



Design of a day–night simulation system using Dynamic Spectrum Lighting (DSL) integrated with artificial intelligence–based automation for regulating the growth of broccoli sprouts

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doi: 10.14456/abe.2026.11

Received 26 March 2026

Revised 13 July 2026

Accepted 22 July 2026

Abstract

This study aimed to design and evaluate a day–night simulation system using Dynamic Spectrum Lighting (DSL) integrated with an artificial intelligence–based automation control to regulate the growth of broccoli sprouts. A factorial experiment was conducted under photoperiods of 12:12 h, 16:8 h, and 18:6 h combined with blue:red light ratios of 40:60 and 25:75. The results indicated that extending the photoperiod significantly increased the average height from 6.8 ± 0.5 to 11.3 ± 1.1 cm and the fresh weight from 92.4 ± 6.1 to 158.9 ± 12.4 g/tray, while the germination rate ranged from 91.2 to 96.8%. The blue:red light ratio of 25:75 consistently produced superior growth performance compared with the 40:60 ratio. The developed system effectively regulated sprout growth and demonstrates strong potential for application in smart agriculture systems.

Keywords: Dynamic spectrum lighting; Photoperiod; Blue:red light ratio; Artificial intelligence; Broccoli sprouts

1. Introduction

Broccoli microgreens are young plants of high nutritional and market interest, as they are classified as functional foods that often have a high density of antioxidants and nutrients compared to many mature plants and have a short production cycle, making them suitable for Controlled Environment Agriculture (CEA) such as greenhouses/growing rooms/vertical farms [1]. However, in indoor plant factories, "light energy" is a major cost, as almost all of the light has to be generated by lamps instead of sunlight, making efficient light management—that is, achieving high yield and quality under low energy consumption—a key research question [2]. In this context, light control should not only consider intensity but should also consider at least three dimensions: (1) photosynthetic light quantity, (2) spectrum/wavelength ratio, and (3) time/photoperiod and day–night pattern. The widely used units that correspond to plant physiology are Photosynthetic Photon Flux Density (PPFD) and Daily Light Integral (DLI) (instead of using lux or lumen based on human vision) [3]. The fundamental framework linking light spectrum to plant growth and quality is grounded in plant photobiology. Plants possess a sophisticated network of photoreceptors that detect distinct wavelength regions: phytochromes perceive red and far-red light, cryptochromes and phototropins respond to blue and UV-A radiation, whereas UVR8 is activated specifically by UV-B. Activation of these photoreceptors triggers downstream regulation of gene expression, hormonal signaling pathways, morphological development, and metabolic processes [4]. In terms of grow lighting design, this means that spectrum adjustment affects not only photosynthesis but also stem elongation or hypocotyl, color, tissue density, and bioactive compounds (e.g., glucosinolates/phenolics/carotenoids) that are key selling points of broccoli and Brassicaceae [1].

DSL refers to controlling the intensity and spectrum to change over time (in a day or across multiple plant life cycles) to create a light recipe that aligns with goals such as increasing yield, controlling height, increasing key compounds, or reducing energy. This concept has been explicitly discussed in the field of LED supplemental lighting, where LEDs offer the opportunity to create "dynamic lighting recipes" that control both intensity and spectrum throughout the day. Ideally, this should be tied to automated spectral and intensity measurements (e.g., spectroradiometers) to form a greenhouse/growing system control strategy [5]. For broccoli microgreens, experimental evidence clearly shows that spectrum alone can significantly alter yield and quality composition. A classic example is broccoli seedling cultivation under LEDs, where several LED formulations yielded higher fresh mass than fluorescent formulations, and formulations with a higher proportion of blue light yielded significantly higher total chlorophyll compared to the control group [6]. In addition, research points to the role of far-red under low-intensity white light. Supplementation with far-red (accounting for 20% of total photons) can increase canopy height or yield in some indicators, but has a trade-off for some quality (e.g., reduced dry matter or

phenolics in some cases) [7]. If an AI Automation Flow concept is applied to adjust the LED spectrum, it will allow for better decision-making. In this context, it means from data acquisition (sensors/images) to processing and evaluating plant status to calculating setpoints to commanding the LED drivers, and then looping back with real data. (closed-loop) The concept of combining IoT with algorithms is well-suited for grow lighting applications because (1) LEDs can be dimmed and spectrum channels adjusted quickly, (2) electricity costs can be time-of-use pricing, and (3) plant light requirements can be determined via DLI/quality targets. Research on supplemental lighting control in greenhouses shows that optimization and forecasting approaches can reduce electricity costs without compromising growth compared to heuristic methods. For example, an IoT-based supplemental lighting control system using solar and electricity cost predictions has shown cost reductions of up to 4.16% in winter and 33.85% in spring compared to heuristic methods, with no significant growth loss. [8] In the field of advanced AI, the greenhouse community has compared Model Predictive Control (MPC) with Reinforcement Learning (RL) approaches and proposed a framework for analyzing the pros and cons, confirming that there is a comprehensive literature of “supplemental lighting control” work using RL concepts (e.g., Q-learning). [9] In addition, deep reinforcement learning AI combined with robust optimization has reported the potential for significant energy savings in greenhouse climate control applications. (Example of a report showing a 57% energy reduction compared to traditional methods in a case study) which reflects that AI frameworks can be designed to be energy efficient while maintaining quality if the constraints are appropriate [10].

Although there is considerable evidence that intensity, spectrum, or photoperiod affects microgreens, there is a systemic gap that prevents dynamic spectrum + AI from being standardized for broccoli seedlings, making it an interesting area for research. Firstly, many microgreen experiments still use fixed spectra (constant throughout the growing period), leaving it unclear how adjusting the spectrum to be different during day-night or developmental stages provides causal benefits. In greenhouse LED supplementation studies, it has been noted that actual intensity and spectrum vary throughout the day, and there is no system to accurately describe mixed lighting conditions (natural light + variable lighting), suggesting the design of a standardized light measurement system for comparison and practical application [5]. Secondly, for Brassicaceae microgreens, data on the effects of light intensity and photoperiod are reported to be limited compared to other dimensions (e.g., spectrum). One study specifically stated that there is little data on the effects of LED intensity or photoperiod on the growth and nutrition of Brassicaceae microgreens, despite some work on light quality [11]. Thirdly, AI/optimization work for grow lights with clear energy outcomes is needed. It is often focused on controlling total intensity/achieving DLI and power costs rather than controlling multi-channel spectrum for specific plant nutritional quality (e.g., glucosinolates in broccoli microgreens) [8].

Therefore, from the information mentioned above, the research problem in engineering research is to design a day-night simulation system with DSL that can adjust the spectrum, intensity, and photoperiod in detail and incorporate AI Automation Flow with feedback from plant conditions to control the growth and quality of broccoli seedlings under energy cost constraints.

2. Materials and methods

2.1 Defining the test conditions

Figure 1 is shown before and after Greenhouse and LED lights used in the experiment and Table 1 is shown independent, dependent, and control variables used in the experiment. Control variables C1 to C6 were systematically defined and controlled to limit the impact of environmental and other physical factors that might interfere with the interpretation of independent variables such as light spectrum and day-night cycles. C1, the air temperature inside the growing system, was measured and controlled at an average of $29.34 \pm 4.52^{\circ}\text{C}$ throughout the experiment by installing a temperature sensor at plant top level. This level reflects the actual thermal environment experienced by broccoli seedlings. This temperature range is consistent with tropical climates and is suitable for the germination and early growth of cruciferous plant seedlings without causing excessive temperature or low temperature stress. C2, the relative humidity of the air, was controlled at $65 \pm 5\%\text{RH}$ to maintain a balance between transpiration and water uptake by seedlings, reduce water loss through stomata, and ensure uniform growth across all experimental groups. For C3, the growing medium and thickness, coco peat of the same grade from the same source was selected for all trials due to its good water retention and aeration properties, suitable for seedling cultivation. For C4, the planting medium thickness was set at $3.5 \pm 0.5\text{ cm/tray}$ to ensure optimal moisture and oxygen supply for the roots and minimize variations due to different planting medium depths.

For C5, broccoli seeds from the same variety and batch were used to ensure uniform genetic quality and consistent germination potential. A total of 20 g of seeds was evenly distributed across each tray to maintain a standardized seedling density and to minimize intra-species competition. For C6, irrigation was controlled at a fixed frequency of twice daily morning and evening, providing 250 ml per application, for a total of 500 ml/tray/day. This approach ensured stable and sufficient moisture within the substrate while preventing waterlogging, a condition known to adversely affect seed germination and early root development. Tap water was preconditioned by allowing it to stand for 24 h to minimize residual chlorine. For C6, the LED–canopy distance was maintained at $30 \pm 3\text{ cm}$, with periodic adjustments made according to seedling height to ensure consistent PPFD and spectral uniformity at the canopy level. Establishing the control variables C1–C6 in this manner was essential for isolating the effects of DSL and AI-based Automation Flow, reducing experimental variability, and enhancing the scientific reliability of the findings.

The independent variables used in this research consisted of (1) the LED light spectrum, with the blue:red light ratio (blue:red) set in the ranges of 25:75 and 40:60, and (2) the day-night duration. (Photoperiod) 3 levels, namely 12:12, 16:8 and 18:6 h and (3) light intensity at plant height (PPFD) in the range of $120\text{--}250\text{ }\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$. The dependent variables used to evaluate the results were the average seedling height (cm), fresh weight per tray (g), germination rate (%), and growth index. The control variables were kept constant throughout the experiment, namely the air temperature inside the system $25 \pm 2^{\circ}\text{C}$, relative humidity $65 \pm 5\%$, the same type of growing medium, and the amount of water given twice a day in the same volume for all experimental groups. The experiment was designed according to a Completely Randomized Design (CRD) or Factorial Design in order to be able to analyze the effects of each factor and the interaction between factors correctly according to statistical methodology and academic principles.

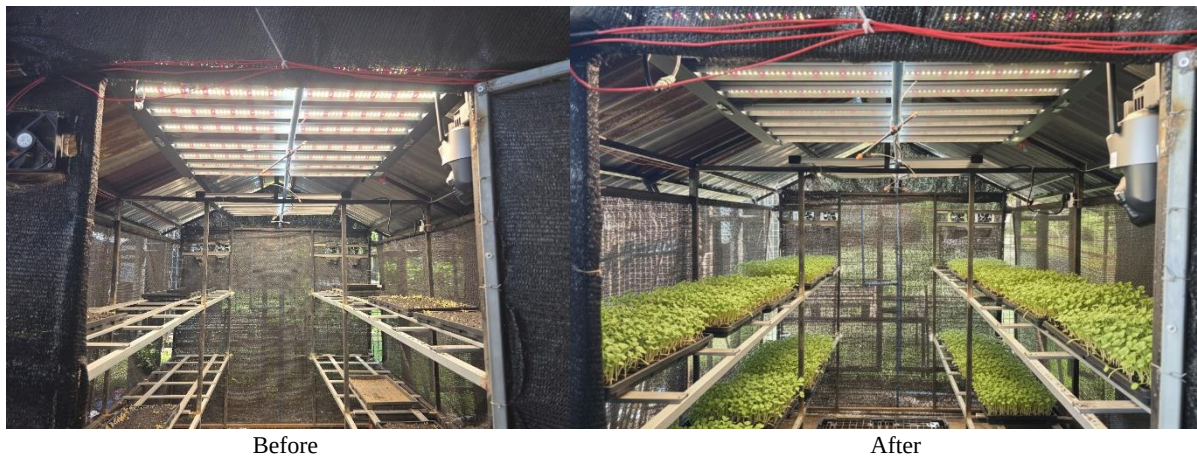


Figure 1 Greenhouse and LED lights used in the experiment

Table 1 Independent, dependent, and control variables used in the experiment

No.	Variable Category	Code	Variable Name	Operational Definition	Unit/ Experimental Values
1	Independent Variable	X1	Photoperiod (Day–Night Cycle)	Duration of light–dark periods used to simulate daytime and nighttime conditions within the cultivation system	12:12, 16:8, 18:6 h (light: dark)
2	Independent Variable	X2	Light Spectrum Ratio	Intensity ratio between blue and red LED light	40:60 and 25:75
3	Independent Variable	X3	PPFD at Canopy Level	Photosynthetic photon flux density reaching the plant canopy	120–250 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$
4	Independent Variable	X4	Dawn–Dusk Light Profiling	Gradual increase/decrease in lighting intensity during switch-on and switch-off	15–30 min
5	Dependent Variable	Y1	Average Seedling Height	Height measured from the stem base to the shoot tip	cm
6	Dependent Variable	Y2	Fresh Weight	Fresh biomass per tray at harvest	g/tray
7	Dependent Variable	Y3	Germination Rate	Percentage of germinated seeds relative to the total number of seeds	%
8	Dependent Variable	Y4	Growth Index	Dimensionless index calculated from defined growth parameters	Unitless
9	Dependent Variable	Y5	Growth Uniformity	Variability of plant growth within the same tray	SD or %CV
10	Control Variable	C1	Air Temperature	Temperature within the cultivation system at canopy level throughout the experiment	29.34 $\pm$ 4.52 $^{\circ}\text{C}$
11	Control Variable	C2	Relative Humidity	Air humidity level inside the cultivation chamber	65 $\pm$ 5 %RH
12	Control Variable	C3	Growing Medium & Depth	Type and thickness of the planting substrate (compressed coco peat)	3.5 $\pm$ 0.5 cm
13	Control Variable	C4	Seed Density	Mass of broccoli seeds sown per tray	20 grams/tray
14	Control Variable	C5	Watering Volume & Frequency	Daily water amount and watering frequency	500 ml/day (250 ml $\times$ 2)
15	Control Variable	C6	LED–Canopy Distance	Distance between LED fixture and seedling canopy	30 $\pm$ 3 cm

2.2 Development of AI Automation Flow and Control System

The AI Automation Flow developed in this research aims to control and adjust the lighting environment to meet the physiological needs of broccoli seedlings at each stage of growth. The focus is on integrating DSL and PPFD control under a closed-loop automatic control system. The system's structure begins with data flow from sensors installed within the growing system, which measure key parameters such as light intensity at the plant top, temperature, and relative humidity. This data is then fed into a central processing unit to evaluate the system's status and compare it to target values set in the AI Automation Flow. The system then makes logical decisions, or AI-assisted decision-making, to adjust the LED lighting parameters, including the light spectrum ratio (e.g., blue to red light ratio) and PPFD intensity, to suit the specified growing time and day–night cycle. Mechanistically, DSL uses dynamic spectrum lighting as the primary tool to control seedling growth patterns, with blue light playing a role in controlling stem elongation and leaf development. While red light plays a crucial role in photosynthesis and biomass accumulation, AI Automation Flow is designed to automatically adjust the light spectrum proportions during different growth stages. Simultaneously, PPFD (Potential Growth Factor) control is used to maintain the optimal amount of light energy received by the plants. The system continuously monitors the actual light intensity at the plant's top and adjusts the power or dimming level of the LEDs to keep the PPFD within the target range, such as 120–250 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$. The link between light spectrum adjustment and PPFD under AI Automation Flow allows the system to systematically control both light quality and quantity, reducing fluctuations in the growing environment and ensuring consistent and predictable response from broccoli seedlings—a key innovation in this research.

Once the yield is obtained, the values are calculated according to the designed dependent variables. The equations used to evaluate growth distribution and serve as indicators of seedling uniformity under the system's control are then applied. The standard deviation

equation (SD) is calculated using Equation 1, where SD is the standard deviation, X_i is the measured value (e.g., height or fresh weight), and $\bar{X}$ is the mean of the data set. The calculated SD can be used to calculate the coefficient of variation as shown in Equation 2. This equation is used to compare the uniformity of growth between experimental sets with different means. A low CV indicates a highly stable environment, which is an important goal of AI-controlled systems.

$$SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2} \quad (1)$$

$$CV = \frac{SD}{\bar{X}} (100) \quad (2)$$

The equation used to assess the effect of light conditions on the initial stages of plant development, particularly the effect of light spectrum on stimulating seed germination in this research, was the Germination Rate (GR) Equation 3, where GR is the germination rate in percentage, N_g is the number of germinated seeds, and N_t is the total number of seeds planted. The germination rate is often used in conjunction with other growth measures such as height, diameter, and biomass to help assess which building material is best suited [12]. The experimental results were calculated to compare the relative growth levels between experimental groups using the Growth Index equation (Equation 4), which is an equation that can reduce the influence of different scales of data, where GI is the growth index (unitless), $\bar{H}$ is the average height of broccoli seedlings in centimeters, and H_{max} is the maximum height found in all experimental groups [13].

$$GR = \frac{N_g}{N_t} (100) \quad (3)$$

$$GI = \frac{\bar{H}}{H_{max}} \quad (4)$$

3. Results and discussion

3.1 Effects of day-night cycle and light spectrum on broccoli seedling growth

The test results are shown in Table 2. Figure 2 shows that adjusting the day-night cycle and light spectrum influences the growth of broccoli seedlings in a direction consistent with plant physiological principles and existing research. Increasing the light duration from 12 to 16–18 h resulted in an average height and fresh weight increase of approximately 30–55%. This can be explained by the plants receiving light energy for photosynthesis for a longer period, leading to significant carbohydrate and biomass accumulation. This result is consistent with the concept of photoperiodism and the principle of photosynthetic carbon assimilation, which states that increasing the light exposure duration under optimal light intensity increases biomass yield in leafy greens. Furthermore, a Blue:Red light spectrum ratio of 25:75 consistently showed better biomass accumulation than a ratio of 40:60. This can be explained by the role of red light in stimulating the efficiency of the photosynthetic system through chlorophyll and phytochrome, while the appropriate ratio of blue light helps control leaf development and stem elongation without causing excessive stunting. Considering the combined results, the T4 experimental package, which used a light cycle of 16:8 h combined with a Blue:Red light ratio of 25:75, provided the best balance between biomass increase and growth uniformity.

Table 2 Effects of photoperiod and light spectrum ratio on broccoli sprout growth

Treatment	Photoperiod (h)	Blue:Red ratio	Average height (cm)	Fresh weight (g/tray)	Germination rate (%)
T1	12:12	40:60	6.8 ± 0.5	92.4 ± 6.1	91.2 ± 2.3
T2	12:12	25:75	7.5 ± 0.6	104.6 ± 7.8	92.1 ± 1.9
T3	16:08	40:60	8.9 ± 0.7	128.3 ± 9.2	95.4 ± 1.6
T4	16:08	25:75	10.2 ± 0.6	149.7 ± 8.5	96.8 ± 1.2
T5	18:06	40:60	10.5 ± 0.9	151.2 ± 10.1	95.9 ± 1.8
T6	18:06	25:75	11.3 ± 1.1	158.9 ± 12.4	95.1 ± 2.0

The interaction graph in Figure 3 shows that both photoperiod and the blue-to-red light ratio affect the growth of broccoli seedlings across all studied variables: average height, fresh weight, and germination rate. Overall, increasing the photoperiod from 12:12 to 16:8 and 18:6 h showed a continuous increase in average height and fresh weight at both photoperiod ratios. This reflects the main effect of photoperiod, which plays a crucial role in biomass accumulation and stem elongation resulting from longer photosynthetic periods. However, considering the blue-to-red light ratio graph, a ratio of 25:75 resulted in higher height and fresh weight than 40:60 at all photoperiod levels, especially at 16:8 and 18:6 h. This indicates the main effect of red light, which promotes stem elongation and fresh weight increase through the mechanism of phytochrome system activation and plant cell expansion.

In terms of interaction effect, the graphs of the two photoperiod ratios are not perfectly parallel, especially in the fresh weight graph. The gap between the Blue:Red ratio lines of 40:60 and 25:75 tends to increase with longer photoperiod, demonstrating that the effect of the light ratio depends on the light duration. Specifically, a high ratio of red light provides the best efficiency when plants receive sufficient light duration. In the case of germination rate, it was found that germination rate increased from a photoperiod of 12:12 to 16:8 h, but tended to stabilize or change slightly at 18:6 h, especially at a Blue:Red ratio of 25:75. This may reflect that the germination process responds more to light signals in the early stages than in later growth stages, and once the optimal period has passed, increasing the light duration may not provide any significant additional benefit.

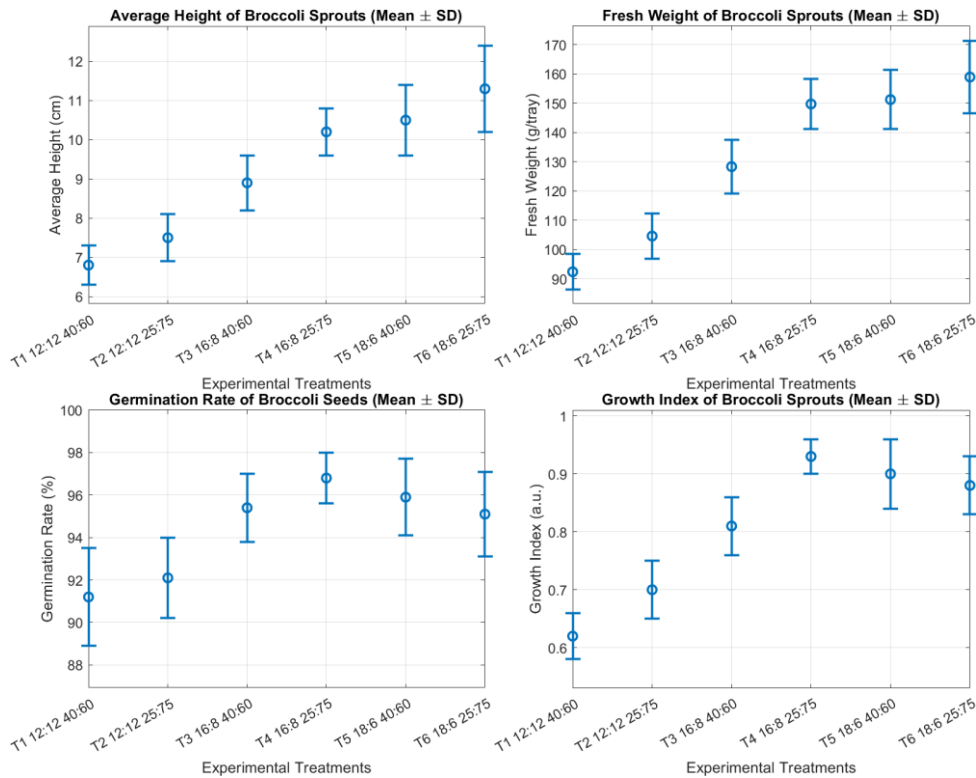


Figure 2 Average height, fresh weight, germination rate, and growth index of broccoli sprouts under different photoperiods and blue:red light ratios (mean $\pm$ SD)

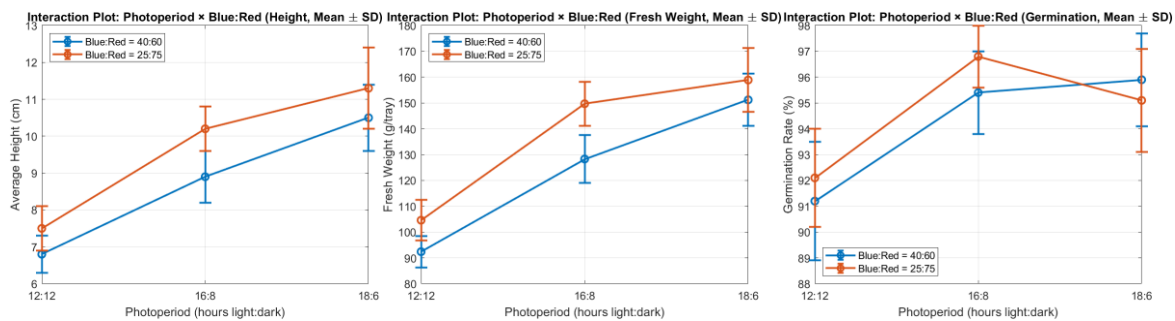


Figure 3 Interaction plots of photoperiod and blue:red light ratio on average height, fresh weight, and germination rate of broccoli sprouts (mean $\pm$ SD)

In summary, this interaction graph indicates that photoperiod is the primary factor controlling quantitative growth, while the Blue:Red light ratio acts as a supplementary factor that directs and optimizes the response. The use of a photoperiod of 16:8–18:6 h combined with a Blue:Red light ratio of 25:75 shows the most optimal growth results for broccoli seedlings, which is consistent with plant physiology principles and the concept of DSL system design for effective growth control.

3.2 Effects of PPFD with AI Automation Flow

Table 3 shows experimental results on PPFD using AI Automation Flow, demonstrating trends consistent with plant physiological principles and research on light management in controlled growing systems. It was found that increasing the PPFD from a low level ($120 \pm 10 \mu\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) to a moderate level (180 ± 12 and $220 \pm 15 \mu\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) significantly increased the Growth Index (GI), accompanied by a decrease in growth variability (%CV of height decreased from 18.6 to 8.7). This reflects that the plants received sufficient light energy for efficient photosynthesis and exhibited a more consistent response. However, when the PPFD was increased to a higher level of $250 \pm 18 \mu\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$, the GI increased only slightly compared to $220 \pm 15 \mu\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$, but growth variability increased, as evidenced by a high %CV of 15.9. This indicates the onset of photosynthetic light saturation and the possibility of photostress in broccoli seedlings. These results support the idea that increasing light intensity does not always yield a linear positive effect, and that controlling PPFD within an optimal range of approximately $200\text{--}230 \mu\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$ under AI Automation Flow is crucial in maintaining a balance between growth performance and yield uniformity. These experimental results highlight the role of feedback automation in reducing fluctuations in actual light conditions received by the plants.

Table 3 Effects of PPFD levels on Growth Index and Growth Uniformity of broccoli seedlings

Treatment	PPFD Range ($\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$)	Growth Index (GI)	Height Variability (%CV)
P1	120 ± 10	0.62 ± 0.04	18.6
P2	180 ± 12	0.81 ± 0.05	12.3
P3	220 ± 15	0.93 ± 0.03	8.7
P4	250 ± 18	0.94 ± 0.06	15.9

3.3 Effects of AI Automation Flow on lighting system stability

Table 4 shows experimental results comparing a static lighting control system with an AI Automation Flow system, demonstrating clear qualitative and quantitative differences in lighting stability. Although the average photon light intensity (PPFD) at the plant top of both systems was in a similar range (approximately 210–215 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$), the AI Automation Flow system significantly reduced PPFD fluctuations. This is reflected in a reduction of the standard deviation from ± 28 to ± 12 and a reduction of the %CV from 13.3% to only 5.6%, representing a reduction of approximately 58%. Academically, these results indicate that a static lighting control system cannot effectively respond to changes in real-world environmental conditions, such as lamp degradation, variations in light position, or temperature changes that affect LED efficiency. In contrast, AI Automation Flow, operating as a closed-loop control system, can continuously adjust the lighting system's operating parameters to maintain PPFD close to the target value, resulting in more consistent light energy supply to the plants. This uniformity of lighting conditions is directly reflected in the uniformity of broccoli seedling growth, which was assessed as high when using AI Automation Flow. These experimental results are consistent with the principles of precision environmental control and agricultural research in controlled environments, which indicates that the stability of environmental factors is no less important than the average value of those factors. This reinforces that AI Automation Flow not only controls lighting to the specified values but also plays a crucial role in reducing system variability, a key factor in increasing reliability, predictability of yield, and the potential for future real-world production applications.

Table 4 Comparison between static lighting control and AI-Driven Automation Flow

Control Mode	Average PPFD ($\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$)	PPFD standard deviation (SD)	PPFD coefficient of variation (%CV)	Growth Uniformity
Static Control (Manual)	210	± 28	13.30%	Moderate
AI Automation Flow	215	± 12	5.60%	High

4. Conclusions

This study empirically demonstrates that a day-night simulation system using DSL combined with AI Automation Flow can effectively control the growth of broccoli seedlings, in accordance with plant physiology principles and research on light management in controlled environments. Numerical experimental results clearly show that increasing the light duration from 12 to 16–18 h resulted in an increase in the average seedling height from approximately 6.8±0.5 cm to 10.2±0.6 cm, and an increase in fresh weight from 92.4±6.1 g/tray to 149.7±8.5 g/tray, or an increase of about 40–60% compared to the control group. Furthermore, the data trends show that increasing the light duration from 12 to 16 h had a significantly positive effect, while increasing it to 18 h resulted in a slower rate of improvement. This reflects the trend towards diminishing return to the light-response saturation phase. Furthermore, a Blue:Red light spectrum ratio of 25:75 consistently yielded better biomass accumulation than a ratio of 40:60 across all photoperiods. Germination rates increased from approximately 91–92 to 96–97%, and the growth index showed a continuous upward trend, demonstrating that increasing the proportion of red light under optimal light levels effectively improves photosynthetic efficiency and biomass accumulation. These results are consistent with the principles of the phytochrome system and the role of red light in photosynthesis in leafy vegetables.

In terms of PPFD, the experimental results clearly show a trend that moderate to relatively high PPFD levels provide the optimal growth results. Increasing the PPFD from 120±10 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$ to 220±15 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$ increased the Growth Index from 0.62±0.04 to 0.93±0.03, while the variability in height (%CV) decreased from 18.6 to 8.7%, reflecting more uniform growth. However, when PPFD was increased to 250±18 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$, the Growth Index increased only slightly, but the variability increased to 15.9%, indicating a tendency towards photosynthetic saturation and a risk of light stress. This confirms that continuously increasing light intensity does not always yield positive results. In terms of the role of AI Automation Flow, a comparison showed that the AI system could reduce PPFD variability from a standard deviation of ± 28 to ± 12 , or approximately a 58% reduction in variability, resulting in a significant improvement in growth uniformity. This trend reinforces the idea that environmental stability is just as important as the median variable. This study highlights that AI Automation Flow is a key mechanism that optimally links light spectrum adjustment and PPFD (Power Production Dynamic Range) for efficient operation. The study concludes that an integrated AI-powered light control approach not only improves broccoli seedling yield and uniformity but also presents a high-potential path for developing smart agriculture systems and sustainable controlled crop production in the future.

5. Acknowledgements

We would like to express our gratitude to the Department of Smart Agricultural Machinery Engineering, Faculty of Engineering and Technology, Rajamangala University of Technology Isan, Nakhon Ratchasima, for providing the testing location and the necessary testing equipment.

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