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Sustainable and effective farming practices: A case study of AI-driven greenhouse technology in India

Asma Fayaz, Aman Raj
University Institute of Agricultural Sciences, Chandigarh University, Mohali, Punjab, India

Abstract
Sustainable and efficient agricultural techniques are becoming essential to meet the growing food demand while preserving natural resources. AI-enhanced greenhouses in India use advanced technologies like sensors, automation, and data analytics to optimize crop growth conditions. These systems help regulate temperature, humidity, and irrigation, resulting in higher yields and reduced resource wastage. Additionally, they minimize the use of pesticides and fertilizers, promoting environmentally friendly farming. This case study highlights how integrating AI with greenhouse farming can improve productivity and sustainability in Indian agriculture. Control of greenhouse conditions. Existing control algorithms commonly rely on closed-loop feedback or simplified models that do not accurately capture the nonlinear, dynamic, and stochastic characteristics of greenhouse conditions. In contrast, the application of reinforcement learning algorithms allows for self-controlled problem-solving by continuously learning the control policy through involvement of the environment. Conceptual framework of AI-enabled greenhouses, greenhouse microclimate factors like temperature, humidity, CO^2 concentration, and illumination intensity, and the implications of reinforcement learning for the optimization of these factors with regards to enhanced plant growth, efficiency, and energy use, will be covered in this chapter. Challenges related to data availability, system safety, model interpretability, and real-world deployment are discussed, along with emerging solutions such as hybrid control architectures and digital twins. By highlighting recent advances and practical considerations. This chapter consist of case study related to Precision viticulture/ AI-Enhanced Greenhouse etc.

Keywords: Artificial Intelligence, greenhouse technology, sustainable agriculture, India, precision farming, controlled environment agriculture

Introduction
Smart Agriculture in the Era of AI and Digital Trust
Agriculture has been the bone marrow of human civilisation, a meaningful structure for societies, economics, and ecosystems for decants. Issues such as climate change, soil degradation, also the food security have driven the need for sustainability.(“State Food Agric. 2021,” 2021) [25] The importance of Agriculture in Human Civilisation is based on several factors, such as Food Security and nutrition, which ensures a stable food supply, which reduces the need for hunting and foraging (H. *et al.*, 2010) [7]; Economic Development- earlier, agricultural economics has raised industrial and technical success, creating diversification(Clark & Thorbecke, 1972) [5]; Social and cultural evolution- traditional practices have enhanced it, rituals and rural past life(Mazoyer & Roudart, 2006) [13]; Environmental impact- has contributed to deforestation and land degradation, but has also encouraged efforts towards sustainable agriculture, aiming to reduce the depleting consequences(Tilman *et al.*, 2011) [26]. Smart farming, is also known as precision agriculture, including modern technology for essential productivity efficiency with sustainability in farming practices. The rapid increase in the global population, coupled with scarcity for natural resources, makes it imperative for countries to embrace application of smart farming with respect to practices for purpose of food security and the conservation of natural resources.(Mathew, 2019) [12].

Challenges in Controlled Environment Agriculture and Supply Chains
Many challenges are being faced, but the control measures prevent the damage by referring the integration of innovative engineering, plant science and IIT- field management systems to optimise p lant growth and development. Most relevant systems are: 1. Greenhouses-equipment with automated climate control (heating, cooling, shading, ventilation) and soilless cultivation systems, including hydroponics, cocopeat. 2. Vertical Farms – multi-layer, full control on surroundings, involving hydroponic or aeroponic systemic body. Ideal for high-density production, but faces challenges. 3. Growth Chambers and Indoor Systems: used primarily for research and propagation but scalable for ultra-high- value products.(Soto Arenas & Dressler, 2013) [23]. In India, 60 accuracy approx of the food quality is vanish in the supply chain from the farm to the end consumer. The consumer is actually paying around 35 acuuracy approx. more than what they could pay if the supply chain is optimized. This is due to wastage and multiple margins in the existing supply chain structure. The farmer in India gets 30 accuracy approx of what the consumer pays at the retail outlet. Compare this with the scenario in developed countries, where the farmer gets 70 accuracy approx. of the final retail price, and the wastage is only 4 to 6 accuracy approx. It is easy to understand the gains that could be achieved by doing what they do and leveraging their expertise in the supply chain in India.”This paper focuses on improving the competitive advantage of Indian rural market through Supply Chain Management and also highlights some of the most important initiatives our government has taken so far(Bishnoi, 2009) [3].

Scope and Contribution
In this chapter of the book we explores the use of smart agriculture with respect to AI-based technologies to improve sustainability, productivity, and efficiency in modern

agriculture systems, particularly in CEA (Controlled Environment Agriculture) with agri-food supply chains in India. Important topics like post-harvest losses, resource depletion, climate change, and food security are also covered.

The significance of this chapter is that it brings together precision agriculture technologies and supply chain management, emphasizing the use of technology to minimize losses, improve farmer remuneration, and develop rural markets. The chapter also brings global best practices to the Indian agricultural context, offering a comprehensive approach to building robust, technology-driven, and sustainable food systems.

Part I: AI-Enhanced Greenhouses

To obtain the accurate real greenhouse measures we use Ai gadgets to treat proper climatic conditions. (Alamri & Elhoseny, n.d.) Developed an IoT-based framework for smart greenhouse management, which used sensors for temperature, humidity, and soil moisture. Their system integrated these sensors with an open-source platform to provide remote monitoring and automated irrigation. Companies like Phytech manufactures such machines and Blue Radix promotes cloud-based monitoring solutions, leveraging IoT sensors to gather informative data on crop conditions, water consumption, andnutrient levels.(Al-Amlih *et al*., 2025) [1].

Reinforcement Learning for Microclimate Control

An agent is required in Reinforcement Learning (RL) to obtain the status of eco-system and must have the most suitable based on the environment's current status. When an agent has made its selection (or taken action), it receives an associated reward for its action taken, along with updated state of the eco-system. By the time, agent is attempting maximise its awards. The optimisation of this problem can be represented using the Markov Decision Process (MDP), a mathematical representation of how decisions are made sequentially (Sutton & Barto, 2018) [24].

When an individual selects an action using the MDP, the MDP returns the agent a new and updated environment state and the agent's reward for the action taken. In the MDP, these values are also subject to probability, e.g. the frozen lake environment where agent is attempting move over a frozen lake that contains pores in it. Objective of the agent is to traverse the frozen lake in a maze-like manner, avoiding falling through any holes that are not present in the frozen lake. Since the ice of the lake may cause an agent to slide and be unable to achieve the exact direction of their intended goal, whenever an agent selects an action they might not arrive at their desired state. Therefore, there will always be some probability of the agent ending at an undesired position and not achieving their objective.(Sutton & Barto, 2018) [24] (these are the transition probabilities .$P:S\times A\rightarrow S$

Greenhouse Microclimate Dynamics

1. Environmental Parameters Affecting Crop Growth

By depending on the equipment fitted along with control means, greenhouse microclimate control options can be achieved at different levels. First control level consists of controlling (automatically) start-up and shut-down of the greenhouse microclimate mode with some form of emergency protection. Second control level can be defined by controlling by stabilizing all parameters of the greenhouse microclimate at the required levels by automatically controlling the operational performance of the various microclimate elements.(Saba *et al*., 2021) [19] The third control level is pertinent to the most efficient means of operating the greenhouse microclimate based upon the criteria of consuming the least possible energy for heating and electric power consumption. (Shamshiri & Wan Ismail, 2014) [22]

The dynamic equation of the Energy Balance have generated using all aerodynamic data to determine the air flow regime of the greenhouse. Due to the influence of gravity and wind, air is flowing through the openings in the walls of the greenhouse via filter action and through vent openings. The equations that define the microclimate conditions of the greenhouse contain boundary conditions that were established experimentally but do not fully align with the experimental data. (Shamshiri *et al*., 2016) [21]

Therefore, the Microclimate conditions can only be approximated by the use of this model because it doesn't take consideration to the change in the parameters of Microclimate by the volume of greenhouse. However, based upon the values from this model, tasks for the design of Microclimate conditions can be calculated and may be used to anticipate the interactive effect of the different Microclimate parameters on Quality Indicators. Dynamic conditions were created using the model, which determined the adequacy of the Model's ability to simulate dynamic conditions in the Greenhouse based on the analysis of the Conditions that were created using the Fisher statistic method. The Maximum Deviation is 11 per cent.(Kadirov *et al*., 2023) [9].

Case Studies

Case Study 1: CV-Driven Disease and Quality Risk Detection in Napa Valley Vineyard

Background: Modules 1 & 2 assessed two fungal diseases (powdery mildew and Botrytis bunch rot), which present a high potential hazard to the quality of grapes in Napa Valley. Early detection of symptoms caused by these diseases provides value by mitigating the risk of quality degradation and minimising the quantity of chemicals needed to produce grapes.(Mohimont *et al*., 2022) [14]

Objectives

1. To use computer vision (CV) to identify any symptoms due to disease that may affect the quality of grapes.
2. To measure the effect of disease on grape clusters, as opposed to just leaves.
3. To allow for targeted (focused) intervention for disease management.

Methods: Physical imaging methods were used, either handheld or tractor-mounted, to capture images of grape clusters at close range. A deep-learning-based computer vision model analysed the resultant images to:

1. Differentiate between healthy grapes and grapes with disease.
2. Quantify the severity of disease at the cluster level.
3. Identify zones within vineyard blocks that are compromised from a quality perspective.(Seng *et al*., 2018) [20]

Disease severity maps were generated, and the maps were linked to vineyard management software.

Results

1. The overall percentage accuracy of detecting disease exceeded 88 per cent based on field conditions.

2. The computer vision system was able to identify early-stage infections that field scouts would not have been aware.
3. Targeted fungicide applications were made to reduce the amount of chemicals used without affecting the quality of grapes.

Impact
By implementing an approach, the vineyard has significantly increased the consistency of grape quality and supports sustainable viticulture practices. CV-based disease monitoring has allowed for the reduction of crop loss and supported compliance/regulation of pesticide application. (Cornelissen *et al*., 2025) [6].

Conclusion
The case studies of Napa Valley exemplify the ability to use computer vision driven precision viticulture to improve grape quality evaluation and provide objective, scalable and spatially explicit information as part of vineyard management. By incorporating CV into vineyard management practices, better decision making is supported in canopy management, harvest planning and disease management. This ultimately provides the foundation for a reputation for producing premium wines in Napa Valley.

Case Study 2: Computer Vision–Based Berry Size and Color Assessment in a Napa Valley Cabernet Sauvignon Vineyard
Vineyards in Napa Valley that produce high-end Cabernet Sauvignon are facing pressure to be able to produce grapes consistently of the utmost quality, regardless of soil, microclimate, and vine growth conditions that vary widely by location. Traditional sampling techniques for measuring grape quality have been time-consuming, subjective, and limited in area covered. To help overcome these difficulties, one mid-sized vineyard in Napa Valley implemented a Precision Viticulture program using a computer vision-assisted grape quality assessment system.(Pothen & Nuske, 2016) [17]

Goals
1. To measure grape size (berry) and color (uniformity) automatically across blocks of grapes in the vineyard
2. To reduce reliance on manual sampling from the field
3. To provide data to make informed harvest and thinning decisions

Working Solution
High-resolution RGB (color) cameras were mounted on utility vehicles (e.g., ATV, truck) to take images of grape clusters during the veraision and pre-harvest periods. Images were taken using available daylight and had proper geotags from GPS.
A computer vision (CV) workflow was developed:
1. Preprocess the images to correct for lighting discrepancies
2. Use convolutional neural networks (CNNs) to identify grape clusters
3. Use segmentation techniques to separate individual berries in an image
4. Use the features of berry in order to quantify diameter and “intensity of color” as it would represent the concentration of anthocyanins.

The CV-based metrics/analyses were generated and represented within Geographic Information System (GIS) mapping throughout the vineyard block locations.(Mohimont *et al*., 2022) [14].

Results
Berry sizes estimated to be over 90% accurate versus manual calipers (within +/- 2 mm).
Maps of variability in berry colour showed how a range of berry colours existed between vines that were growing together but were not represented in normal sampling.
The managers of the vineyard were able to identify areas of low uniformity that needed specialised management of the vine canopy

Impact
The system allowed for targeted harvesting and intervention, allowing for the improvement of grape uniformity and reduced cost of labour. Also, the CV method provided a means of scaling the system to continuously monitor grape quality throughout the growing cycle..

Key Takeaways
CV systems provide quantitative data to replace visual judgements about grape quality
Spatial maps of grape quality provide the ability to utilise precision management at the sub-block level
The ability to identify variability at an early stage will result in efficiencies in the time required to make decisions.

Background
The environmental conditions of modern greenhouse agriculture such as temperature, humidity, CO_2, light, and ventilation etc done carefully controlled if the growers want to maximize the growth of the plants, use their resources efficiently, and maximize the quality of their crop. Fixed set-point controls and classical feedback control approaches are not designed to perform well with rapidly changing environments. Additionally, these techniques typically require a substantial amount of manual calibration and specialized knowledge from the growers. The inability to create a fixed control solution for the environment in the greenhouse becomes extremely obvious when working in a greenhouse that exhibits nonlinear dynamic behaviour and experiences unpredictable and/or unmeasured weather effects, variability in the plants growing inside of the greenhouse, and extremely complex interaction among the various control systems.(Li *et al*., 2025) [10]
To solve these problems, researchers and practitioners are beginning to utilize reinforcement learning (RL), which is a subfield of the artificial intelligence (AI) field of research. Reinforcement learning, an agent who learns to execute a particular control strategy by learning through trial and error as they interact with their environment. This is important for greenhouses because an agent can learn how to adaptively optimize multiple greenhouse performance goals, including crop performance, energy required to produce a crop, and total energy consumption through a single control strategy, and does not require a definitive mathematical model of the greenhouse system in order to be successful.(Li *et al*., 2025) [10]

Reinforcement Learning Framework
A greenhouse is one of the example of a Reinforcement Learning (RL) environment representation of MDP (Markov Decision Process). It states that environment are a set of microclimate measures (e.g., air temperature, moisture level, etc.) and could also include indicators of how well the plants are growing. The actions available to the RL agent would be

changing the settings of the actuators (e.g., turning on or off heaters, etc.). The RL agent would receive rewards for maintaining the desired environment, for not using too much energy, and for not wasting other resources (e.g., fertilizer, water, etc.). Policies are learned and refined through continuous interactions with the agent. (Cao *et al*., 2022) [4]
Another method of incorporating expert knowledge into reinforcement learning is through "interactive" reinforcement learning which uses the expertise of growers as a human-in-the-loop to influence policies; to guide exploration; and to decrease training time. Comparative results from using interactive schemes versus strictly autonomous RL agents suggest that there would be greater performance improvement when combining less than perfect input from human experts than when using only an autonomous RL agent under conditions of uncertainty such as climate.(Xiao *et al*., 2026) [27]

Results & Insights

Improved Environmental Stability

Greenhouses managed by real-time learning systems had microclimate variables such as Temperature, Humidity, and Moisture closer to optimal ranges than those controlled by traditional methods. The systems were more responsive to outside influences and unexpected variables.(Platero-Horcajadas *et al*., 2024) [16]

Improvement in Resource Use

Using real-time learning systems allowed growers to utilize control methods for actuators, such as heaters or fans, before the actuation was necessary. This proactive approach resulted in energy / water savings while not compromising plant growth.(Platero-Horcajadas *et al*., 2024) [16]

Combining Grower Knowledge and AI

The performance and reliability of Real-Time Learning systems that combined expert grower information were significantly better than the performance and reliability of the non-combined systems. This indicates that hybrid human and AI systems are of value in agricultural practices. (Xiao *et al*., 2026) [27]

Conclusion

The case study provides evidence that using reinforcement learning and a combination of IOT sensor networks with human input will provide a viable method of controlling microclimate conditions in greenhouses. Reinforcement learning-enhanced systems are capable of improving the adaptive capabilities of greenhouses, increasing resource efficiency and promoting scalable automation. This represents a major advance towards AI-Enhanced Greenhouses that can intelligently regulate their environment with a minimum amount of human interaction.

Future Directions and Research Opportunities

Advancements of artificial intelligence, Reinforcement Learning, and Blockchain Technology will create an irreversible transition point in current agricultural practices. The application of these three technologies within Controlled Environment Agriculture (CEA) and agri-food supply chains has already demonstrated a number of measurable results, but there is still a large opportunity to improve these systems through greater independence, scalability and sustainability. The remainder of this section identifies key future research directions that can further strengthen the role of AI-enabled greenhouses and intelligent supply chains to build on existing food systems towards more resilient food systems
In order to transition from isolated technological innovations to all-encompassing, intelligent agri-food ecosystems, future research on the integration of autonomous greenhouses and supply chains, privacy-preserving analytics and policy-compliant AI deployment will be crucial. By leveraging reinforcement learning, blockchain technology and inclusive governance structures, agriculture can transition towards (more) productive, efficient, resilient, transparent and socially sustainable systems.

References

1. Al-Amlih A, Shehadeh D, Ai-E’mari S, Sakha MA. IoT-Based Greenhouse Environment Monitoring and AI-Driven Crop Optimization. 2025 1st International Conference on Computational Intelligence Approaches and Applications, ICCIAA 2025 - Proceedings. , 2025. https://doi.org/10.1109/ICCIAA65327.2025.11013701
2. Alamri SM, Elhoseny M. IoT-based smart greenhouse monitoring and control for sustainable agriculture. IEEE Transactions on Industrial Informatics,n.d.:18(1):1-18.
3. Bishnoi V. Supply Chain Management: A key to Success in Indian Rural Markets. , 2009. https://www.researchgate.net/publication/306285754
4. Cao X, Yao Y, Li L, Zhang W, An Z, Zhang Z, et al. iGrow: A Smart Agriculture Solution to Autonomous Greenhouse Control. Proceedings of the 36th AAAI Conference on Artificial Intelligence, AAAI 2022, 2022, 36, 11837–11845. https://doi.org/10.1609/aaai.v36i11.21440
5. Clark C, Thorbecke E. The Role of Agriculture in Economic Development. Econometrica,1972:40(3):591. https://doi.org/10.2307/1913193
6. Cornelissen C, De Coninck S, Willekens A, Leroux S, Simoens P. In-Field Mapping of Grape Yield and Quality with Illumination-Invariant Deep Learning. IEEE Internet of Things Journal. , 2025. https://doi.org/10.1109/JIOT.2025.3617805
7. H CJG, John RB, Ian RC, Lawrence H, David L, James FM, et al. Food Security: The Challenge of Feeding 9 Billion People. Science, 2010, 327(5967). https://kns.cnki.net/kcms/detail/detail.aspx?FileName=SFJG479F4B5E329818147DA6B810429A96DC&DbName=GARJ0010_6
8. Hasan I, Habib M. Blockchain Technology to Ensure Traceability of Agriculture Supply Chain Management. International Supply Chain Technology Journal, 2022, 8(9). https://doi.org/10.20545/isctj.v08.i09.01
9. Kadirov Y, Samadov A, Goziev O. Equation of dynamics of greenhouse microclimate parameters. E3S Web of Conferences, 2023, 390. https://doi.org/10.1051/e3sconf/202339004019
10. Li K, Shi J, Hu C, Xue W. The Intelligentization Process of Agricultural Greenhouse: A Review of Control Strategies and Modeling Techniques. Agriculture (Switzerland), 2025, 15(20). https://doi.org/10.3390/agriculture15202135
11. Lv G, Song C, Xu P, Qi Z, Song H, Liu Y. Blockchain-Based Traceability for Agricultural Products: A Systematic Literature Review. Agriculture

(Switzerland), 2023, 13(9). https://doi.org/10.3390/agriculture13091757
12. Mathew J. Smart Farming In Agriculture Sector. Data Driven Investor. , 2019. https://medium.datadriveninvestor.com/smart-farming-in-agriculture-sector-3b95964f0ffd
13. Mazoyer M, Roudart L. A history of world agriculture, from the neolithic age to the current crisis. PhD Proposal, 2006, 1, 525. https://books.google.cl/books?id=5GpFT9NQS1gC&printsec=frontcover&dq=history+of+the+agriculture&hl=es&sa=X&ved=0ahUKEwiQoLGC5pvLAhVDlZAKHVT7DRAQ6AEIGjAA#v=onepage&q=history of the agriculture&f=false
14. Mohimont L, Alin F, Rondeau M, Gaveau N, Steffenel LA. Computer Vision and Deep Learning for Precision Viticulture. Agronomy, 2022, 12(10). https://doi.org/10.3390/agronomy12102463
15. Morales EF, Zaragoza JH. An introduction to reinforcement learning. Decision Theory Models for Applications in Artificial Intelligence: Concepts and Solutions, 2011, 63–80. https://doi.org/10.4018/978-1-60960-165-2.ch004
16. Platero-Horcajadas M, Pardo-Pina S, Cámara-Zapata JM, Brenes-Carranza JA, Ferrández-Pastor FJ. Enhancing Greenhouse Efficiency: Integrating IoT and Reinforcement Learning for Optimized Climate Control. Sensors, 2024, 24(24). https://doi.org/10.3390/s24248109
17. Pothen Z, Nuske S. Automated Assessment and Mapping of Grape Quality through Image-based Color Analysis. IFAC-PapersOnLine,2016:49(16):72-78. https://doi.org/10.1016/j.ifacol.2016.10.014
18. Reddy BR, Vahoniya DR, Bagda B, Damor AB. Post-Harvest Losses in Mango Supply Chains in India: Causes and Preventive Measures. Journal of Experimental Agriculture International,2025:47(10):293–302. https://journaljeai.com/index.php/JEAI/article/view/3813
19. Saba D, Sahli Y, Maouedj R, Hadidi A, Medjahed MB. Contribution to the realization of a smart and sustainable home. Studies in Computational Intelligence, 2021, 912, 261–290. https://doi.org/10.1007/978-3-030-51920-9_14
20. Seng KP, Ang LM, Schmidtke LM, Rogiers SY. Computer vision and machine learning for viticulture technology. IEEE Access, 2018, 6, 67494–67510. https://doi.org/10.1109/ACCESS.2018.2875862
21. Shamshiri A, Ahmad D, Zakaria AJ, Wan Ismail WI, Man HC, Yamin M. Evaluation of the reduced state-variable TOMGRO model using boundary data. 2016 American Society of Agricultural and Biological Engineers Annual International Meeting, ASABE 2016. , 2016. https://doi.org/10.13031/aim.20162454205
22. Shamshiri R, Wan Ismail WI. A comprehensive comparison between wave propagation and heat distribution via analytical solutions and computer simulations. Research Journal of Applied Sciences, Engineering and Technology,2014:7(1):111–122. https://doi.org/10.19026/rjaset.7.228
23. Soto Arenas MA, Dressler RL. A revision of the Mexican and Central American species of *Vanilla* plumier ex miller with a characterization of their its region of the nuclear ribosomal DNA. Lankesteriana. , 2013. https://doi.org/10.15517/lank.v0i0.12065
24. Sutton RS, Barto AG. Reinforcement learning - second edition. In The Lancet, 2018, 258(6685).
25. The State of Food and Agriculture 2021. The State of Food and Agriculture 2021. , 2021. https://doi.org/10.4060/cb4476en
26. Tilman D, Blazer C, Hill J, Befort BL. Global food demand and the sustainable intensification of agriculture. Proceedings of the National Academy of Sciences, 2011, 108, 20260–2026.
27. Xiao M, Lan J, Yu J, Ma W, Xie Q, Sun C. Grower-in-the-loop interactive reinforcement learning for greenhouse climate control. Computers and Electronics in Agriculture, 2026, 242. https://doi.org/10.1016/j.compag.2025.111312
28. Zhang Y, Wu X, Ge H, Jiang Y, Sun Z, Ji X, et al. A Blockchain-Based Traceability Model for Grain and Oil Food Supply Chain. Foods, 2023, 12(17). https://doi.org/10.3390/foods12173235