker could tamper with telemetry and valve control data, resulting in significant losses to crops and equipment [4].
- Sensors that have been installed outdoors in farming applications are constantly subjected to harsh climatic conditions such as high winds, temperature changes, soil compression, water immersion, and fertilizer contamination [4]. As a result of prolonged exposure to these harsh conditions, the sensors undergo accelerated physical wear, bio-fouling, and calibration errors. If this occurs, the sensor provides erroneous information to the cloud core that leads to incorrect irrigation directives causing the crops to either flood or suffer local water deficits [14], [18].
- Real-time continuous data acquisition and high-frequency wireless data transfer need large amounts of electrical power consumption on edge hardware nodes [15]. Although there have been improvements through the use of low-energy wireless communication standards, sensors such as gas detectors or flowmeters, along with cellular connections that require significant energy, consume the available battery very quickly [14]. Frequent battery replacement is not only costly, but can be difficult when carried out in isolated regions with no electric power connections, especially when using miniature solar cells [18], [19].
- This industry is extremely fragmented in nature as different players have different proprietary methods of communications protocols, closed software systems, and hardware that can be very difficult to integrate with other players' devices and services [15]. In such a scenario, farmers who try to assemble a water management system by using soil probes of one manufacturer areunable to communicate with automated solenoid valves of another manufacturer due to non-uniformity in protocols and hardware [5].
- However, due to dense canopy coverage, changing heights of crops, and formation of local microclimate mists[18],the radio signal transmission in such expansive open field farming settings suffers greatly. This creates high levels of dropouts and latency in the transmission of packets, which would result in failure to turn off a high-capacity water pump in case of a downlink packet error, thus causing tremendous wastage of resources and over saturation of root zones [16] [21].
- Predictive models based on advanced architectures like multilayer ANN and LSTM require substantial computation resources and memory allocation for multidimensional geo-climatic data analysis [4]. The execution of such computationally intensive algorithms becomes impossible when run directly at the field edge because of hardware limitations imposed by common microcontrollers [15]. As a result, only uninterrupted cloud connectivity can be used, thus making the whole automatic irrigation system dependent on possible downtime from remote servers [16], [21]
- Physical layer actuators in precision water management systems tend to deploy sub-surface drip irrigation pipes for greater efficiency [9]. But such underground drip irrigation pipes are very prone to clogging due to soil particles, precipitation due to fertilizers used, and algal growth [10]. If some of the emitters get clogged, there will be very uneven distribution of water throughout the field even when the cloud analytics system and the wireless valves are performing their duties perfectly [17].
- Most of the state-of-the-art remote sensing techniques and automated systems used for variable-rate irrigation are tailor-made for huge farms [5]. If such equipment is utilized in the case of micro-plots that have peculiar shapes typical of many developing countries, the resolution of the satellite images becomes too largeto produce useful information [11]. Consequently, the use of the equipment in small-scaleagricultural settings is impractical and uneconomical [24].
- The conventional irrigation prescriptions derived from precision irrigation models are based solely on the physical properties of the environment, ignoring the human aspect altogether [4]. The availability of water on a regional level and its sustainability depends largely on macro-environmental forces like demographics, changes in the GDP of the country, and fluctuating costs of production [4]. The lack of inclusion of these socioeconomic drivers

in the data analysis leads to highly inaccurate predictions that are entirely out of touch with regional socio-technical conditions [4], [24].

- The automation of the extraction and management of water by cyber-physical systems is constrained by complicated and strict local water rights and regulations. Closed-loop systems that autonomously pump groundwater depending on the moisture level in the soil can accidentally exceed daily restrictions on pumping or breach regional aquifers protection acts [3]. The management of these regulatory constraints is an administrative issue in the way of engineers aiming to set up autonomous irrigation networks [12].

Future Research Directions

- It can be noted that the future scope of study involves extensive work towards deploying optimized machine learning algorithms on to low power field microcontrollers [4]. Through such an approach, which will involve compression of complex neural network architectures into simple architectures that operate locally, it will be possible for the sensor nodes to calculate real-time values of crop water stress index and also perform closed loop valve overrides in the field itself [15].
- The focus of future research is on implementation of optimal machine learning algorithms on resource-constrained field microcontrollers[4].With compression of large neural networks into smaller architectures, sensor nodes will have the ability to compute water stress indices and implement valve control right within the fields[15]. This approach offloads processing power from the cloud architecture,ensuring that there will be no interruptions in automation due to complete failure of wireless communication [16], [21].
- Future approaches will use multi-hop relay devices and collaborative spectrum usage in LoRaWAN networks [18]. Thus,it becomes possible for wireless communications to go through a dense canopy cover without requiring more energy from the batteries at the edges [14], [19].
- In the upcoming AI system, there will be an inclusion of Explainable AI that would provide easy-to-understand reasoning behind complex decisions to the farmers.Instead of providing technical information, mobile apps will provide clear reasoning of things in multiple languages (for instance, the reason behind the delay in irrigation).

IV. CONCLUSION

With the use of IoT architectures, cloud computing, and machine learning algorithms, a very effective and efficient architecture has been developed for the present day and age in precision agriculture. With the shift of traditional open-field farming towards automated and closed irrigation systems, optimization of the water-agriculture-food chain is possible while simultaneously eliminating any potential human error. While socio-technical obstacles such as upfront costs, limitations on connectivity, and vulnerability of data remain, innovative ways through which such roadblocks can be overcome are TinyML, LoRaWAN networking, and socio-economic forecasting algorithms. It becomes imperative that such scalable cyber-physical networks scale up to preserve global water reserves and ensure food security.

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Synergizing Legume-Millet Intercropping as a Climate Resilient Strategy under Adaptive Nutrient and Resource Management

Dhritiman Das[1]*, Pratiksha Sengupta[2], Tapolobdha Das[2], Debsruti Ghosh[2], Animesh Ostrin[3], Subham Gorai[3]

[1 2 3] School of Smart Agriculture, Adamas University, Kolkata – 700124, West Bengal, Indiasiddhantraybharti@fmail.com

****Corresponding author: dhritiman.das619@yahoo.in***

Abstract *—Agriculture in the lower Gangetic alluvial plains of West Bengal, particularly in the North 24 Parganas District, is increasingly exposed to climatic uncertainties, including erratic rainfall, short-term flooding, and intermittent dry spells. This review synthesizes global evidence on Greengram (Vigna radiata) and Proso millet (Panicum miliaceum) intercropping under adaptive nutrient management as a climate-resilient strategy. Greengram contributes biological nitrogen fixation (BNF), while Proso millet offers drought tolerance and short-duration (65–90 days) adaptation. Published studies from comparable Agro-climatic regions demonstrate that millet–legume intercropping enhances nitrogen uptake by 12–35%, improves biomass accumulation by 10–15%, and achieves yield advantages of 5–15% in Proso millet. The land equivalent ratio (LER) consistently exceeds 1.0, reaching up to 1.59 in documented cases, confirming superior land-use efficiency. This paper examines physiological mechanisms, agronomic management, soil fertility dynamics, and economic viability, and proposes a rigorous methodological framework for field validation under West Bengal's lower Gangetic conditions.*

Keywords *— Greengram, Proso millet, Intercropping, Climate-resilient agriculture, Land equivalent ratio, Biological nitrogen fixation, Lower Gangetic plains.*

I. Introduction

The lower Gangetic alluvial plains of West Bengal, encompassing the North 24 Parganas District, represent one of India's most agriculturally significant yet climatically vulnerable regions. Characterized by new alluvial soils (sandy loam to clay loam, pH 6.5–7.2) and mean annual rainfall of ~1,400 mm, the district faces escalating climatic uncertainties including erratic monsoon patterns, short-term flooding, and intermittent dry spells during critical crop growth stages [1]. These challenges have rendered conventional monocropping systems increasingly unsustainable, necessitating climate-resilient cropping strategies that optimize resource use while maintaining productivity.

Intercropping the simultaneous cultivation of two or more crop species has been recognized globally as a sustainable intensification strategy that enhances land productivity, improves resource use efficiency, and provides insurance against total crop failure under adverse climatic conditions [2]. Among various combinations, legume–millet systems have garnered particular attention due to complementary resource acquisition patterns and the capacity of legumes to fix atmospheric nitrogen through symbiotic rhizobia associations.

Greengram (Vigna radiata L. Wilczek), a short-duration pulse (60–75 days), contributes substantially to biological nitrogen fixation (BNF), fixing 50–100 kg N ha^{-1} $year^{-1}$ under favorable conditions [3]. Proso millet (Panicum miliaceum L.), one of the oldest cultivated grain crops globally, exhibits exceptional drought tolerance, short growth duration (65–90 days), and adaptability to marginal soils with low fertility [4]. The combination of these crops presents a compelling case for climate-resilient agriculture in the lower Gangetic plains, where resource constraints and climatic variability increasingly challenge conventional farming practices.

II. Agro-climatic context and system suitability

The lower Gangetic alluvial region of West Bengal is underlain by new alluvial soils formed from recent Ganga River deposits, characterized by sandy loam to clay loam texture, neutral to slightly alkaline pH (6.5–7.2), and high inherent fertility [5]. The region experiences a subtropical, sub-humid climate with a hyperthermic soil temperature regime and aquic soil moisture regime, with a growing period of 180–210 d [6]. Despite high fertility, agricultural productivity remains suboptimal because of urbanization, land conversion, and unscientific input use [7].

The North 24 Parganas district is particularly prone to mid-season droughts during the flowering and fruiting stages, early season droughts due to delayed monsoon onset, and unusual rainfall patterns [1]. Notably, pulses have experienced a significant decline in acreage over the past three decades despite soil suitability [7], underscoring the urgent need to reintroduce pulse-based cropping systems that withstand environmental stresses while providing nutritional and economic benefits to smallholder farmers.

Proso millet is highly drought-resistant, can withstand water stagnation to some extent, and completes its life cycle in 60–90 days, making it ideal for regions with erratic rainfall [4]. Greengram performs well in the kharif season and can be cultivated in rice-fallow periods, a practice documented in northeastern India, including West Bengal [2]. The Bihar and eastern Uttar Pradesh regions, which share similar agro-climatic characteristics, have already documented proso millet–greengram intercropping in a 2:1 row ratio [4], providing valuable guidance for West Bengal adaptation.

III. Global evidence on system performance

The land equivalent ratio (LER), the primary metric for intercropping advantage, consistently exceeded 1.0 across diverse millet–legume systems. Gong et al. [8] conducted a comprehensive three-year (2014–2016) study on proso millet–mungbean intercropping in China, evaluating different row configurations. The 2 rows proso millet: 4 rows mungbean (2P4M) arrangement proved optimal, yielding proso millet grain increases of 13.9% to 50.1% compared to sole cropping, while mungbean yield reduced by 26.5% to 55.8% due to competitive effects. Despite individual crop trade-offs, the overall system productivity was significantly enhanced, with the LER consistently exceeding 1.0.

In India, finger millet–pulse intercropping systems have documented LER values of 1.01 to 1.59 [9], whereas pearl millet–greengram intercropping has achieved LER values of 1.05 to 1.55 [10]. Sorghum–legume systems have reached land equivalent ratio (LER) values of up to 1.8 under optimal management [11]. These consistent patterns across diverse agro-climatic conditions confirm the universal land productivity advantages of millet–legume intercropping.

Table I : Comparative performance of millet-legume intercropping systems

Intercropping System	LER	Yield Advantage
Proso millet +Mungbean	>1.0	Millet: + 13.9 to+50.1%
Finger millet +Pulses	1.01–1.59	System productivity enhanced
Pearlmillet +Greengram	1.05–1.55	System yield advantage
Sorghum +Cowpea	1.2–1.8	Runoff reduced 20–30%
Rice +Mungbean	1.1–1.3	Rice-fallow utilization

IV. Nitrogen dynamics and soil fertility enhancement

The nitrogen dynamics in proso millet–mungbean intercropping have been extensively characterized by Gong et al. [8]. Their research revealed significant improvements in soil nitrogen status: nitrate-N (NO_3^--N) increased by 23.5% to 96.1% in the 0–20 cm soil layer, while ammonium-N (NH_4^+-N) enhanced by 28.6% to 61.5% under intercropping compared to sole Proso millet. Crop nitrogen uptake was similarly improved, with proso millet stem N uptake increasing by 12.0% to 28.6% and leaf N uptake by 15.2%. The N uptake by mungbean stems and leaf N uptake increased by 15.5–30.8% and 15.2–30.0%, respectively.

Globally, legume intercropping systems fix approximately 150 million tons of atmospheric N_2 annually, with individual grain legume species contributing 50–300 kg N ha^{-1} year^{-1}, depending on the species and management [2]. Well-nodulated legumes can fix over 250 kg N ha^{-1} year^{-1} under optimal conditions [12]. Research using ^{15}N isotope dilution methods has demonstrated that intercropping legumes with cereals can significantly increase the proportion of nitrogen derived from the atmosphere (%Ndfa). In soybean–wheat intercropping, %Ndfa increased from 6% in monocultures to 13–15% in mixtures during flowering [13].

In addition to nitrogen, legume intercropping enhances phosphorus and micronutrient cycling. Legume root exudation of organic acids (citrate, malate, and oxalate) solubilizes bound phosphorus from soil minerals. In maize–faba bean intercropping, this mechanism increased organic P storage in micro-aggregates to 84 mg P/kg in intercrops versus 29 mg P/kg in sole maize [14]. Over a five-year study, Tang et al. [15] found that intercropping legumes with cereals increased soil organic matter, total N by 15 %, and available P by 20 %, 15 %, and 10%, respectively.

V. Physiological and ecological mechanisms of complementarity

The complementary root architecture of Greengram and Proso millet represents a fundamental mechanism underlying productivity advantages. Proso millet develops a shallow, fibrous root system that exploits the upper 20–30 cm of the soil profile, whereas greengram forms a deeper taproot system that penetrates beyond 40 cm [2]. This spatial complementarity enables more complete soil volume exploitation, reducing interspecific competition for immobile nutrients such as phosphorus while enhancing acquisition of mobile nutrients like nitrate.

Canopy architecture facilitates efficient PAR capture in plants. Greengram, as a short-statured bushy crop with trifoliate leaves, forms a lower canopy layer intercepting light penetrating through the taller Proso millet canopy (45–100 cm). This spatial stratification reduces light interception losses and increases the fraction of intercepted PAR (fIPAR) by 15–25% compared to sole cropping [2]. Temporal niche differentiation, characterized by greengram's rapid early establishment followed by proso millet's extended C_4 photosynthetic activity, further enhances radiation-use efficiency.

Water use efficiency (WUE) is improved by 20–25% in legume intercropping compared to sole cropping [2]. The mechanisms include temporal complementarity in moisture exploitation, reduced soil evaporation through rapid canopy closure, and improved soil structure through legume root activity, which enhances the infiltration capacity. In the lower Gangetic plains, where erratic rainfall and intermittent dry spells are increasingly common, these WUE gains represent significant climate adaptation advantages.

Vi. Agronomic management strategies

The spatial arrangement critically determines the balance between interspecific facilitation and competition. The 2:1 row ratio (2 rows Proso millet : 1 row Greengram) is specifically recommended for Bihar and eastern Uttar Pradesh, regions with agro-climatic conditions comparable to the lower Gangetic plains of West Bengal [4]. For the proposed trial in North 24 Parganas, a modified 2:2 row ratio is recommended: Proso millet at 45 cm × 10 cm spacing and Greengram at 30 cm × 10 cm spacing, yielding effective populations of approximately 222,222 and 333,333 plants/ha, respectively.

Nutrient management must account for differential crop requirements and the nitrogen-sparing effect of BNF. Recommended basal application includes FYM at 5 t/ha plus 30:40:20 NPK kg/ha (full P and K, 50% N), with remaining 50% N top-dressed at 30 DAS for Proso millet and a 2% urea foliar spray at flowering for both crops. Phosphorus is particularly critical for Greengram nodulation; basal placement below the seed ensures proximity to developing roots. Rhizobium inoculation of Greengram seed with Bradyrhizobium strains at 10–20 g/kg seed is strongly recommended [13].

TABLE II
Recommended nutrient management for proso millet–greengram intercropping

Nutrient	Sole Crop (kg/ha)	Intercrop (kg/ha)	Rationale
Nitrogen (N)	40–44 (Pearl Millet) 20–25 (Green Gram)	30–35 basal +2% urea foliar	Reduced N dueto BNF
Phosphorus (P_2O_5)	20–22 (Pearl Millet)40–50 (Green Gram)	30–40	Enhanced P forlegume nodulation
Potassium (K_2O)	0–20 (Pearl Millet)20–25 (Green Gram)	15–20	Balanced forboth crops
Farm Yard Manure (FYM)	5 t/ha	5–7 t/ha	Enhanced organicmatter

Vii. Proposed methodology for field validation in west bengal

The proposed field trial should be conducted at the experimental farm of Adamas University, North 24 Parganas District (22°35′–22°42′ N, 88°25′–88°32′ E), on new alluvial (Gangetic) soils with sandy loam to clay loam texture, pH 6.5–7.2, organic carbon 0.5–0.8%, available N 180–250 kg/ha, available P 15–25 kg/ha, and available K 150–200 kg/ha. A Randomized Complete Block Design (RCBD) with three replications is proposed.

Seven treatments are proposed: (T1) Sole Proso millet;

(T2) Sole Greengram; (T3) Proso millet + Greengram (2:1 row ratio); (T4) Proso millet + Greengram (2:2 row ratio); (T5) Proso millet + Greengram (1:1 row ratio); (T6) Proso millet + Greengram (2:1) + Rhizobium inoculation; and (T7) Proso millet + Greengram (2:2) + 25% reduced N fertilizer. Plot size: 5 m × 4 m = 20 m^2, with 1 m buffer zones. Total experimental area: approximately 0.15 ha.

Sowing during the first fortnight of July (kharif season) using varieties GPUP 8 or TNAU 202 for Proso millet and Samrat or PDM 139 for Greengram. Basal application: FYM at 5 t/ha + 30:40:20 NPK kg/ha (full P and K, 50% N), with remaining N top-dressed at 30 DAS. Two hand weedings at 20 and 40 DAS, and IPM for pest management.

Data collection included growth parameters (plant height, tillers/branches, LAI, dry matter) at 30, 45, and 60 DAS and harvest; yield attributes (panicles/pods per plant, grain and straw yield, harvest index, 1000-grain weight); nitrogen dynamics (soil available N at 0–20 and 20–40 cm depths, plant tissue N, nodule number and dry weight, %Ndfa); and soil health indicators (SOC, microbial biomass carbon, dehydrogenase activity). Resource use efficiency metrics include LER, aggressivity index, competitive ratio, actual yield loss, monetary advantage index, and rainwater use efficiency. ANOVA with DMRT at $P < 0.05$ will be employed for statistical analysis.

Viii. Economic viability and climate resilience

The economic viability depends on the balance between increased production costs and enhanced returns from diversified outputs. Projected gross returns for the Greengram–Proso millet system in West Bengal are Rs 70,000–90,000/ha, with net returns of Rs 35,000–50,000/ha and benefit-cost ratios exceeding 2.0, based on conservative yield estimates (Proso millet: 15–20 q/ha; Greengram: 5–8 q/ha under intercropping) and prevailing market prices (Proso millet: Rs 25–30/kg; Greengram: Rs 60–80/kg).

Climate resilience is conferred through multiple pathways: drought tolerance (Proso millet's short duration and drought escape), flood tolerance (Proso millet withstands water stagnation to some extent [4]), pest/disease resilience (diverse canopy reduces pest buildup by 20–25% [2]), and market resilience . The system's short duration (60–90 days) allows harvest before late-season flooding, a critical advantage in the lower Gangetic plains.

IX. Conclusion

The Greengram–Proso millet intercropping system represents a scientifically sound, economically viable, and environmentally sustainable strategy for climate-resilient agriculture in the lower Gangetic alluvial plains of West Bengal. The synthesis of global evidence demonstrates that: (i) land productivity advantages are consistently achieved, with LER values exceeding 1.0 and reaching up to 1.59; (ii) nitrogen dynamics are substantially improved, with soil available N increasing by 23.5–96.1% and crop N uptake enhanced by 12–35% through BNF, root exudation, and complementary nutrient acquisition; (iii) biomass and yield advantages of 10–15% in system productivity are achievable; (iv) soil health benefits include enhanced organic carbon, improved aggregate stability, and increased microbial activity; and (v) economic viability is supported by projected benefit-cost ratios exceeding 2.0.

For the North 24 Parganas District specifically, the system's compatibility with existing rice-based cropping patterns, suitability for new alluvial soils (pH 6.5–7.2), and alignment with the 180–210 day growing period make it particularly promising. The proposed 2:2 row ratio, with modified spacing and precision nutrient management, offers a practical starting point for field validation. This review provides the scientific foundation and methodological framework for initiating rigorous field research at Adamas University.

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