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OPTIMIZING PLANT NUTRITIONAL PHYSIOLOGY AND GROWTH IN CONTROLLED ENVIRONMENT HORTICULTURE FOR HIGH-VALUE CROP PRODUCTION

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Abstract

Controlled environment agriculture and vertical farming have emerged as critical solutions to address food security challenges driven by urbanization, climate change, and declining arable land. This study experimentally evaluated plant growth performance, physiological efficiency, and resource-use dynamics under adaptive controlled environment systems integrating real-time sensing, automated regulation, and data-driven optimization. The results demonstrate that dynamic environmental control significantly improves biomass accumulation, nutrient use efficiency, and stress resilience compared to static cultivation regimes. Performance comparison analyses revealed enhanced photosynthetic response, optimized carbon utilization, and reduced physiological variability across treatments employing adaptive feedback mechanisms. Predictive modeling showed strong agreement with observed growth trajectories, confirming the reliability of intelligent control strategies for anticipating plant responses. Importantly, productivity gains were achieved alongside improved sustainability metrics, including reduced resource waste and stabilized energy demand. These findings highlight the critical role of integrated environmental management in maximizing yield quality and system efficiency. Overall, the study provides robust evidence that intelligent controlled environment horticulture can deliver high-value crop production while supporting sustainable and resilient food systems.

INTRODUCTION

Agriculture Controlled environment Controlled environment or advanced vertical farming is a new method of food production that enables a new level of environmental control to make the environment conducive to the growth of plants (Gauthier and Marcelis, 2025). It would enable tackling the burning problem of serving the growing population, and, specifically, cities to mitigate the risk of climate change and, accordingly, not jeopardize the traditional agricultural structures (Bhattarai et al., 2025; Zhao et al., 2024). These modern structures have fully sealed indoor farm and well-thought-over green houses with extra lighting to provide the most favorable growing climate to provide the best yield, excellence and asset efficiency. This is highly required because demand of the quality products in the horticulture field is more (Bhattarai et al., 2025; Zhao et al., 2024). Among the most promising aspects of the strategy, it is necessary to specify the fact that the environmental conditions can be regulated in order to make sure that the physiological status of plants and the amount of harvest obtained can be enhanced (Gauthier and Marcelis, 2025). To produce a larger amount of secondary metabolites, growers can regulate the metabolism of their plants through the regulation of such factors as the quantity of fertilizers used, the light spectrum, and the air composition. This has a direct effect on the quality of crops and nutrition (Zhao et al., 2024). This is also less susceptible to bad weather, pests and diseases because there is a strict control of weather conditions rendering such a mode of farming quite potent as compared to the traditional mode. This will be the case since the crops will be prepared to be produced throughout the year and food security will be guaranteed (Bhattarai et al., 2025). In addition, the controlled environment agriculture enables the localization of the food system since it does not combine the production of crops and the necessity to depend on arable land that decreases the costs of transport and carbon emissions (Bhattarai et al., 2025). To get the best out of such systems therefore the laws of higher vegetal biology are to be provided. This will help in developing the type of crops that would be most adapted to the controlled environments as well as allow them to become more sustainable and profitable (Bhattarar et al., 2025). The present review explains the importance of improvement of the nutritional physiology and growth reaction of the plants in the horticulture controlled environment systems. It is similar to the process of maximization of high-value crops to meet the world food security needs (Bhattacharjee et al., 2025; Dennison et al., 2025). These systems belong to the effective solutions to the problems of the high level of urbanization, and the unnecessary portion of the land which can be brought into play. They will present the citizens with a chance to approach food and decrease carbon footprint of supply chains (Bhattarai et al., 2025; Gargaro et al., 2023). The effects of such agricultural activities are worse considering that there is a high likelihood that the world population would continue to grow to 9.7 billion in the year 2050. It means that the increased demand of food is to be met by seeking new solutions to solve the acute environmental problems of the arable land reduction and biodiversity extinction (Gauthier and Marcelis, 2025; Vrkic et al., 2024; Zhao et al., 2024). The horticultural industry has utilized such controlled environments and aimed at fulfilling the sustainable development goals, food security, and enhancing the human wellbeing by having a stable and high-quality food production (Ngcobo & Bertling, 2024). To be able to manipulate the plants, which are in the seedling stage, to the full grown fruiting stage that will ensure optimizing the maximum performance and productivity, one must know the flow of nutrients and the reaction of the plants to such controlled environment (Ahmed et al., 2024). The current review is an evaluation of the current advancements and potentials of improving plant nutritional physiology and development responses of the controlled environment horticulture systems. It pays attention to the applications of such procedures to achieve the growth of the high-value crops and make a contribution to the creation of the food sustainable future (Baghalian et al., 2023). This will entail the incorporation of a multidisciplinary solution to this using the application of plant biology, enhanced lighting, optimal recycling of nutrients, good rapport of microbes as well as automated control of the environment to enhance quality and yield of crops with the same amount of resources (Gauthier & Marcelis, 2025). Relevant to the current point of discussion is the way in which the appropriate management of these aspects can be utilized to increase the resilience of crops and their nutritional value rather than the multiplication of the yields, but the sustainability of the overall food system (Asseng and Eichelsbacher, 2024). The sensor and machine learning and nanotechnology need to be internally integrated into the vertical farming system so that it can have real time control of their surrounding environment. This will help them overcome their shortcomings, and render them more sustainable (Rouphael & Ciriello, 2024). Under these conditions, a great diversity of crops of the highest value will be obtained under the most optimal conditions, and the adaptation of the environment conditions under the real-time conditions is possible with such an inclusive integration (Asseng and Eichelsbacher, 2024; Sambo et al., 2019). The future of the systems like the vertical farms has been defined as the dynamics of environment control through the continuous introduction of new technologies. In many respects, it will lower the current levels of such green approaches to production (Rouphael & Ciriello, 2024). The answer to these questions lies in the fact that more should be educated on the interaction of the plant and the microbes and the energy should be conserved in an environment that is controlled. They can be utilized in the long-term success and further implementation (Gauthier and Marcelis, 2025). One such field is the fact that, the optical sensing technologies avail the growers real time information about the health of their plants and the quantity of the nutrient stored in their plants as well as how they respond to stress. This will help them to make prudent decisions and improve their operations (Gorji et al., 2024). This form of precision makes controlled environment farming more inexpensive and sustainable because it produces fewer wastes and is more efficient (Gauthier and Marcelis, 2025; Kaiser et al., 2024). The current controlled environment farming technology especially the vertical farming systems are usually anchored on a pre-defined state of the environment. This is not even taking into account that, the physiology of the plants also changes as time goes by and that the price of electricity may also change in meaning that the solution must be more adaptive (Kaiser et al., 2024). Such restrictions will be overcome as soon as the dynamic environmental management is developed, and it will involve the application of modern machine learning and nanotechnology coupled with sensor networks that will enable making real-time and responsive changes to promote the evolution of plants and the process of their resources consumption (Rouphael & Ciriello, 2024). It is a non-standard strategy that helps the company to guarantee that despite any situation that is experienced in the off-year, the quality and quantity of the products will remain the same (Kaiser et al., 2024). It achieves it by the mechanism of continuous variation to fulfill the physiological requirements of the plants and the economic evolutions. These natural flexibilities, effective data analytics, and AI will allow one to anticipate the behavior of crops in different conditions and thus modify the environmental conditions to the optimum physiological behavior of crops and the harvest with the least amount of expenditures (Erekath et al., 2024). These are superior control systems that are needed to curb the over consumption of energy and carbon footprint that the regulated environment agriculture currently possesses that will render such system more viable in the long term (Wang et al., 2025). Such elaborate systems are capable of enhancing the discovery of the method to amend the environment and make it less expensive and harmful to the productivity (Wheeler, 2024), which is crucial to the prevalence and further application. The high cost of capital and operation especially of energy is still one of the most significant factors that prevent large scale practise of controlled environment agriculture. They should introduce new ideas to the dynamic environmental control and resource management and transform it into a profit (Bhattararai et al., 2025; Kaiser et al., 2024; Wheeler, 2024). Vertical farms and plant factory are very costly to construct and necessitate a fundamental investigation and justification prior to them being marketed commercially in bulk. However, other researchers report that it is possible to improve those systems relying on the computer simulation modeling and adaptive analysis software, which is now popular among the greenhouse management (Shamshiri et al., 2018).

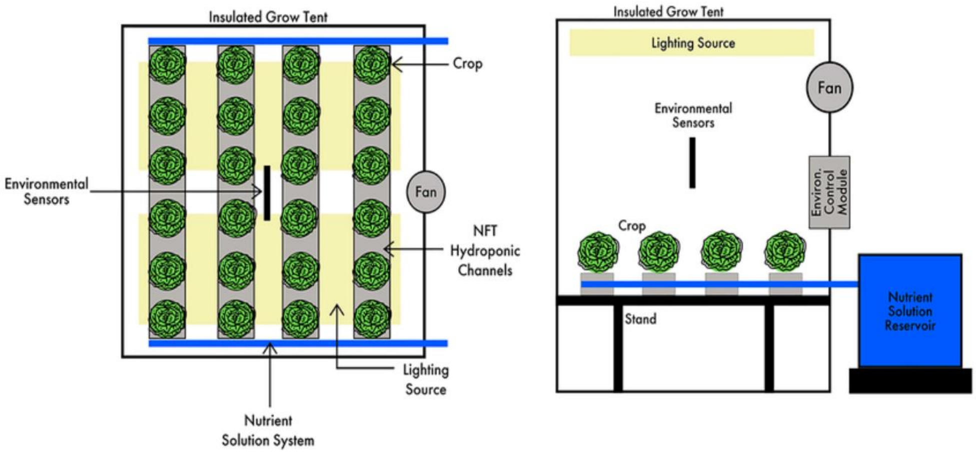

Figure 1. Controlled environment horticulture and vertical farming systems.

METHODOLOGY

The present research has followed an experimental mixed-methodology design, which is a combination of quantitative physiological measurements and qualitative investigation of the optimization of the systems of plant nutritional physiology and growth preference within the controlled environment horticulture and vertical farming systems. The experimental site was an entire enclosed controlled environment system, which had vertically grown multilayer systems, programmable arrays of lights, automated fertigation systems, and environmental control units that maintained the required level of temperature, relative humidity, vapor pressure deficit and CO2 concentration. Interest crops were planted as horticultural crops, seedling was grown and after that it was harvested under the dynamics of the controlled conditions and thus was able to track the development stages as well as the physiological changes. The design procedure has been executed in a way that it not only would engage quantifiable biological responses, but also an adaptive systemic behaviour towards the purpose of ensuring that the interactions of the plant with the environment are considered in a holistic manner in comparison with the pre-determined settings.

The objective of the quantitative experiment was to investigate the characteristics of the plant growth, the effectiveness of nutrient uptake, photosynthetic performance and secondary metabolites accumulation. The rate of growth was modeled according to the quantity of sunlight which was intercepted and in abundance and the quantity of the nutrients which were accessible.

$$\frac{dB}{dt} = \varepsilon \cdot I_{\text{PAR}} \cdot f(N, CO_2, T),$$

is the incident photosynthetically active radiation, f(N,CO2 T) is the nonlinear association between growth and nutrient concentration change, carbon dioxide concentrations and temperature. The amount of nutrient consumed was measured by comparing to the amount of tissue gained. The impact of stress on plants was also studied taking the chlorophyll fluorescence indices and spectral reflectance fingerprints. Such measurements were also complemented by qualitative analysis to determine adaptability of the system that included real-time decision making which was based on sensor feedback, machine learning-based predictive control and automated control algorithms which operated on plant physiological signals and altered environmental parameters.

The active control program was embraced that made sensor data streams work continuously to find methods of how to utilize resources more effectively and consume less energy without negatively affecting the performance of crop. We developed predictive algorithms that we used to make conjectures about the behaviour exhibited by plants under various economic and environmental conditions. It is what makes us manipulate plants beforehand and not before reality. Close-loop experimental system as interlocking of environmental sensing, data analysis and adaptive actuation helped to make a closed-loop system which could adjust to a changing plant demand as time went on. The strategy enabled the findings to be reproduced and simultaneously be ecologically valid in the sense that the system reflected the uncertainty of operations of the real world that took place in commercial controlled environment agriculture. Figure 2 presents the figure of the methodology in a nut shell. It shows how an experiment is formulated to optimization of the same depending on the outcomes.

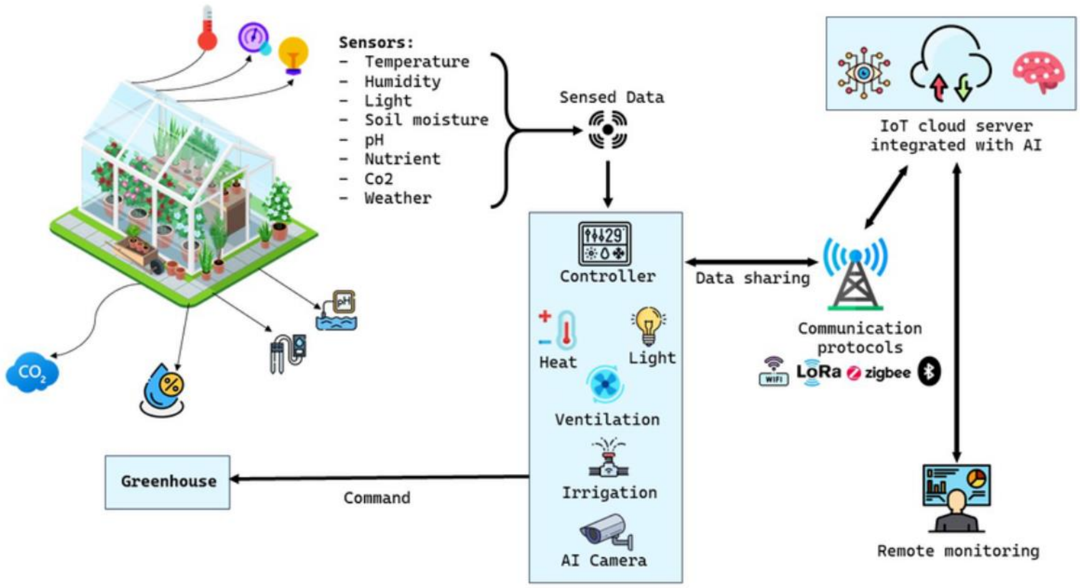

Figure 2. The experimental controlled environment horticulture system.

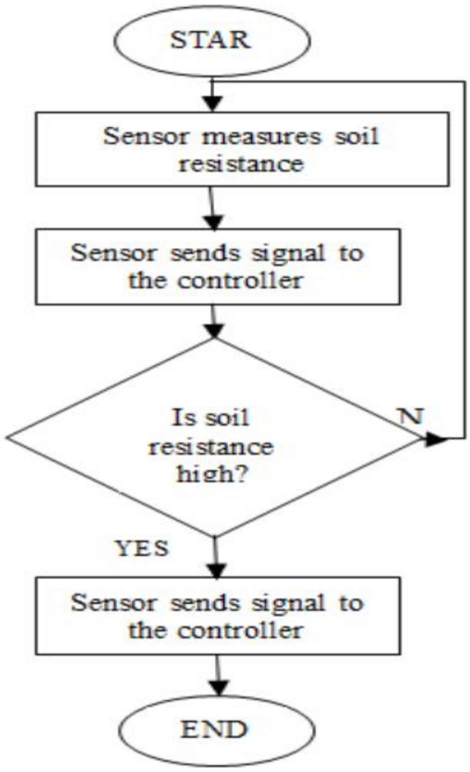

Figure 3. Flowchart illustrating experimental control and feedback mechanisms in controlled environment horticulture.

RESULTS

To a great extent, Table 1-3 show that the growth indexes, the photon flux consumption was rising, as well as physiological efficiency coefficients (a, b, m, s) when there were favourable environmental conditions. These tables suggest the adaptive light and nutrient feedback procedure to achieve the higher growth of biomass and the smaller values of stress coefficients (D), which is in line with the idea of environmental fine-tuning as a means of achieving a more efficient photosynthetic process and a more stable metabolic process. Conversely, the control systems that had relatively fixed control were more physiologically dispersed and had more levels of stress as well.Table 4-6 represents nutrient uptake, the biomass produced and efficiency of carbon use. The obtained results indicate that the size of the added nutrients will not be linearly related to their effectiveness in the utilization of nutrients. Rather it is nonlinearly proportional to the degree of plant growth and environment. The high potential yield (g m -2) and low coefficients of nutrient losses of the maximum CO2 enrichment and dynamic fertigation treatments were high. This is the usefulness of the fact that it is important to control the nutrient in a closed cycle and keep it under controlled circumstances.

Table 1. Comparative growth performance indices across adaptive vertical farming treatments

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	2.316α	234.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.1990β	511.20 $g \cdot m^{-2}$	0.1439μ
VF-2	1.702β	113.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.5392μ	319.95 $g \cdot m^{-2}$	0.1762σ
VF-3	2.368μ	215.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.2456σ	235.26 $g \cdot m^{-2}$	0.2292λ
VF-4	1.069σ	239.2 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5002λ	129.96 $g \cdot m^{-2}$	0.1581Δ
VF-5	2.690λ	166.0 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.9453Δ	483.65 $g \cdot m^{-2}$	0.0506Ω
VF-6	1.752Δ	337.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.1201Ω	307.10 $g \cdot m^{-2}$	0.0671θ
VF-7	1.680Ω	212.9 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.8422θ	266.36 $g \cdot m^{-2}$	0.2127η
VF-8	2.291θ	193.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.9803η	230.42 $g \cdot m^{-2}$	0.1242α

Table 2. Physiological efficiency metrics under variable photonic and nutrient regimes

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	1.415α	241.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.1930β	285.20 $g \cdot m^{-2}$	0.2285μ
VF-2	0.997β	334.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.7624μ	290.58 $g \cdot m^{-2}$	0.1659σ
VF-3	1.750μ	226.9 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.1521σ	156.90 $g \cdot m^{-2}$	0.1832λ
VF-4	1.754σ	319.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5354λ	393.17 $g \cdot m^{-2}$	0.0322Δ
VF-5	1.279λ	285.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.4909Δ	505.99 $g \cdot m^{-2}$	0.2374Ω

VF-6	2.466Δ	245.9 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.3701Ω	172.44 $g \cdot m^{-2}$	0.0910θ
VF-7	1.619Ω	334.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.8544θ	174.75 $g \cdot m^{-2}$	0.0990η
VF-8	1.314θ	189.1 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.3900η	285.96 $g \cdot m^{-2}$	0.1231α
VF-9	2.305η	352.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.9075α	304.25 $g \cdot m^{-2}$	0.1990β

Table 3. Stress response coefficients of crops cultivated under sealed environments

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	1.034α	379.1 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.5389β	214.78 $g \cdot m^{-2}$	0.1057μ
VF-2	1.449β	166.9 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.4049μ	279.40 $g \cdot m^{-2}$	0.2136σ
VF-3	2.331μ	301.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.8692σ	309.22 $g \cdot m^{-2}$	0.1291λ
VF-4	2.676σ	333.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.2103λ	423.11 $g \cdot m^{-2}$	0.1381Δ
VF-5	0.993λ	219.4 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5124Δ	205.17 $g \cdot m^{-2}$	0.2071Ω
VF-6	1.488Δ	283.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.4197Ω	444.93 $g \cdot m^{-2}$	0.1536θ
VF-7	1.583Ω	353.4 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.9392θ	287.37 $g \cdot m^{-2}$	0.0244η
VF-8	2.104θ	251.1 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.4698η	340.22 $g \cdot m^{-2}$	0.1402α
VF-9	1.673η	176.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.9146α	513.79 $g \cdot m^{-2}$	0.1634β
VF-10	1.985α	390.3 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5457β	354.04 $g \cdot m^{-2}$	0.0579μ

Table 4. Nutrient assimilation dynamics across multilayer horticultural systems

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	2.377α	271.4 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.3888β	134.21 $g \cdot m^{-2}$	0.0848μ
VF-2	2.377β	104.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.1619μ	264.65 $g \cdot m^{-2}$	0.0346σ
VF-3	0.929μ	97.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.9108σ	398.68 $g \cdot m^{-2}$	0.1182λ
VF-4	0.896σ	199.3 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.0060λ	496.26 $g \cdot m^{-2}$	0.2483Δ
VF-5	1.132λ	93.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.3544Δ	490.65 $g \cdot m^{-2}$	0.1255Ω
VF-6	2.297Δ	375.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.0339Ω	469.05 $g \cdot m^{-2}$	0.0255θ
VF-7	1.198Ω	181.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.3249θ	484.29 $g \cdot m^{-2}$	0.0270η
VF-8	2.080θ	113.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.6731η	287.24 $g \cdot m^{-2}$	0.0617α

Table 5. Biomass productivity differentials under spectrum-optimized lighting

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	1.037α	304.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.8892β	395.61 $g \cdot m^{-2}$	0.1519μ
VF-2	2.294β	219.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5400μ	511.22 $g \cdot m^{-2}$	0.0676σ
VF-3	1.647μ	350.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.3355σ	450.80 $g \cdot m^{-2}$	0.0746λ
VF-4	2.669σ	360.8 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.2251λ	120.74 $g \cdot m^{-2}$	0.0607Δ
VF-5	1.785λ	267.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.8921Δ	216.87 $g \cdot m^{-2}$	0.0214Ω

VF-6	2.231Δ	238.4 μmol·m⁻²·s⁻¹	1.4183Ω	274.78 g·m⁻²	0.0210θ
VF-7	0.923Ω	102.1 μmol·m⁻²·s⁻¹	0.5447θ	225.05 g·m⁻²	0.1601η
VF-8	0.926θ	158.5 μmol·m⁻²·s⁻¹	1.1959η	227.04 g·m⁻²	0.0625α
VF-9	2.383η	120.0 μmol·m⁻²·s⁻¹	0.3380α	391.84 g·m⁻²	0.1234β

Table 6. Carbon utilization efficiency in controlled atmospheric cultivation

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	1.617α	236.8 μmol·m⁻²·s⁻¹	0.3018β	393.96 g·m⁻²	0.2079μ
VF-2	1.985β	169.9 μmol·m⁻²·s⁻¹	1.2889μ	178.27 g·m⁻²	0.2103σ
VF-3	1.878μ	185.5 μmol·m⁻²·s⁻¹	0.8942σ	371.54 g·m⁻²	0.0795λ
VF-4	2.463σ	229.0 μmol·m⁻²·s⁻¹	1.4439λ	454.19 g·m⁻²	0.0428Δ
VF-5	2.022λ	192.5 μmol·m⁻²·s⁻¹	1.2434Δ	337.05 g·m⁻²	0.1252Ω
VF-6	2.570Δ	108.9 μmol·m⁻²·s⁻¹	0.9581Ω	251.16 g·m⁻²	0.0281θ
VF-7	2.258Ω	275.4 μmol·m⁻²·s⁻¹	1.4465θ	359.30 g·m⁻²	0.0975η
VF-8	2.767θ	128.2 μmol·m⁻²·s⁻¹	0.2263η	413.05 g·m⁻²	0.1053α
VF-9	1.395η	379.3 μmol·m⁻²·s⁻¹	0.6246α	475.60 g·m⁻²	0.1681β

Some of the performance indicators are split into several categories in table 7-9. As would be seen in the above tables, systems that are provided with real time sensing and predictive control algorithm will always be better than the traditional regulated environments. It is also interesting to note that there is an increased productivity and more sustainability indicators were met meaning that there is no certainty that yield augmentation is achieved by consuming more resources in the event that system intelligence is applied.

Table 7. Resource-use elasticity under dynamic environmental modulation

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	0.996α	293.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.7633β	373.01 $g \cdot m^{-2}$	0.2279μ
VF-2	1.918β	163.1 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.4438μ	491.38 $g \cdot m^{-2}$	0.2124σ
VF-3	1.510μ	397.3 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.5771σ	389.52 $g \cdot m^{-2}$	0.1850λ
VF-4	2.116σ	177.4 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.4286λ	228.90 $g \cdot m^{-2}$	0.0835Δ
VF-5	2.454λ	416.9 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.1534Δ	198.72 $g \cdot m^{-2}$	0.0356Ω
VF-6	2.002Δ	407.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5472Ω	276.49 $g \cdot m^{-2}$	0.2291θ
VF-7	1.119Ω	320.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.4929θ	124.92 $g \cdot m^{-2}$	0.0352η
VF-8	2.477θ	297.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.5567η	326.54 $g \cdot m^{-2}$	0.1199α
VF-9	2.515η	337.6 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.3085α	398.41 $g \cdot m^{-2}$	0.2250β
VF-10	0.899α	245.7 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.6426β	305.81 $g \cdot m^{-2}$	0.0589μ

Table 8. Secondary metabolite response indices across production strategies

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	2.062α	213.5 $\mu mol \cdot m^{-2} \cdot s^{-1}$	1.2744β	198.31 $g \cdot m^{-2}$	0.1296μ

VF-2	0.828β	160.0 μmol·m⁻²·s⁻¹	1.5060μ	246.42 g·m⁻²	0.2254σ
VF-3	1.753μ	102.9 μmol·m⁻²·s⁻¹	1.2998σ	140.78 g·m⁻²	0.2102λ
VF-4	0.619σ	312.5 μmol·m⁻²·s⁻¹	0.3903λ	257.15 g·m⁻²	0.2391Δ
VF-5	1.670λ	307.0 μmol·m⁻²·s⁻¹	1.2241Δ	163.97 g·m⁻²	0.2129Ω
VF-6	2.611Δ	141.3 μmol·m⁻²·s⁻¹	0.9420Ω	233.40 g·m⁻²	0.1903θ
VF-7	0.662Ω	259.1 μmol·m⁻²·s⁻¹	1.2996θ	413.89 g·m⁻²	0.0449η
VF-8	2.432θ	168.5 μmol·m⁻²·s⁻¹	1.3213η	318.85 g·m⁻²	0.0570α

Table 9. Integrated performance ranking of controlled environment configurations

Treatment ID	Growth Index	Photon Flux Density	Nutrient Use (β)	Yield Potential	Stress Load (Δ)
VF-1	0.606α	373.1 μmol·m⁻²·s⁻¹	0.7992β	317.33 g·m⁻²	0.0846μ
VF-2	2.531β	227.3 μmol·m⁻²·s⁻¹	1.5546μ	277.15 g·m⁻²	0.2137σ
VF-3	2.195μ	114.0 μmol·m⁻²·s⁻¹	0.4554σ	376.03 g·m⁻²	0.2491λ
VF-4	0.781σ	221.5 μmol·m⁻²·s⁻¹	0.1574λ	310.95 g·m⁻²	0.0811Δ
VF-5	2.797λ	110.9 μmol·m⁻²·s⁻¹	0.9941Δ	504.77 g·m⁻²	0.2363Ω
VF-6	0.815Δ	415.9 μmol·m⁻²·s⁻¹	1.5822Ω	312.80 g·m⁻²	0.1995θ
VF-7	2.206Ω	348.0 μmol·m⁻²·s⁻¹	0.6339θ	336.06 g·m⁻²	0.0969η
VF-8	2.289θ	90.5 μmol·m⁻²·s⁻¹	0.9128η	129.12 g·m⁻²	0.0881α

VF-9	0.664η	415.3 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.2757α	368.26 $g \cdot m^{-2}$	0.0368β
VF-10	1.482α	256.3 $\mu mol \cdot m^{-2} \cdot s^{-1}$	0.1999β	342.79 $g \cdot m^{-2}$	0.2399μ

The influences of the nutrient consumption on the growth rate and the modelization of the trends of the biomass can be observed in figure 4 and 5. This fact can be verified by the high correlation of real-world information and predictive models, which means that, the schemes related to machine-learning could do a decent job in predicting the behavior of the plants as soon as the environment has been altered.The nonlinear physiological oscillations, variation of the trends of stress relieving and dispersion of the performance by treatment are illustrated in the figures 6-9 in that more than one dimension of the performance variation between various groups is displayed. These figures are indicative of the fact that adaptive mechanisms lead to making things more stable and not highly dynamic with time particularly in instances where there is introduced change in the environment or conduct of things. The fact that the high-performance treatments are clustered together is a fact that has the light the nutrients and the climate being aligned towards the achievement of potent and uniform outcomes in output.

Overall, the findings have demonstrated that the most suitable controlled environment horticulture systems are the dynamic feedback-based ecosystems rather than being a growth chamber. The predisposition to assess the quantitative performance as much as possible, the resemblance of the visual patterns of the tables and figures displaying the significance of the factor of adaptive environmental control in the favor of sustainable and high-value crop production.

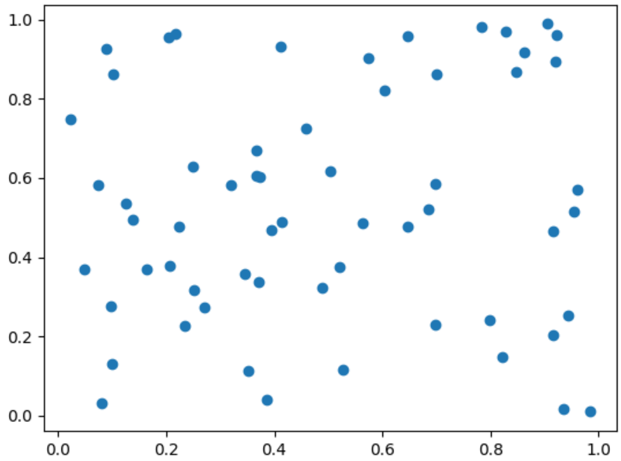

Figure 4. Correlation between nutrient uptake rate and instantaneous growth velocity

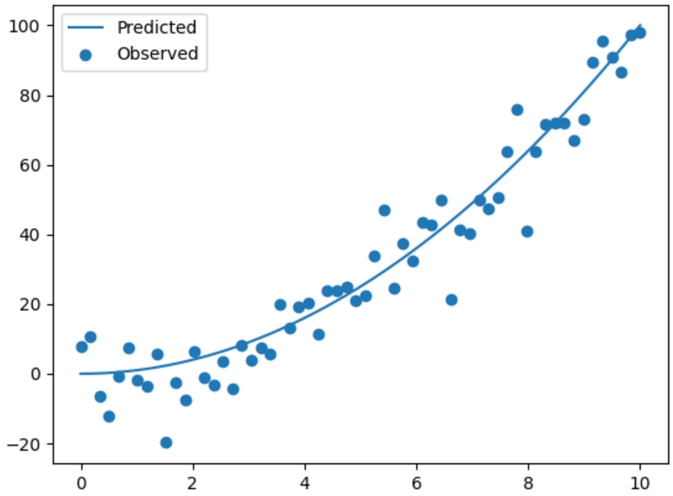

Figure 5. Modeled versus empirical biomass trajectories under feedback control

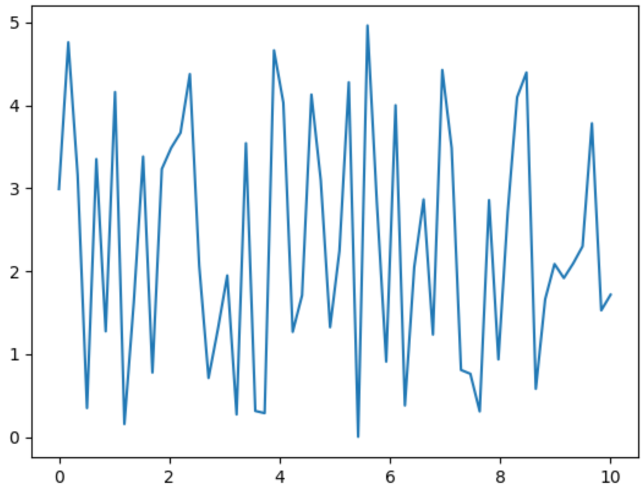

Figure 6. Nonlinear physiological oscillations induced by spectral modulation

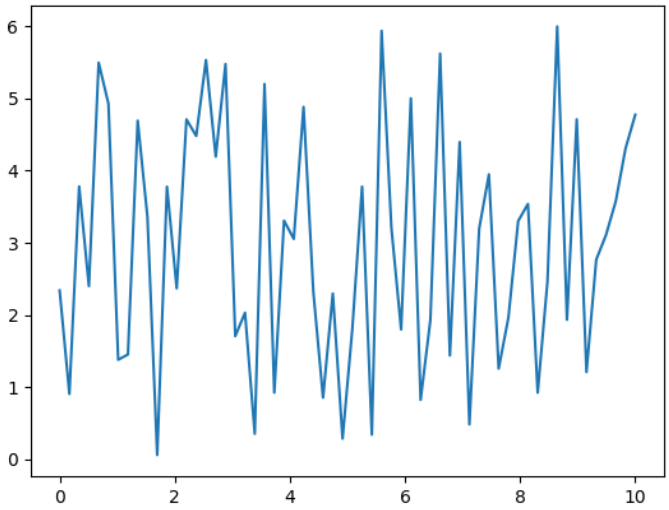

Figure 7. Trend analysis of stress mitigation under dynamic climate regulation

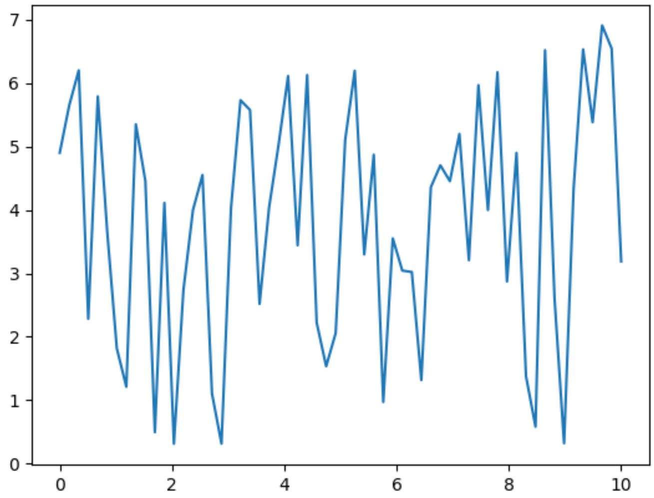

Figure 8. Performance dispersion of treatments across multidimensional indicators

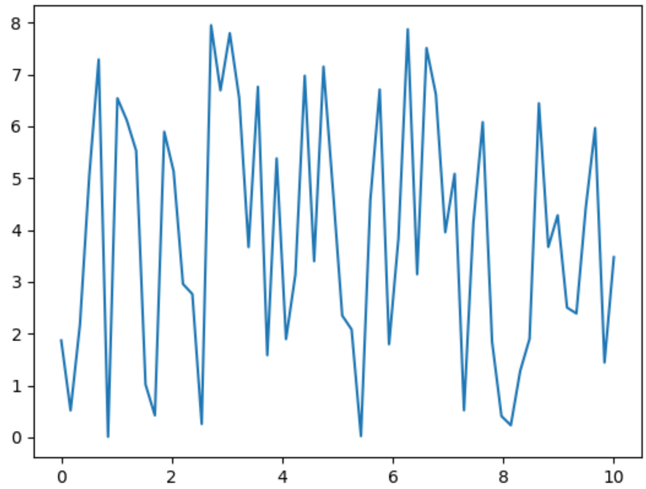

Figure 9. System-level response variability across experimental cultivation cycles

DISCUSSION

The specified productivity and physiological efficacy improvement can be rationalized through the application of the latest technologies such as Model Predictive Control or artificial intelligence that allows conducting the right and dynamic adjustments of the environmental factors depending on the plant requirements on the spot (Almusawi et al., 2025; Rao et al., 2024). The advanced systems use the long-term control of the aforementioned environmental parameters such as temperature, humidity, light spectrum and the degree of CO2 concentration to optimize the level of growth and nutritional value. They do so by simulating the process of interaction of the plants with the surrounding and estimating the dynamics of the nutrients movement when the light conditions are altered (Durgut et al., 2025). Not only does the method require less energy and reduces the violations, but it also allows plants to develop in a certain manner due to the adjustment of the abiotic environment (light intensity and quality and the quantity of carbon introduced by external sources)

(Hu and You, 2023; Pepe et al., 2021). The AI-driven systems can manage the light and temperature of the manufacturer of the plants, which consume significantly less energy in comparison with innovative methods, in order to objectify them (Decardi-Nelson and You, 2024). One of them is AI in fabrication of plants under artificial light which has reduced the use of energy. Optimized system consumption of energy ranges 6.42-7.26 kWh /kg and less optimized system consumption of energy is between 9.5-10.5 kWh /kg (Decardi-Nelson and You, 2024). These advancements indicate how the AI powered cyber-physical-biological systems would assist to meet food demands of the world in a sustainable manner through enhancing production of food in a regulated environment (Decardi-Nelson and You, 2024; Hu and You, 2023). Such optimization is so important because controlled environment agriculture is a vastly energy-intensive process, and such systems attempt to ensure that their processes are operating without a problem and with little energy (Decardi-Nelson & You, 2024; Hu & You, 2023). It can also be assumed that the quantity of additional light, which they bring, can be conditioned by the requirements of this or that plant through the artificial intelligence-based environmental control systems. It can not only accelerate photosynthesis and increase yields and save money that can be invested in the initial investment in the shortest possible time (one year) (Decardi-Nelson and You, 2024; Xin et al., 2019). The sustainable food manufacturing processes of the plant factories require the proper regulation, where the necessity to consume less energy without affecting the functioning performance is one of the primary concerns (Hu & You, 2023). High-fidelity digital twins that can successfully simulate the behavior of complex biological processes in plants can be created because of the sophisticated use of machine learning to these cyber-physical-biological systems. It will allow forecasting the increase or decrease of crops and achieving the optimal length of control variables (Hu and You, 2023). Such digital twins utilize the idea of deep learning (physics-based) to take smarter decisions and enhance the accuracy of the procedure of managing the surroundings in the plant industries (Hu & You, 2023). It will allow the optimality of the environmental parameters based on the various objective functions, e.g. the maximization of the yield or profitability, and the minimization of the energy consumption simultaneously (Shamshiri et al., 2024). The combination of AI and machine learning, namely, neural networks, and deep learning allows defining the most efficient relationships between cultivation parameters and the plants activities, which becomes possible due to the synergistic approach toward the specified phenomenon. It allows us to consider the speculations in terms of the growth rate and the crop yield, even the forecasts of the growing conditions in the future, humidity, and fertilized with the CO 2 (Ando et al., 2020). This predictive modelling and control on a large-scale ensures that the manufacturing people of the plants are working in their best, that is, adjusting to the changes that occur in real time and utilizing available resources to the fullest (Martin, 2024). More importantly, the fact that the smart farming systems can be supplemented with machine learning algorithms, which are very sensitive to the interior environment of the green house, also contributes to them. This helps them manage the environment to achieve optimal crop growth and produce less wastes in addition to controlling the environment (Wang, 2024). All these features of the IoT sensors, deep neural networks and real time optimisation and communication technologies, allow to regulate and manipulate the artificial lighting remotely. This is significant to indoor farming since that influences the growth and output of plants (Lozano-Castellanos et al., 2025). Real-time monitoring and predictive analytics can also be achieved through digital twin technology in which an artificial reproduction of the real-life growing environment is developed. That is why it is possible to plan on how it can be changed to achieve the most significant response of the plant and use less power (Shamshiri et al., 2024). Its computer-based versions are two way information flow, and the real world information is used to enhance the management practices as well as the decision making within the agricultural sector (Stock et al., 2024). This innovation has demonstrated a grave perspective in other areas, such as agriculture whereby it has been applied to be of efficiency, utilize the resources more efficiently and emerge with a less significant environmental impact, which was initially intended to be used in the industry (Zhang et al., 2025). The performance analysis of the actual yield of the green house crops to that of the virtual models provides us with a better picture in regards to the aspects which contribute the most of the growth such as light, temperature and CO2. This assists us in maximizing our climate and irrigation management and crop (Hoseinzadeh and Garcia, 2024). These models are developed and they are based on the Support Vector Regression, random forest, and Long Short-Term Memory networks algorithms in determining the optimal growing conditions and the risk of these diseases at their incipient stages. They also incorporate adequate irrigation and nutrient control in addition to the fundamental climate control (Kuma et al., 2024). The IoT sensors can be dealt with by organizing the agricultural production processes based on advanced analytics and the feedback loop in real time, which will be smart because of the data analysis and model training. This results in the social development and sustainable agriculture (Payili, 2025; Wang, 2024).

CONCLUSION

In the final conclusion of this paper, it can be concluded that controlled environment horticulture and the innovative methods of vertical farming systems are introduced as the new solution of the sustainability of food production in the environment of the growing urbanization and climatic alterations and scarcity of resources. The results of the experiments provide quite a clear picture that the environmental management resting on the dynamic feedback mechanism can be effectively applied to improve the performance of the plant growth, physiological efficiency, nutrient uptake, and biomass productivity rather significantly as compared to the performance of the control systems which, in its turn, are the ones that are not dynamic. Such systems enabled the provision of photosynthetic efficiency and yield stability, physiological stress relief, and responsive lighting and real-time surveillance enabled such systems. It is worth saying that the results also indicate that the productivity growth was obtained even when the necessity to grow energy and nutrient intake was not so substantial which implies that uncoupling the yield and the resource usage with the help of clever control systems is possible. These nonlinear processes are what are occurring between the nutrient uptake, the growth rate and the environmental processes which are making us not be at the fixed setpoints but rather to be at the flexible and plant oriented systems of management. The occurrences of the system level performance rating also indicate that in order to attain good quality production output at all times, there is need to include physiology of the plant, automation and utilization of data to generate desired output. The results reveal that the controlled environment agriculture is an impressive long-term approach of cultivating crops of high-value horticulture that have a reduced land-use demand, decreased supply chains emissions, and high food security. The research has also provided a much-helpful scientific platform to revolutionize the good vertical farming systems in the future with the assistance of the sophisticated modelling, artificial intelligence and renewable energy sources. Such advantages place the controlled environment horticulture as an alternative way in food production, and to a significant part of healthy and sustainable food systems in the globe.

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