Application of Smart Sensors to Monitor the Interactive Effects of Temperature and Lighting on Plant Growth in a Simulated Controlled Environment Facility

by

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ABSTRACT

This thesis explored the potential use of smart sensors to monitor and integrate multiple environmental factors that play crucial roles in the intricate dynamics of plant growth in response to varying environmental conditions, such as lighting and temperature in controlled environment crop production systems.

A controlled environment chamber was designed and built to conduct experiments across a range of temperatures (15 - 35°C) and under varying lighting duration (7, 10 and 14 h) and intensity (100 and 150 µmol/m^2.s). A set of wireless smart sensors were used to monitor the environmental conditions, including air and soil temperatures, relative humidity, light intensity, and carbon dioxide level. The study demonstrated that the wireless smart sensors were effective in collecting reliable data for monitoring the environmental conditions, and sensor data could be fused to optimize the environmental conditions for plant growth. From the sensor data, it was found that both fresh biomass and dry biomass were significantly influenced by the three tested environmental factors. The highest biomass accumulation was observed at moderate temperatures (25-27°C), with diminished growth at both lower and higher temperatures. Light duration and intensity were found to have a noticeable effect on biomass production, with longer lighting periods and higher intensity fostering greater fresh and dry biomass production. Similar effects of environmental conditions on leaf development were found: the best environmental condition was the moderate temperatures and long lighting duration and high light intensity. However, the benefits of increased lighting were modulated by temperature, indicating a complex interplay between these factors.

This study contributed valuable insights into the optimization of environmental parameters for plant cultivation in controlled environment systems through the use of smart

sensors. The findings highlighted the importance of carefully balancing temperature and lighting conditions to maximize plant growth. The study demonstrated the successful use of an array of wireless smart sensors in monitoring multiple environmental parameters in controlled environment crop production and multiple sensor data could potentially be fused to optimize the environment in smart vertical farming (plant factories).

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To my friends and family, your encouragement and support have been my strength and motivation. This accomplishment is not only mine but also yours.

DEDICATION

With much love and appreciation, I would like to dedicate my thesis to my mom and dad, Qunxia Li and Peigang Sun, and my brothers, Chenhao Sun and Max.

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CHAPTER 1. INTRODUCTION

Providing an optimal environment to plants in controlled environment crop production systems can improve crop quality and quantity, as well as saving resources (e.g., water and energy). The major environmental factors that affect plant growth include air temperature, lighting, air humidity and carbon dioxide. Temperature influences many aspects of plant growth, including photosynthesis, transpiration, respiration, germination, and flowering. The optimum temperature for a plant depends on a range of factors, including the type of plant, stage of plant development, lighting, and CO_2 concentration in the air. Light is the main energy source for photosynthesis and other physiological processes (Bayat et al., 2018). Plants are sensitive to light intensity and spectra, as well as lighting period. Relative humidity affects the evapotranspiration processes, as well as microbes in the controlled environment crop production systems. Carbon dioxide is the key ingredient in plant photosynthesis. These factors interact with each other in controlled environment systems for crop production. For example, higher temperature generally leads to higher transpiration, but this effect may be compensated to some degree by more water vapour (higher relative humidity) in the warmer air. Another example is that the effect of CO_2 concentration on plant growth is lighting and temperature dependent (Idso, 1987). Therefore, to provide the optimal environment to plants, these factors should be considered together. Multiple sensors may be used to simultaneously monitor these environmental factors in controlled environment systems for crop production, and the sensor data from these sensors may be fused to gain a full picture of the plant environment.

Controlled environment agriculture (CEA) presents a potentially viable solution to vegetable production in cold climate regions, where traditional agriculture faces significant seasonal challenges. The primary obstacles in these regions include maintaining desirable

temperature conducive to plant growth and the extended use of artificial lighting due to shorter daylength. These challenges can significantly increase the consumption of energy, leading to higher operational costs and negative environmental impacts.

Digital technologies in CEA may potentially address these challenges. For example, smart sensors allow for real-time monitoring and precise control of environmental parameters. An sensor-based intelligent heating system can control environmental temperatures based on the plants' growth stages and external weather conditions, thereby reducing unnecessary heating. Similarly, a smart control system can optimize the timing and intensity of LED lighting, which not only aligns with the plants' photoperiod requirements but also minimizes energy usage.

Data from smart sensors may be analyzed and interpreted by sophisticated data analytics methods, such as machine learning to make the “smart” control decisions to ensure the optimal environmental conditions for plants with minimum resource input, thus enhancing crop yield and quality at minimum costs. A challenge in using digital technologies in CEA is the lack of data for developing and validating intelligent algorithms or training AI models. By providing accurate and detailed environmental and crop performance data, researchers can analyze the impacts of various growth conditions on plants that adjust to the plants' needs, ensuring optimal growth, leading to a better understanding and further improvements in CEA practices. As the agricultural sector moves towards sustainability, the role of digital technologies in enhancing CEA systems, particularly in cold climate regions, becomes increasingly valuable not only for crop production but also for environmental stewardship.

The goal of this thesis was to explore the potential of digital technologies (smart sensors) in monitoring and optimizing environmental conditions for plants in CEA by i) using smart sensors to collect experimental data on plant growth under variable environmental conditions;

and ii) analyzing the sensor data to quantify the interactive effect environmental factors on plant growth. The specific objectives were:

(1) to evaluate the effectiveness of using multiple smart sensors in monitoring temperature, humidity, lighting, carbon dioxide, and soil conditions in a CEA system;

(2) to use the sensor data to quantify the effects of air temperature and artificial lighting on plant growth; and

(3) to demonstrate the use of data analytic methods (regression and K-means clustering) in fusing and interpreting multiple sensor data for optimization of environmental conditions for plant growth.

CHAPTER 2. LITERATURE REVIEW

2.1 Environmental Conditions Affecting Plant Growth in CEA

Controlled environmental agriculture (CEA) such as greenhouses, plant factories and growth chambers, are enclosed spaces designed for the cultivation of plants under meticulously managed environmental conditions (Tuntivivatnaruuk et al., 2006; Kozai et al., 2015; Saito et al., 2010; Zhang et al., 2018). These specialized facilities are increasingly utilized for the commercial production of leafy vegetables and fruits, plant research, and the generation of high-quality transplants (Chintakovid et al., 2002; Fujiwara et al., 2004; Goto, 2012; Kozai, 2013; Meena et al., 2015; Nicole et al., 2016). The advantages of producing plants in controlled environmental systems include consistent and predictable growth and development, enhanced value of crops per production area, and reduced time frames for crop production (Dreesen and Langhans, 1991, 1992). CEA offers significant benefits over traditional greenhouse or open-field vegetable production by allowing for the precise management of the plant growth environment, thereby enabling the enhancement of plant growth rates through optimizing environmental conditions.

2.1.1 Temperature Effect on Plants

The critical role of temperature in shaping the physiological processes and development of plants is well-documented, reflecting its significance in controlled environment agriculture (Hatfield and Prueger, 2015). Fujiwara et al. (2004) conducted a seminal study on the propagation of sweet potato cuttings under artificial lighting, identifying air temperature as a crucial factor in growth outcomes. Their research showed a linear increase in the number of harvestable propagules with air temperatures ranging from 23°C to 35°C, emphasizing the importance of optimizing temperature conditions for vegetative propagation efficiency. This

correlation between air temperature and vegetative propagation efficiency is vital for controlled environment agriculture, highlighting the potential for temperature optimization to enhance the production rate and quality of propagules. Wang and Lin (2006) explored the impact of growth temperature on membrane lipid composition in strawberries and found that lower temperatures increased unsaturated fatty acids in membranes, aiding in cold tolerance by maintaining membrane fluidity. This underscores the significant biochemical changes induced by temperature, which is crucial for plant stress resilience strategies and crop production optimization.

2.1.2 Carbon Dioxide (CO_2) Effect on Plants

Enrichment of CO_2 (raising the CO_2 concentration in the air) has been a common practice in CEA to improve the productivity in greenhouses and growth chambers. Elevated CO_2 levels have been linked to various plant growth metrics improvements, including photosynthetic activity and plant dry mass (Knight & Mitchell, 1988; McKeehen et al., 1996; Ryu et al., 2014; Tian et al., 2014; Xu et al., 2014). An increase in atmospheric CO_2 concentration is typically correlated with an upsurge in photosynthetic activity, resulting in heightened carbohydrate synthesis and plant growth (Morrison & Lawlor, 1999). Ainsworth et al. (2006) reported transcriptomic changes in soybeans under increased CO_2, indicating a molecular adaptation to optimize photosynthetic efficiency and growth. Zhang et al. (2017) observed a 21% increase in Italian lettuce production in a plant factory with CO_2 concentration elevated to 1000 ppm, and also highlighted the species-specific and growth stage-dependent nature of optimal CO_2 concentration. In other words, the optimal CO_2 concentration should be determined by plant species, growth stage, and other factors (Tong et al. 2014). Idso et al. (1987) further elucidated the complex interaction between CO_2 levels and ambient air temperature, suggesting the necessity of considering both factors together in predicting plant responses to environmental

changes. Incorporating the findings of Wang et al. (2006), the aggregation of scholarly work by Zhang et al. (2013) and Morrison & Lawlor (1999) presented an understanding of the interplay between temperature and CO_2 concentration in terms of plant biology.

2.1.3 Humidity Effect on Plants

The influence of humidity on plant transpiration rates and water use efficiency is significant, with the optimal relative humidity for plant growth identified between 70-80% (Ahmed et al., 2022). Mortensen (1986) found that increase in relative humidity from 55% to 95% could enhance the growth rate of certain plant species by 17% to 68%, demonstrating the critical role of humidity in plant development and stress responses. Talbott et al. (2003) investigated the acclimation of stomatal response to CO_2 under different humidity levels and found that high relative humidity increased stomatal sensitivity to CO_2, thus optimizing photosynthetic efficiency.

Another important parameter related to relative humidity is the vapour-pressure deficit (VPD). VPD is the difference (deficit) between the water vapor pressure in the air and the vapour pressure when air is saturation at a given temperature. In other words, VPD measures the difference between the amount of moisture in the air and how much moisture the air can hold when it is saturated. Higher VPD may cause wilting because the root water intake can't keep up with the leaf evaporation loss. The ideal VPD is around 0.8 – 1.2 kPa (Charlotte Grossiord et al. 2020).

2.1.4 Light Effect on Plants

Light quality and intensity significantly influence plant growth and development, as evidenced by numerous studies exploring the effects of different spectral qualities on photosynthesis and physiological processes (Bayat et al., 2018; Ahmed et al., 2020). LED lighting, offering a range of spectral options and energy efficiency, has emerged as superior to

conventional lighting for plant cultivation in CEA (Gupta and Jatothu, 2013; Nakano et al., 2014). LEDs offer several advantages, including energy efficiency, a variety of spectral options, and minimal heat emission (Bian et al., 2015; Bourget, 2008; Gupta and Jatothu, 2013; Johkan et al., 2010; Kim et al., 2004a; Morrow, 2008; Saito et al., 2010; Singh et al., 2015; Tian et al., 2014; Zhang et al., 2018). Goto (2003) explained the varied effects of light quality on plant growth and the intricate dynamics between plant responses and light regimes. Research by Muneer et al. (2014) and Wang et al. (2016) on the impact of LED lights on lettuce growth underlined the importance of optimizing light regimes for enhancing plant growth and nutrient content. Tanaka et al. (2017) provided insights into species-specific responses to different light wavelengths, indicating the potential of photoreceptor-mediated growth mechanisms in agricultural optimization. Ohtake et al. (2018) found that alternating red-blue light with long photoperiods significantly promoted growth rate in comparison with white fluorescent lamps.

Miao et al. (2023) conducted a controlled study to assess the influence of varying LED light intensities on the growth and nutrient content of lettuce and spinach cultivars in a plant factory. Their research demonstrated that light intensity not only significantly affected plant height, leaf number, and biomass but also altered the accumulation of key nutrients such as soluble sugars, proteins, and ascorbic acid. These findings are instrumental in designing light regimes in plant factories to maximize crop yield and nutritional value while considering the specific requirements of different cultivars.

Monostori et al. (2018) explored the impact of LED lighting on the growth, metabolism, yield, and flour composition of wheat, highlighting how different spectral qualities and intensities of light can significantly alter physiological processes. The study demonstrated that LED lights, particularly those with blue and pink spectra, could enhance wheat quality by

modifying starch and protein contents, influencing the milling quality of flour. These findings demonstrated the potential of targeted LED lighting strategies in optimizing wheat production and quality. Urrestarazu, Nazarideljou, and Carrillo (2016) investigated the effects of LED lighting on the growth and development of several horticultural crops. They found that different spectral qualities and intensities of LED lights significantly influenced plant growth, photosynthetic activity, and electric efficiency. Specifically, high-intensity LEDs were shown to enhance the growth rate and photosynthetic efficiency, suggesting that the strategic use of LED lights can be a viable method to optimize crop production in controlled environments.

The customizable features of LEDs allow for precise control over light intensity and quality, which is paramount for simulating the varying light conditions that crops would naturally encounter. This capacity for customization facilitates a tailored light environment that can significantly boost photosynthesis and plant growth. (Bian et al., 2015; Bourget, 2008; Gupta & Jatothu, 2013). The study by Samuolienė et al. (2021) delved into the optimization of artificial lighting as a means to improve both the biomass yield and the nutritional value of leafy green vegetables and reported that lighting could be optimized to enhance the biomass yield and nutritional quality of leafy greens. Research has also been reported on the potential of using artificial lighting to fine-tune growth conditions to enhance crop predictability and development (Dreesen & Langhans, 1992; Chintakovid et al., 2002; Nicole et al., 2016). Zhang et al. (2018) reported that optimizing light conditions not only influences plant biomass and quality but also the efficiency of artificial lighting systems in terms of energy consumption, which would lead to sustainable plant production methodologies in controlled environments. Kjær et al. (2012) delved into the optimization of light for enhancing plant growth for cost-effective and sustainable greenhouse production.

2.1.5 Interactive Effects of Environmental Factors

It's generally acknowledged that the effects of environmental variables on plants are interconnected, exerting complex influences on plant physiological processes. Understanding and optimizing the interplay between various environmental factors is crucial for maximizing plant growth and development. The interactive effects of temperature, light, CO_2, and humidity necessitate an integrated approach to environmental control in CEA. Temperature emerges as a pivotal factor that modulates the plant response to CO_2 with optimal outcomes often noted at moderate, rather than extreme, temperatures. As Morrison & Lawlor (1999) have elucidated, while higher CO_2 levels may boost overall biomass generation, it is the temperature that crucially dictates how this biomass is distributed within the plant's structure. While elevated CO_2 levels foster plant growth, temperature modulates this effect in a species- and context-dependent manner. This dynamics significantly impacts not only the biomass quantity, but also the quality of produce, affecting such properties as grain dimension and nutritional value. Zhang et al. (2013) have noted that in bulbous species such as Hippeastrum vittatum, bulb size and carbohydrate reserves were significantly influenced by the interplay of CO_2 and temperature. Martel et al. (2020) explored the interplay between temperature and light intensity in determining plant growth and development. Bejarano et al.'s (2010) investigated the intricate balance between abiotic factors and plant development. Choi et al. (2011) conducted a study examining how air temperature and light intensity influence the germination and growth rate of lettuce seedlings in a controlled environment. In a separate study, Choi et al. (2000) discovered that the growth rate of both butterhead and leaf lettuce improved as the temperature rose.

Furthermore, the joint influence of CO_2 and temperature affects not only the productivity, but also plant-to-plant interactions within ecosystems. Elevated temperatures may truncate the

grain-filling duration, thereby influencing yield size and quality. Consequently, this alters resource availability for photosynthesis and nutrient uptake, potentially reshaping competitive dynamics within plant communities.

Park et al. (2012) examined how the combination of different light qualities and CO2 levels influences lettuce growth. It reported that photosynthetic rate of lettuce grown under red, blue, and white light significantly increased when the CO2 concentration increased.

While many studies have investigated the effects of individual environmental factors to establish the optimal ranges of these factors for specific plants (Ahmed et al., 2019), there is a collective call within the scientific community for more longitudinal studies to fully untangle the complex interactions among environmental factors. Future research should focus on elucidating these interactions and developing comprehensive models for environmental optimization.

2.2 Digital Technologies in CEA

Tian et al. (2014) advocated for the advancement of smart farming methodologies, indicating a trajectory towards the incorporation of intelligent algorithms, data fusion, and refined modeling techniques in CEA technologies. As the global demand for green and organic produce escalates against the backdrop of diminishing arable land, such technological strides are becoming increasingly critical for the future of food production.

2.2.1 Smart Farming Technologies

The integration of smart farming technologies, such as LED lighting, UAV-based monitoring systems, multi-sensor data fusion, and AI, represents a paradigm shift in controlled environment agriculture. Tian et al. (2014) highlighted the potential of intelligent crop management systems, emphasizing the role of LEDs in achieving high yield and quality crops through optimized environmental control. Ryu et al. (2014) introduced the "GREENBOX"

technology that offer innovative solutions for urban agriculture by integrating LED lighting and hydroponic systems in modular units, demonstrating the potential for sustainable food production in non-arable urban spaces.

The Smart indoor farming replies on multiple sensors for monitoring environment and plants, and large amount of data is collected and processed to increase the productivity and product quality, as well as reduce the resource utilization.

In the realm of precision agriculture, the innovative use of Verilog Hardware Description Language to create an Application-Specific Integrated Circuit (ASIC) has marked a technological leap, as exhibited by Patidar et al. (2019). Their system adeptly monitors and regulates critical environmental parameters, such as temperature, moisture, pH, and light, ensuring optimal conditions for plant growth. This intersection of hardware programming and sensor networks is indicative of a transformative phase in agriculture, propelling the industry towards more sustainable and efficient production practices.

2.2.2 Wireless Monitoring Systems

Palagin et al. (2011) delved into the innovation of remote electronic data collection systems, pivotal for the precise and immediate tracking of diverse metrics including plant health, soil properties, and ecological conditions. The study centered on the "Floratest" series of portable wireless gadgets, engineered to integrate seamlessly with current mobile communication infrastructures like GSM/GPRS. Chen and Zhao (2012) present a comprehensive mobile GIS framework designed to facilitate the real-time collection and integration of agricultural data. This innovative system leverages web services and a widget-based architecture, offering a scalable solution for "one-stop" data collection and processing.

Advancements in wireless sensor networks (Li and Deng, 2008) and data fusion techniques (Dong et al., 2009) are enhancing precision agriculture, enabling real-time monitoring and control over environmental conditions for optimal plant growth. These technological innovations are leading to intelligent farming practices, such as managing temperature, CO_2, humidity, and light for the sustainable advancement of controlled environment agriculture.

The Internet of Things (IoT) based greenhouse monitoring is a new trend. It is significantly increasing the accuracy, availability, and efficiency in data collection and data sharing. Shamshiri et al., (2020) developed a WSN greenhouse monitoring system, in which each sensor node contained air temperature, RH and soil temperature sensors. These sensors communicated with a gateway to store the collected data on the cloud. Meanwhile, data could also be directly transferred from sensor nodes to the cloud by using an onboard Wi-Fi module if internet connection is available inside the greenhouse.

Based on the literature review, it became evident that while substantial progress had been made in understanding the impacts of environmental factors on plant growth, but there are few models for predicting the interactive effects of multiple environmental factors, and limited datasets that could be used to develop and train data-driven (AI) models for optimizing the environmental conditions in CEA. Digital technologies, such as IoT, have been used more and more in CEA, but research on multiple sensor data fusion, as related to the interactive effects of multiple environmental factors on plants, is lacking.

CHAPTER 3. METHODOLOGY

3.1 Experimental System

A series of experiments were carried out to assess the optimal conditions for plant growth in controlled environment systems. A simulated CEA system (test chamber) was designed and constructed to conduct the experiments. An indoor gardening unit (planter) equipped with LED lights was placed in the test chamber to grow plants. A set of wireless smart sensors were installed in the chamber to monitor the environmental conditions.

3.1.1 Test Chamber

A test chamber was designed and constructed to simulate controlled environment systems for crop production. The chamber measured 1.2 x 1.2 x 1.2 m and was built with wood framing and rigid insulation boards (thermal resistance RSI=5.63 m^2 ·K/W) (Fig. 1). The high thermal insulation ensured a relatively stable internal environment (temperature) by minimizing external thermal interference. The top part of the chamber could be removed to open chamber completely when placing the test plants into the chamber. Each face of the chamber had an access hole of 127 mm in radius. The access holes allowed quick viewing of plants inside the chamber, as well as making adjustments to test setups without opening the whole chamber.

Temperature inside the chamber was regulated by using a 500 W heater (Amazon Basics 500-Watt Ceramic Small Space Personal Mini Heater). The heater was plugged in to a wireless thermostat outlet (DIGITEN WTC200 Remote Control Thermometer, DIGITEN), which had a temperature range of -10 to 80℃, with an accuracy: ±0.1℃ and a remote refresh frequency of 20s. Because no cooling system was used for environmental control, the ambient temperature was kept at least 10°C below the desirable temperature inside the chamber so only heating was required to maintain the test temperature. When the heater was turned on, two small recirculation

fans were turned on simultaneously to ensure uniform distribution of air temperature within the chamber. It should be noted that relative humidity and CO_2 were not regulated in the chamber.

Figure 1. Photo of test chamber to simulate controlled environment systems for plants.

The LED light was dimmable and experiments were designed for two photosynthetic photon flux density (PPFD) levels: 100 and 150 µmol/m².s. These intensity levels are within the range that is considered suitable for a variety of plant species during the vegetative growth phase, ensuring that the plants receive sufficient light for photosynthesis without the risk of light saturation or photoinhibition. While PPFD in µmol/m².s was used in this study, the light intensity measurement by the smart sensor was in lux. To covert the lux reading by the smart sensor to PPFD, light intensity was measured first manually with a spectrometer (Lighting Passport, Asensetek) that had a unique feature of reporting the light intensity in both lux and µmol/m².s (PPFD) (Fig. 2). This unique feature allowed for easy conversion from lux to µmol/m².s without

using complicated conversion equations. Specifically, based on the spectrometer readings, a simple regression equation was then developed (discussed in details in the following section).

Figure 2. A screenshot of Photosynthetic Photon Flux Density (PPFD) measurement with Lighting Passport spectrometer.

The LED spectrum was also measured with the Lighting Passport spectrometer (Fig. 3). The spectral output showed prominent peaks in both the blue (around 450-500 nm) and red (around 650-700 nm) regions and the spectral distribution was heavily weighted towards the red zone. The blue light is crucial for the vegetative growth of plants, affecting leaf expansion, stomatal opening, and phototropism and the red peak aligns with the photosynthetic efficiency peak for plants.

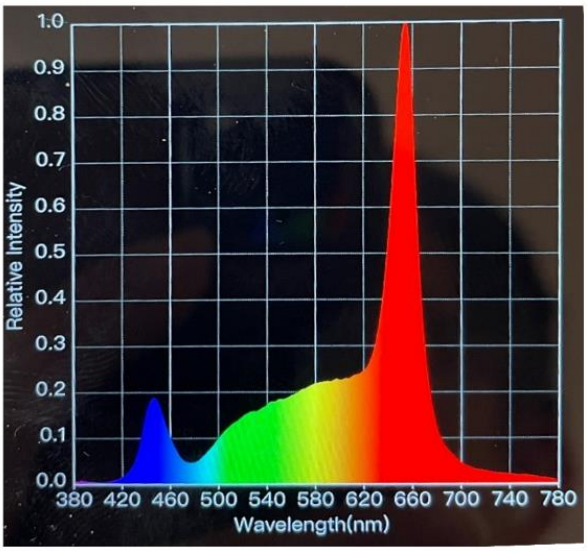

Figure 3. A screenshot of LED light spectral distribution measured with Lighting Passport spectrometer.

It should be noted that the light intensity range (100-150 µmol/m².s) tested in this study seemed lower than commonly recommended values of 200-400 µmol/m² for indoor gardening.

However, photosynthesis mostly needs red and blue wavelengths and the middle wavelengths of light simply bounce off the plant surfaces. That means that much of light in middle wavelengths is not used by the plants. Therefore, light intensities of 100-150 µmol/m².s concentrated in the red and blue regions should be sufficient for plant photosynthesis (Tian et al., 2014). Furthermore, young seedlings tested in this study could thrive under lower PPFD levels, while too high light intensity could lead to photoinhibition or stress, especially in the initial stages post-germination (Powles & Critchley, 1980).

There was a plant tray at the bottom the planter, which was designed for versatile cultivation, accommodating either hydroponic or soil-based cultivation. Soil-based cultivation was used in this study (Fig. 4).

Figure 4. Photo of soil-based grow tray

Temperature, relative humidity, barometric pressure, carbon dioxide concentration, and soil temperature were tested to verify the accuracy and stability of environmental conditions inside the chamber. All monitored environmental parameters displayed excellent consistency (the measured data is presented and discussed in the Results section).

3.1.2 Wireless Sensors and Sensor Network

This study utilized the SenseCAP Wireless Smart Agriculture Kit (Seeed Technology Co.,Ltd.), which is designed to monitor environmental conditions within greenhouses. The kit comprised a total of five wireless sensors respectively for barometric pressure, temperature, light intensity, relative humidity, and CO_2 (Table 1). The SenseCAP Wireless Barometric Pressure Sensor measures the atmospheric pressure in a range of 300 to 1100 kPa, with an accuracy of ±1.0 kPa under temperatures between 0°C and 65°C. The light intensity sensor has the capability to capture readings ranging from 0 to 188,000 lux, with a resolution of 0.045 lux. The combined temperature and humidity sensor is capable of measuring air temperature ranging from -40°C to +85°C with a resolution of ±0.2°C, and relative humidity levels from 0 to 100% RH, with a resolution of 1.5% RH at ambient temperature of 25°C. The carbon dioxide sensor has a measurement range from 0 to 40,000 ppm with accuracy of ± 30 ppm + 3% of the measured value in the range of 0 to 10,000 ppm.

Table 1. Smart sensors for monitoring environmental conditions and data collection in test chamber

Sensor	Wireless Network
Barometric pressure sensor	LoRaWAN US915MHz
Light intensity sensor	LoRaWAN US915MHz
Air temperature and humidity sensor	LoRaWAN US915MHz)
Soil moisture and temperature sensor	LoRaWAN US915MHz)
CO_2 sensor	LoRaWAN US915MHz)

As noted earlier that the light intensity sensor measured the light intensity in lux, while the photosynthetic photon flux density (PPFD) was needed for quantifying plant lighting. The conversion of lighting intensity from lux to PPFD, expressed as micromoles of photon per second per square meter (μmol/s.m²), was conducted through a calibration process. The procedure is summarized as follows:

1) A spectrometer (Lighting Passport, Asensetek) was used to measure the light intensity in lux and PPFD simultaneously at the two targeted levels of PPFD (150 and 100 µmol/s.m²).
2) Assuming a linear relationship between lux and PPFD, a linear equation was fitted to the data, with PPFD as the response variable and lux as the predictor:

$$PPFD\ (\mu mol/s.m^2) = 0.0157 \times lux + 48.8116 \quad (1)$$

3) The above calibration equation was used to convert the data collected by the wireless light intensity sensor from lux to PPFD in µmol/s.m².

The wireless temperature and humidity sensor and the CO_2 sensor were placed on the top of the planter, while the light sensor was placed at the plant level (Fig. 5). Another temperature and humidity sensor was placed near the chamber floor and the readings from this sensor were compared with readings from the wireless sensor to detect any temperature gradient along the chamber height, which could otherwise lead to inconsistent growth conditions and potentially skew experimental results. Soil conditions are critical for plant health, affecting water uptake, root growth, and nutrient absorption. The wireless soil moisture and temperature sensor was inserted into the soil to continuously monitor soil temperature and moisture levels.

All wireless sensors were linked to a gateway (SenseCAP LoRaWAN Gateway, Seeed Technology Co.,Ltd), which transmitted the sensor data via Wi-Fi to the cloud server of Seeed Technology. The accompanying software was then used to view and download the data (Fig. 6-8). There was also an option to keep the data in cloud-based storage so historical datasets could be accessed and evaluated. In rural areas, the communication range of these wireless sensors could reach 10 km, whereas in urban situations, their effective range was around 2 km.

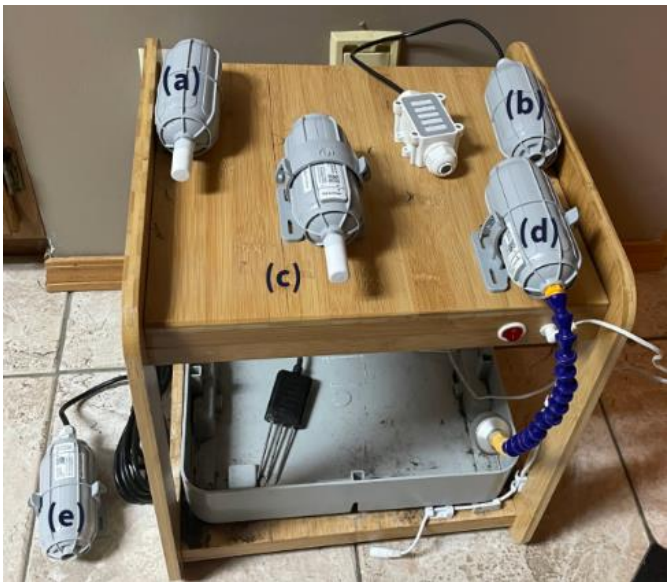

Figure 5. Sensor layout: (a) Barometric pressure sensor, (b) CO_2 sensor, (c) Air Temperature and humidity sensor, (d) light intensity sensor node with the probe placed in the plant tray, (e) Soil moisture and temperature sensor node with the probe inserted in soil.

Figure 6. Screenshot of real-time data monitoring CO_2 level (ppm), light intensity (lux), and barometric pressure (Pa). The horizontal axis shows days (January 19 to 29).

Figure 7. Screenshot of real-time data monitoring of air temperature (°C), soil temperature (°C), and a second air temperature (°C). The horizontal axis shows days (January 19 to 29).

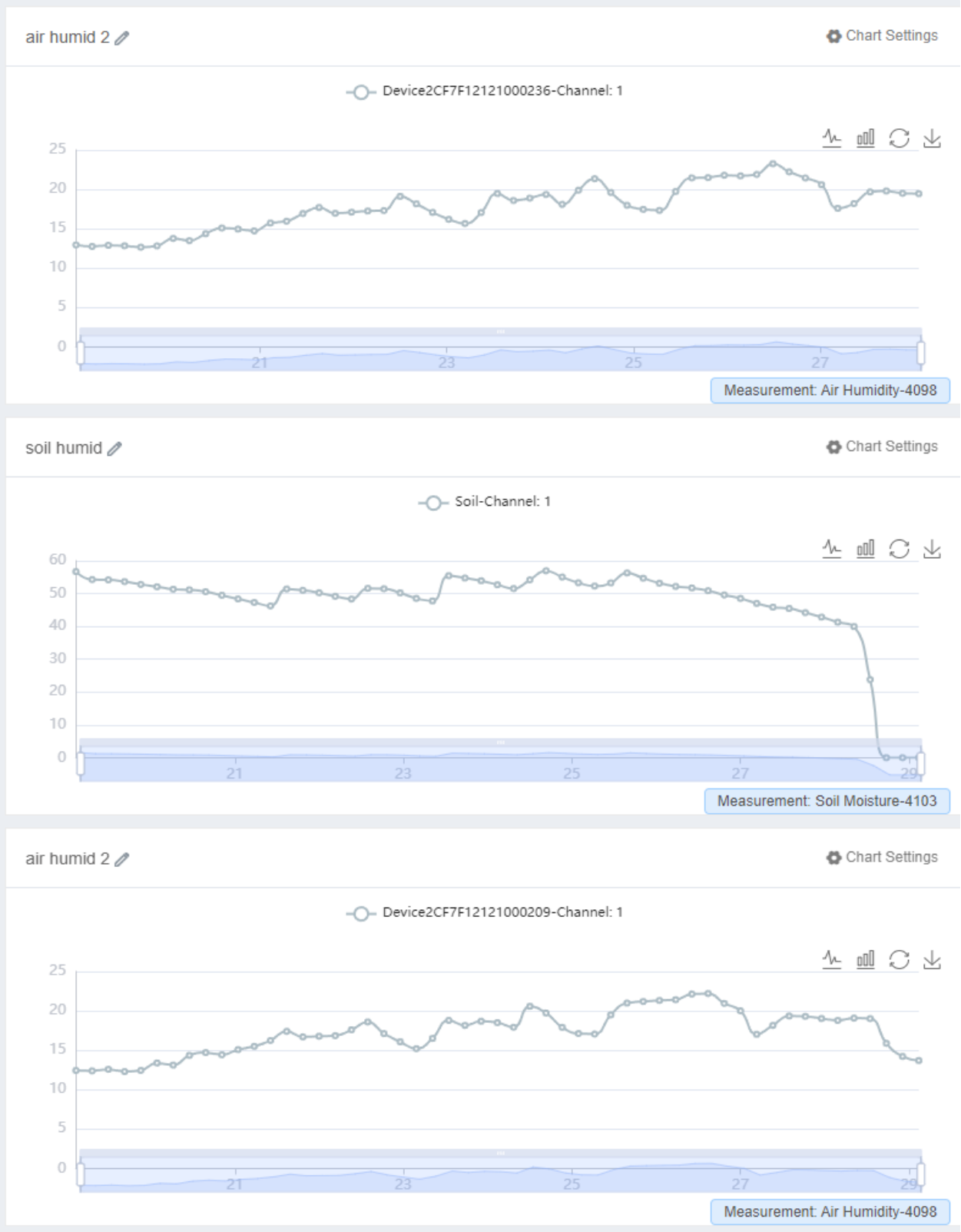

Figure 8. Screenshot of real-time data monitoring of air humidity (%), soil moisture (%), and a second air humidity (%). The horizontal axis shows days (January 19 to 29).

3.2 Test Plants

Round Pod Kidney Wax Beans were used as the test plants. Beans were selected for their rapid growth and the simplicity of their developmental structure. This specific type of bean is known for its speedy maturation and the production of a single node, which offers a straightforward procedure for experimental observation and data collection.

The Round Pod Kidney Wax Bean thrives under specific environmental conditions. The optimal temperature range is 21-27°C for germination and 10-29°C during the growth phase. These beans demand full sunlight, requiring at least 6-8 hours of direct exposure daily to support their photosynthetic processes. The soil should be well-drained and rich in organic matter, with a slightly acidic to neutral pH of 6.0 to 6.8. Consistent moisture is required, especially from the flowering stage to harvest, with the plants needing approximately 25 mm of water per week. However, care must be taken to avoid overhead watering to minimize the risk of disease. Adequate spacing is necessary to ensure good air circulation around the plants, which is essential for preventing fungal infections. In terms of nutrition, beans are moderate feeders but are capable of nitrogen fixation, which reduces the need for high nitrogen fertilizers.

3.3 Test Conditions

The test program was designed to evaluate the temperature and lighting effects on plant growth, while relative humidity and CO_2 were kept constant. Temperature is considered to a pivotal factor in plant environment, and therefore, a broad range of temperatures was tested in this study:

1) 15°C and 20°C were tested to simulate the conditions often observed during the transition from late winter to early spring.
2) 25°C and 27°C tested to represent ideal growth temperatures.

3) 30°C was chosen to serve as the warm condition to investigate potential physiological responses to heat-induced stress.
4) 35°C was tested as an extreme condition to evaluate the maximum limits of resilience and adaptation processes.

Two lighting levels, 100 and 150 μmol/m^2.s were tested. Light intensity of 100 μmol/m^2.s may be seen as simulating diffused light, resembling the light intensity often observed on a cloudy day. On the other hand, a light intensity of 150 μmol/m^2.s represents the circumstances experienced on a clear day. The three lighting durations were tested: a short-day condition of 7 hours, a transition phase of 10 hours, and 14 hours of lighting for the long-day condition mirroring summer days in temperate regions. The combination of light intensity and duration resulted in six levels of daily light integral (DLI): 2.5, 3.6, 3.8, 5.4, 5.0, and 7.6 mol/m^2.day.

As mentioned earlier, relative humidity and CO_2 were not regulated in the test chamber. Measured relative humidity levels fluctuated between 20 to 50% during tests and CO_2 fluctuated between 400 to 600 ppm.

3.4 Plant Sample Preparation and Handling

To facilitate optimal germination, bean seeds were originally positioned within a germination tray that had a transparent plastic cover, ensuring a conducive environment with high humidity. The tray was maintained at a consistent temperature of 30°C, which is considered optimal for bean seed germination. The seeds were planted in germination trays that were filled with an indoor seed start mixture (Miracle-Gro 8.8-L Indoor Seed Start Mix) to ensure sterility and minimize external factors during the initial growing phase. When the radicles were visibly emerging from the soil, the seedlings were carefully transferred to separate pots filled with indoor potting mixture (Miracle-Gro 0.25-0.13-0.19 Indoor Potting Mix 8.8 L). The composition

of this mixture consisted of peat, vermiculite, and perlite in predetermined proportions, aiming to maintain uniformity in the soil's texture, nutrient composition, and drainage characteristics throughout all specimens. The seedlings were then transferred to the test chamber. It should be noted that only those seedlings that exhibited robust and timely germination were selected for testing. Seedlings that did not germinate fully, or that demonstrated significantly slower rates of germination, were excluded from the study. This measure was taken to minimize the effects of germination on the experimental outcomes of plant growth, thus ensuring that subsequent analyses accurately reflect the responses of the plants to the experimental conditions imposed.

Plants were grown (tested) in the test chamber for a duration of 7 days, during which several parameters including plant height and leaf size were measured daily. The height of each plant was measured from the base of the stem at the soil line to the apical tip using a ruler with a resolution of 1 mm. The length and width of the largest leaf on each plant were measured. Leaf length was measured from the base where the leaf petiole meets the stem to the tip of the leaf blade. Leaf width measurement was taken at the widest point of the leaf blade, perpendicular to the length.

In addition to measuring leaf dimensions, leaf health was assessed visually for signs of chlorosis, necrosis, or any pest damage. Such qualitative data complemented the quantitative measurements, offering a comprehensive overview of the plants' condition. The plants were labeled to ensure consistency in subsequent measurements.

At the end of 7-day test period, the plants were carefully pulled out from the soil and biomass production was measured, following the procedure outlined below:

1) Remove the plants from the soil and wash off any loose soil.
2) Blot the plants to remove any surface moisture.

3) Weigh the plants to obtain fresh mass with a precision scale (Sartorius Top-Loading Balance Excellence E2000D) with a margin of error of ± 0.01g

4) Dry the plants in an oven (Jeio Tech Lab Companion AAH14026U Economy Mechanical Convection Oven 3.5 cu.ft) at 103°C for 12 hours

5) Cool the dried plants in a moisture-proof environment and then weigh them to determine their dry mass.

6) The water content was determined from measured fresh and dry biomass.

Based on the measured fresh biomass, the relative growth rate (RGR) was calculated as follows (Hunt, 1982):

$$RGR = \frac{\ln W_2 - \ln W_1}{t_2 - t_1} \quad (2)$$

where W_1 and W_2 are plant fresh biomass measurements (g) at times t_1 and t_2 (day)

Typically, the calculation of Relative Growth Rate (RGR) is derived by sampling individuals from a uniform cohort at two distinct time intervals (Evans, 1972). For this experiment, since all plants were grown from seeds, it was assumed that the initial mass (W_1) was 1 gram, and consequently, the natural logarithm of W_1 ($\ln W_1$) was taken as zero for the RGR analysis over a period of 7 days.

3.5 Test Procedures

In terms of experimental design, there were a total of six levels of temperature (15, 20, 25, 27, 30, and 35°C); three levels of lighting periods (7, 10 and 14 h); and 2 levels of light intensity (100 and 150 mol/m^2.s). There was insufficient time to execute a fully balanced experimental design. Therefore, Phase 1 tests were conducted to determine the temperature effect while keeping the lighting duration at 14 h and intensity at 150 mol/m^2.s. The optimal temperature

determined in Phase 1 was then used in Phase 2 tests with variable lighting periods, and in Phase 3 tests with variable lighting intensity. Each test condition was replicated three times and a total of 33 tests were performed.

Before commencing a test, the test chamber was pre-conditioned for 72 hours to ensure stable temperature, humidity, and lighting conditions when plants were placed in the chamber. All sensors were connected to the LoRa gateway, and data recording was started during chamber pre-conditioning to monitor the actual conditions in the chamber. The planter was placed at the center of the test chamber floor.

Each test was performed for 7 days in all three phases. A week was sufficient to observe the pant responses and short-term changes in plant growth without waiting for the full life cycle of bean plants. This period was particularly useful for detecting early indicators of plant health, stress responses, and vigour. It also provided enough time for plants to show physiological changes in response to light, such as adjustments in chlorophyll content, leaf expansion, and stomatal conductance. A seven-day period not only struck a balance between obtaining a meaningful set of data but also a quick turnaround in experimental cycles, enabling more experiments to be conducted over a given period to achieve the objectives of this study. Although longer-term studies might be more valuable in understanding the plant behavior in a complete life cycle, a seven-day testing period could serve as a preliminary screening to identify which treatments may warrant further and extended examination.

3.6 Data Collection and Analysis

Dada from the smart sensors, including air temperature (T °C), relative humidity data (RH%), CO_2 concentration (ppm), and light intensity (lux), soil temperature (ST °C), soil moisture (SRH%) and barometric pressure (Pa) was recorded every 60 minutes. The plant leaves

were counted daily. Given the natural variations in plant growth, it was expected that not all plants would grow leaves at the exact the same rate. Therefore, the total number of leaves of all plants in a trail was counted and then divided by the total number of plants to obtain a nominal value for the number of leaves per plant. This meant that there was only one data point of leave development daily although nice plants were used in each test. In essence, this measurement represented the average growth of all plants used in a trail. This “averaging” procedure was also applied to other measurements of plant growth.

The data were analyzed by using various statistical analyses, including Analysis of Variance (ANOVA), regression, and multivariate analysis. ANOVA served as a tool in the comparison of group means across different experimental conditions, enabling the identification of statistically significant differences in plant growth outcomes. Regression analysis was used to model the intricate relationships between dependent variables (e.g., plant growth metrics) and a suite of independent variables (temperature, and light intensity and duration). Cluster Analysis was applied to distill complex data into actionable insights, identifying underlying structures and groupings that single-variable analyses might overlook. Statistical analyses were performed by using two primary software tools - Microsoft Excel and RStudio.

CHAPTER 4. RESULTS AND DISCUSSION

4.1 Effectiveness of Environmental Control in Test Chamber

Environmental data inside the test chamber was collected for 14 days (two regular test periods) to evaluate the stability and controllability of test chamber. The test condition was set at 25°C for air temperature and 150 µmol/m^2.s for light intensity, while RH and CO_2 were not regulated.

The average temperature recorded over a 14-day period was 25.5°C (Fig. 9), which was close to the set point of 25°C (Table. 2). The standard deviation was quite low at 0.3°C and the calculated bounds of the mean ± 3 standard deviations were (24.8°C to 26.2°C), suggesting that there were minimal fluctuations in chamber temperature during testing. This indicated excellent stability and controllability of temperature in the test chamber.

Relative humidity which was not regulated and stayed low but relatively constant during test (Fig. 10). The mean RH was 16.9% with a standard deviation of 2.3%. Similarly, the unregulated CO2 concentration averaged at 408 ppm with a standard deviation of 16 ppm (Fig. 11). The barometric pressure showed a mean of 98817 Pa with a standard deviation of 637 Pa (Fig. 15).

Light intensity was targeted for 150 µmol/m^2.s in the chamber stability and controllability test and the measure mean value was 140 µmol/m^2.s with a standard deviation of 10.4 µmol/m^2.s, indicating the light level were relatively steady (Fig. 12).

The temperature measured by the soil temperature sensor was 12.9°C on average with a standard deviation of 1.2°C (Fig. 13). The soil temperature was much lower than the air temperature (dry-bulb) because the soil was fresh. At air temperature of 25.5°C (dry-bulb) and RH of 16.9%, the web-bulb temperature was 12°C. This meant that the temperature measured by

the sensor inserted in the soil was about the same as the web-bulb temperature of air. The measured mean soil moisture was 17.9% with a standard deviation of 3.4% (Fig. 14). The pattern of variation in soil moisture followed the watering pattern, specifically, it decreased from 26% to 13% after the first watering, and increased back 25% after the second watering.

In summary, the environmental parameters within the test chamber were maintained with high stability for a 14-day period, as evidenced by the low standard deviations. Also all the wireless sensors functioned well in sensing the environmental parameters and transmitting the data.

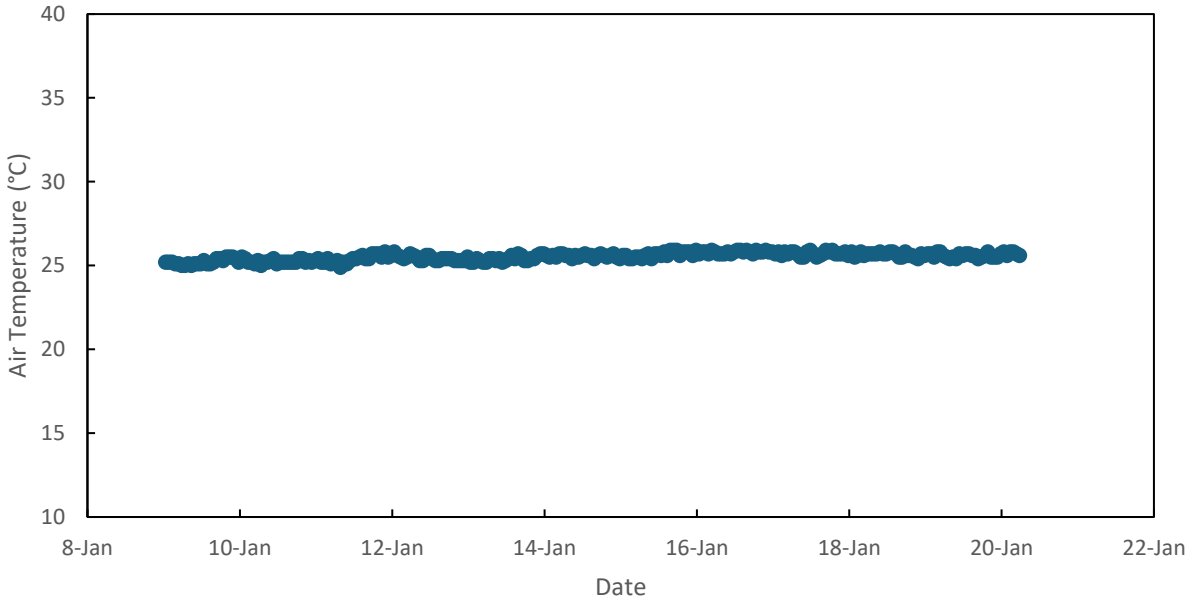

Figure 9. Variation of air temperature during a 14-day period at set temperature of 25°C.

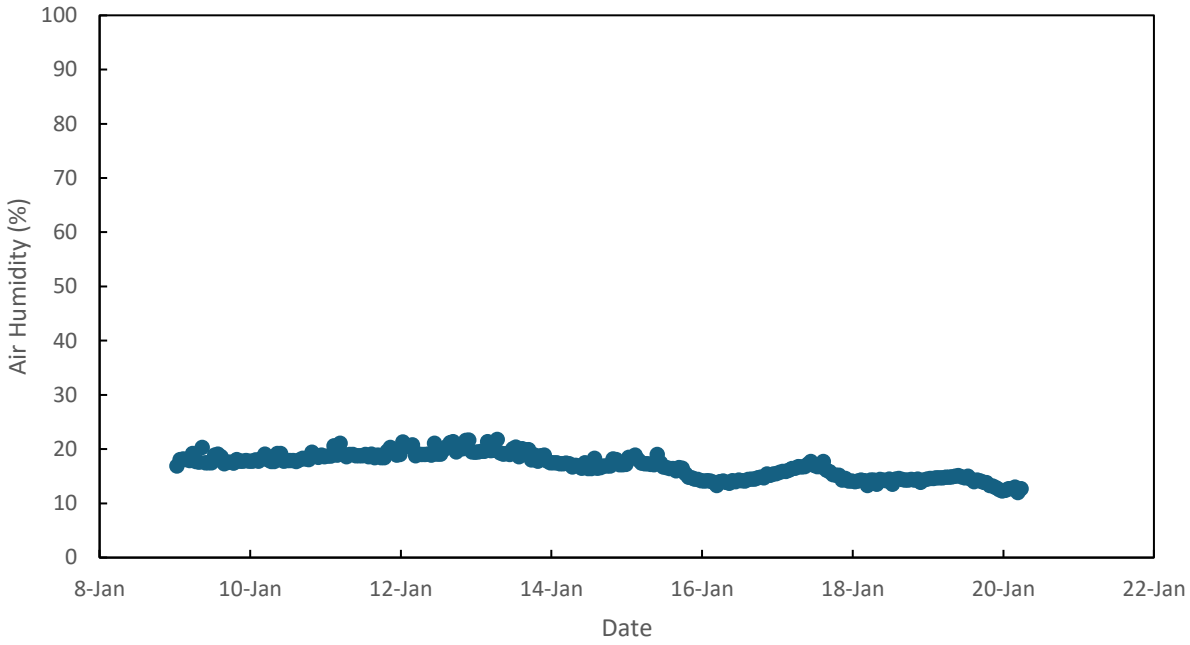

Figure 10. Variation of air relative humidity during a 14-day test period at set temperature of 25°C.

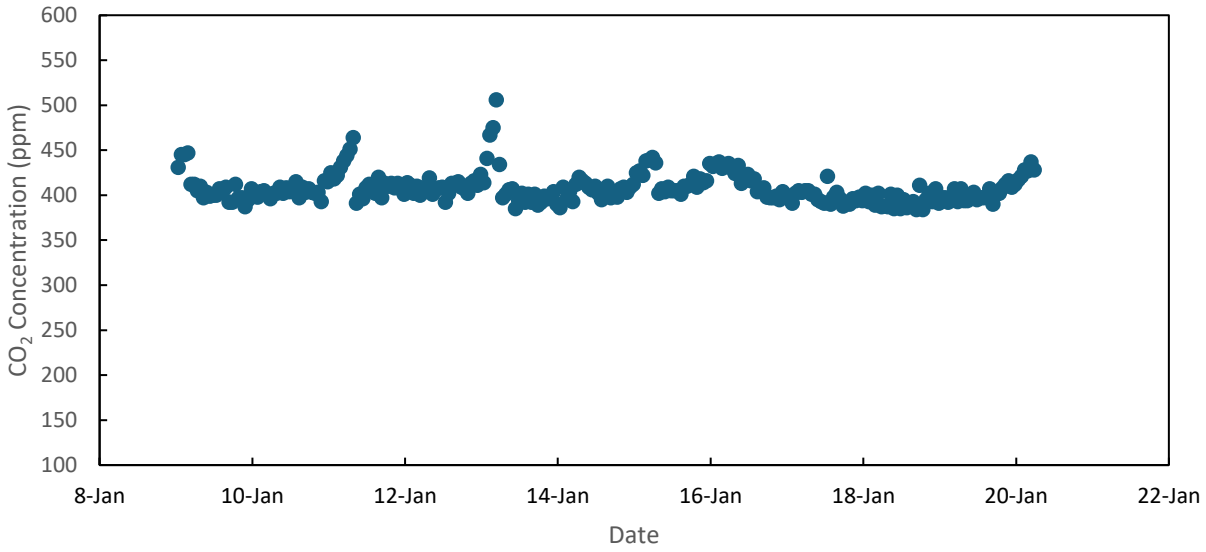

Figure 11. Variation of CO_2 concentration during a 14-day test period at set temperature of 25°C.

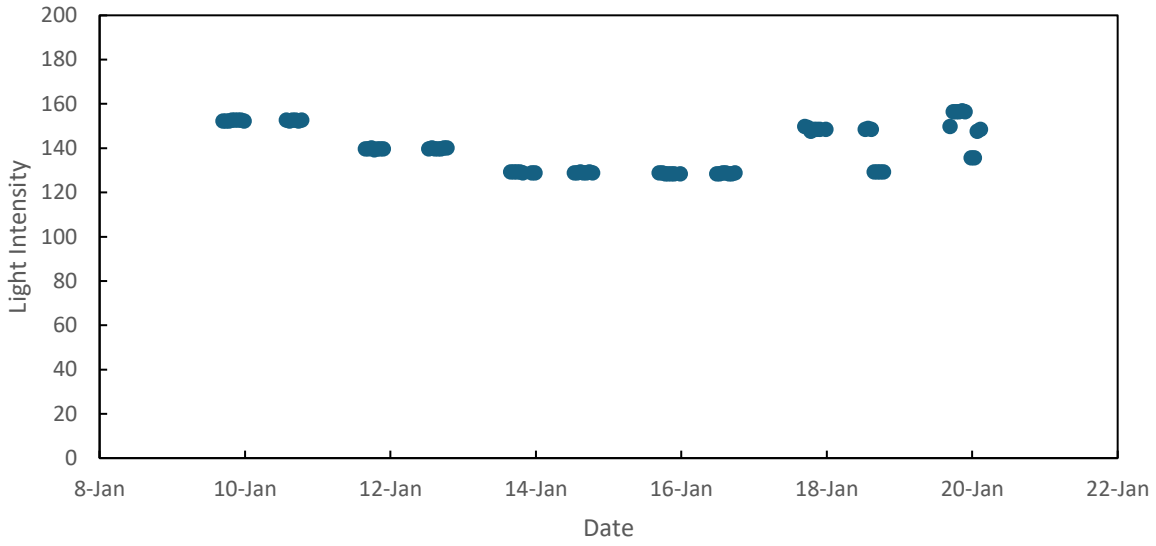

Figure 12. Variation of light intensity during a 14-day test period at set temperature of 25°C.

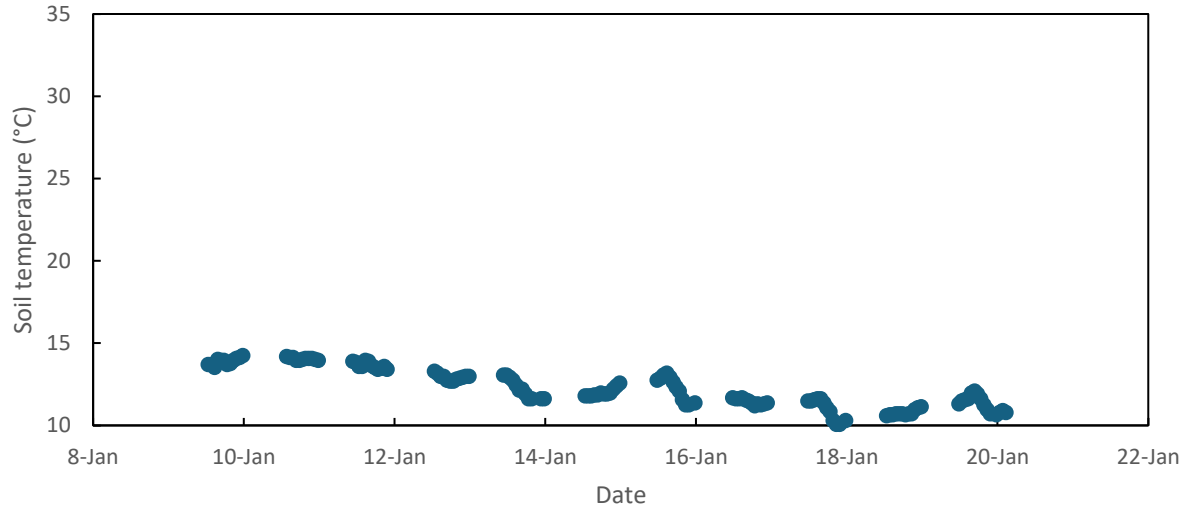

Figure 13. Variation of soil temperature during a 14-day test period at set temperature of 25°C.

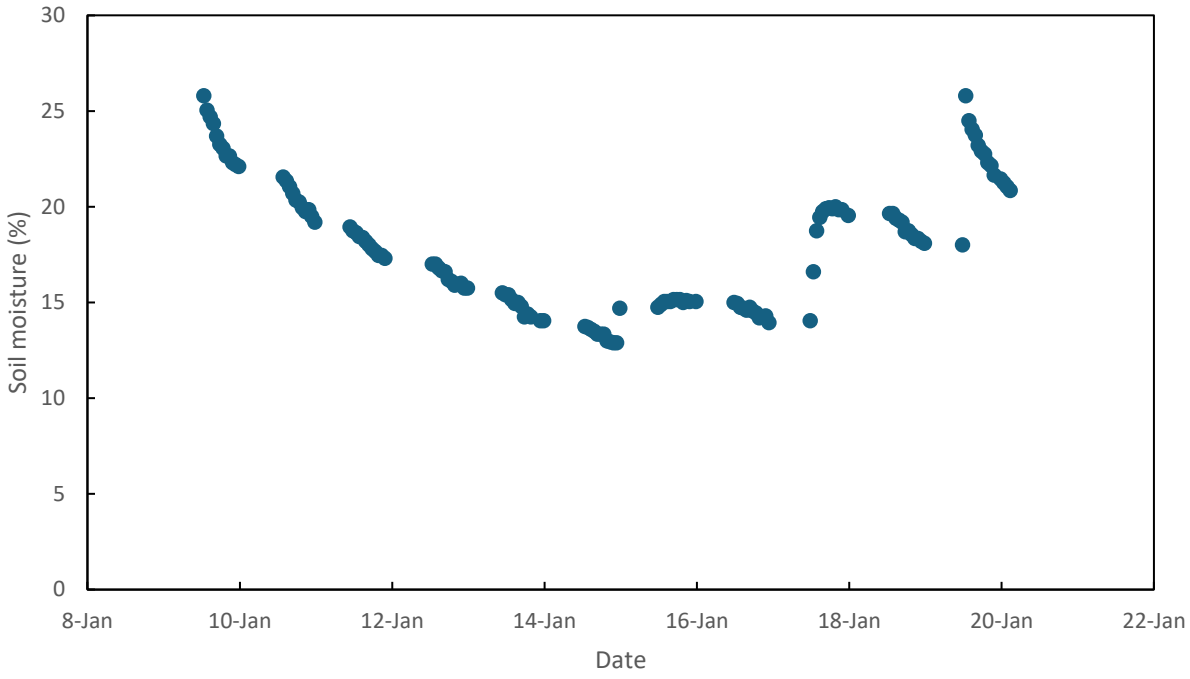

Figure 14. Variation of soil moisture content during a 14-day test period at set temperature of 25°C.

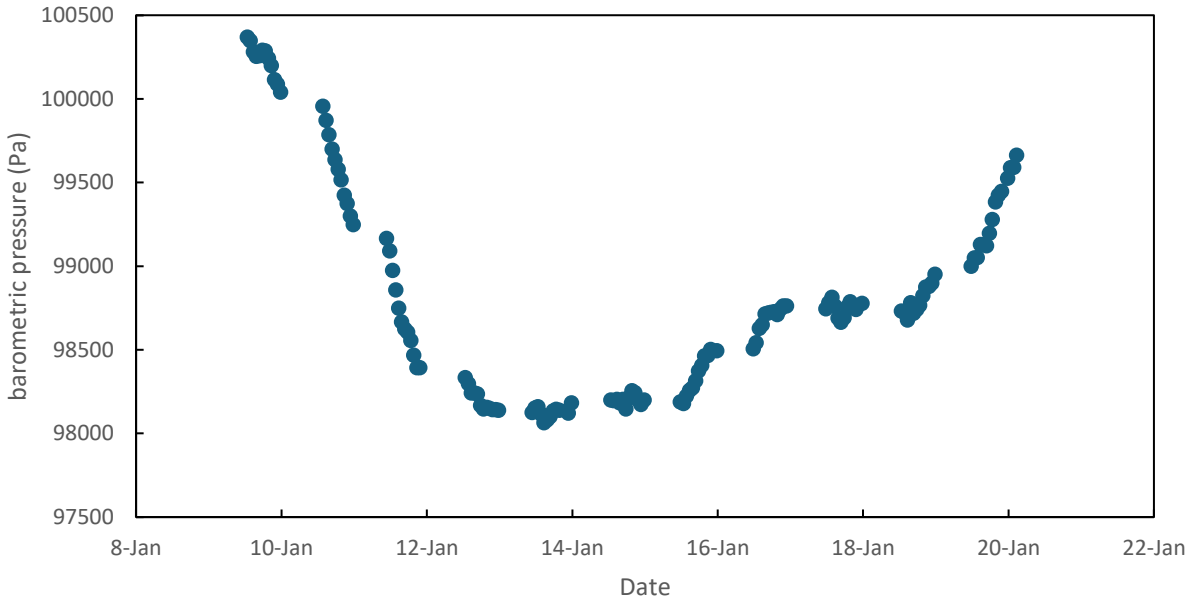

Figure 15. Variation of barometric pressure during a 14-day test period at set temperature of 25°C.

Table 2. Summary of measured environmental parameters for evaluating the test chamber.

	Mean	Standard deviation	Mean - 3 standard deviations	Mean + 3 standard deviations
Air temperature (°C)	25.5	0.23	24.8	26.2
Relative humidity (%)	16.9	2.27	10.1	23.8
CO_2 concentration (ppm)	408	16.02	360	456
Light intensity (µmol/m_2.s)	139.99	10.36	108.91	171.08
Soil temperature (°C)	12.3	1.17	8.8	15.8
Soil moisture (%)	17.9	3.36	7.8	28.0
barometric pressure (Pa)	98817	638	96904	100730

4.2 Temperature Effect on Plant Growth

Visual inspection showed that plant growth was markedly affected by the temperature (Fig. 16). The plants were visibly larger at 25, 27, and 30°C than other temperatures. The smallest plants were observed for 15°C.

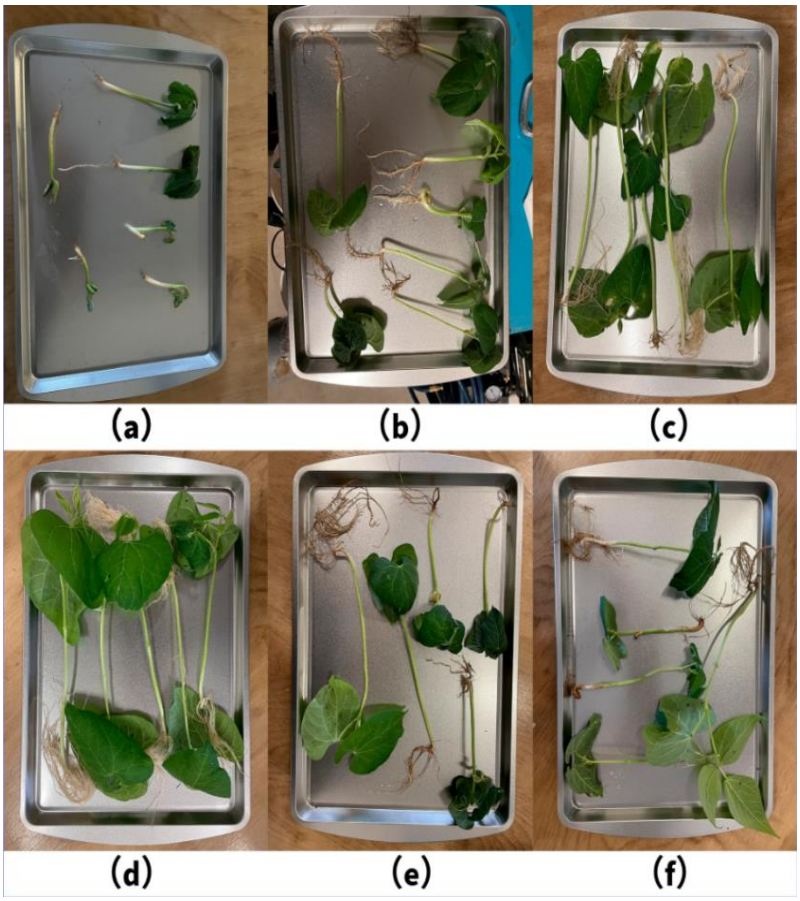

Figure 16. Plant samples taken at the end test before drying at six different air temperature settings. (a) 15°C, (b) 20°C, (c) 25°C, (d) 27°C, (e) 30°C, (f) 35°C).

To quantify the effect of air temperature, several measured parameters were analyzed including leaf development, plant height, fresh and dry biomass, and water content (Tables 3 and 4).

Table 3. Leaf development and plant height at six different air temperature settings (15°C, 20°C, 25°C, 27°C, 30°C, 35°C) for 14 hours lighting at 150 μmol/s.m^2, with Standard Error of the Mean (SEM)

Temperature (°C)	Leaf number (N)	Leaf Length (mm)	Leaf Width (mm)	Plant height (with root) (mm)
15	0.59 (0.23)	9 (3)	8 (2)	87 (5)
20	1.70 (0.22)	28 (3)	27 (3)	114 (5)
25	5.37 (0.43)	91 (2)	87 (2)	214 (5)
27	3.33 (0.20)	93 (3)	114 (5)	251 (5)
30	2.14 (0.14)	55 (2)	60 (2)	199 (6)
35	2.00 (0.18)	39 (3)	40 (3)	156 (7)

Leaf development

As the temperature increased from 15°C to 25°C, the average leaf number experienced a staggering increase of approximately 826.7%, from 0.6 to 5.4 leaves (Table 3). However, further temperature increases to 27°C and beyond showed a decline of 37.7% at 27°C and a total decrease of 62.6% at 35°C compared to the peak at 25°C. In other words, the greatest number of leaves was observed at 25°C.

The average leaf length at 15°C was recorded at 9 mm, and increased to 919 mm (867.8%) at 25°C. A slight increase of 2.7% was observed from 25°C to 27°C, but subsequent increases in temperature to 30°C and 35°C resulted in a decrease in leaf length by 39.8% and 57.9%, respectively, from the maximum length observed at 27°C (Table 3).

Similar to leaf length, leaf width at 15°C was 9 mm and peaked at 27°C: 114 mm, or substantial increase of 1244.4%. However, the leaf width reduced by 47.4% and 64.9% when temperature was increased to 30°C and 35°C, respectively, in comparison with 27°C (Table 3).

The onset of leaf development in plants can be significantly affected by ambient temperature. At the low temperature of 15°C, the time taken for the first leaf to emerge was observed to be the longest, 5.6 days (Fig. 17). This duration gradually decreased with increasing temperatures to 4.8 day for 20°C, and a substantial reduction recorded at 25°C and 27°C, where the first leaves were visible at 2.5 days and 2.3 days, respectively, suggesting an optimal temperature range for this particular growth phase. Further increases in temperatures resulted in decreases in leaf emerge, specifically, the first leaf appeared after 3.0 and 3.5 days at 30°C and 35°C, respectively.

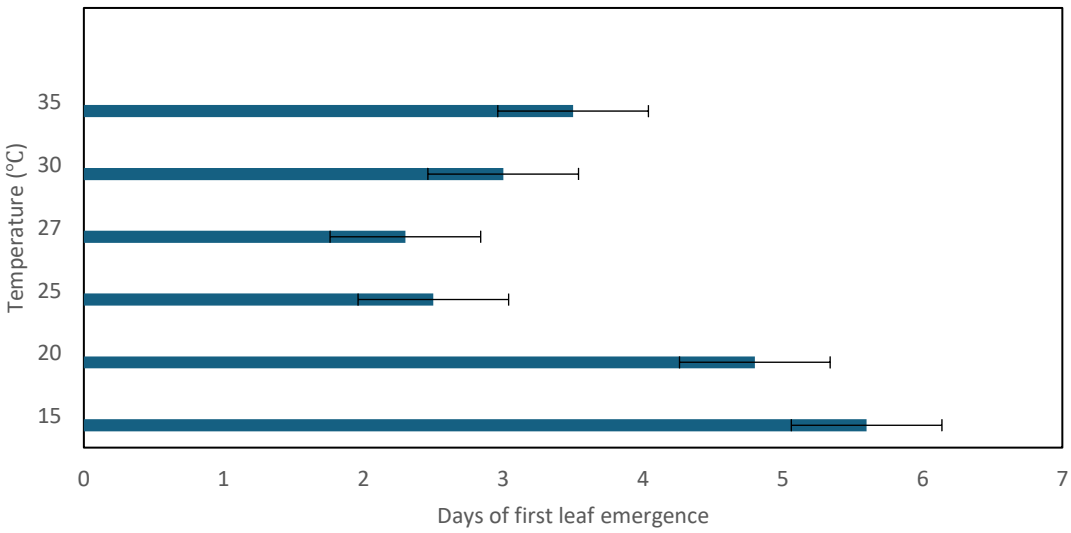

Figure 17. Leaf development by days at six different air temperature settings (15°C, 20°C, 25°C, 27°C, 30°C, 35°C) (the error bars represent standard error).

To further quantify the leaf development as affected by temperature, all leaves were categorized into three size ranges according to leaf length: small (20-35mm), medium (36-50mm), and large (51mm and above). At the lowest temperature of 15°C, about 40% and 60% of leaves were in the small and medium size ranges, respectively (Fig. 18). As the temperature increased to 25°C and 27°C, over 90% of leaves were in the large category. However, as the

temperature increased to 30°C and 35°C, there was a decline in large size leaves, which reflect the thermal stress effect, i.e., higher temperatures began to impede cellular processes critical for growth, resulting in stunted leaf development.

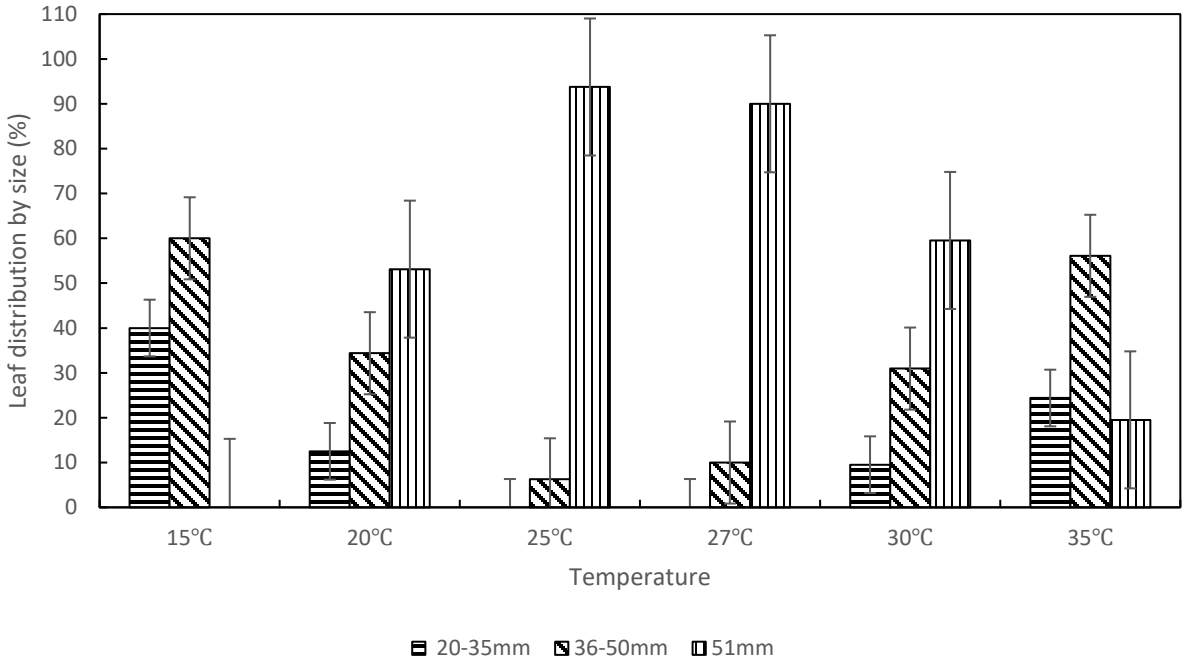

Figure 18. Leaf Size Distribution at six different air temperature settings (15°C, 20°C, 25°C, 27°C, 30°C, 35°C) (the error bars represent standard error)

The final height of plant (including roots) showed an optimal growth of 251 mm at 27°C, which was 288.5% of that at the lowest temperature of 15°C. A higher temperatures of 30°C and 35°C, the final height decreased by 20.7% and 37.8%, respectively, compared to the height at 27°C (Table 3).

Plant biomass

The dry biomass production was markedly affected by the environmental temperature (Fig. 19). The highest dry mass was at 27°C and the lowest at 15°C, while higher temperatures also resulted in lower biomass production. Specifically, the dry mass increased by 525.0% from 0.16 g at 15°C to the highest of 1.00 g at 27°C (Table 4). The subsequent temperature rises

resulted in a decrease of 82.8% and 85.0% at 30°C and 35°C, respectively. Similarly, the average fresh mass of plants increased significantly from 1.13 g at 15°C to 7.32 g at 27°C, or 547.8%. At higher temperatures of 30°C and 35°C, the fresh mass decreased by 61.4% and 68.7%, respectively, from the maximum observed at 27°C (Table 4). The decline in fresh mass at higher temperatures indicated possible thermal stress on plant metabolism. It was noticed that the water content varied little with temperature. It was 85.9% at 15°C, increased slightly to 89.7% at 25°C, and changed little at higher temperatures (Table 4). A parabolic relationship between temperature and dry mass, suggesting that there is an optimal temperature range for maximum plant growth.

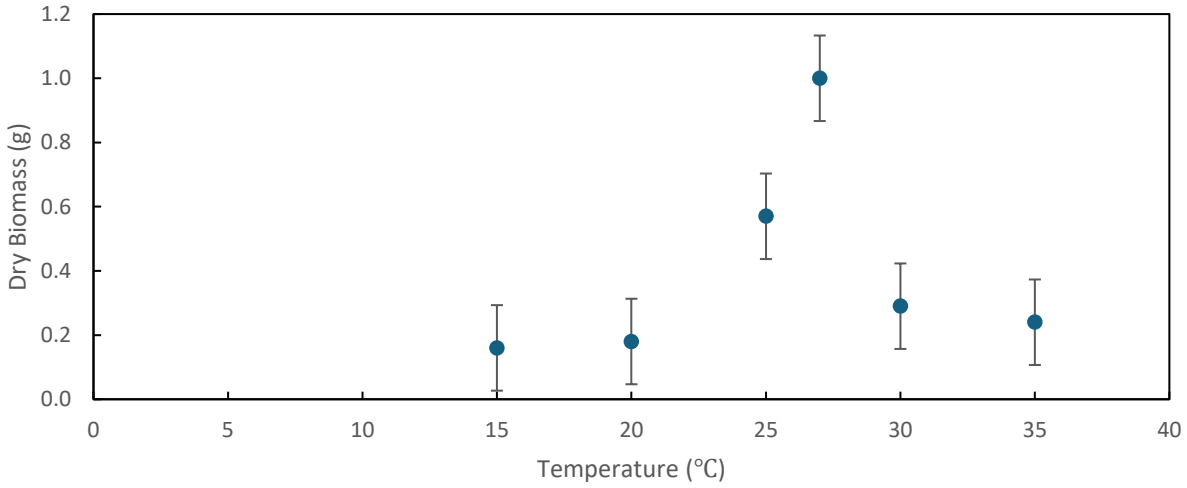

Figure 19. Dry biomass from samples taken after 7 days of testing at six different air temperature settings (15°C, 20°C, 25°C, 27°C, 30°C, 35°C).

Table 4. Plant mass and water content at six different air temperature settings (15°C, 20°C, 25°C, 27°C, 30°C, 35°C) for 14 hours of lighting at 150 mol/s.m^2, with Standard Error of the Mean (SEM)

Temperature (°C)	Fresh Biomass (g)	Dry Biomass (g)	Water Content (%)	Growth Rate (g/day)
15	1.13 (0.07)	0.16 (0.01)	85.92 (0.75)	0.017 (0.010)
20	1.46 (0.08)	0.18 (0.01)	87.57 (0.68)	0.054 (0.007)
25	5.53 (0.24)	0.57 (0.03)	89.66 (0.37)	0.244 (0.007)
27	7.32 (0.27)	1.00 (0.03)	86.10 (0.54)	0.282 (0.005)
30	2.82 (0.18)	0.29 (0.02)	89.83 (0.32)	0.148 (0.010)
35	2.29 (0.15)	0.24 (0.01)	89.25 (0.38)	0.118 (0.009)

At the lower end of the temperature spectrum (15°C), plants demonstrated a modest growth rate of 0.017 g/day (fresh biomass) (Table 4). As the temperature increased to 20°C, the growth rate experienced a slight uptick to 0.054 g/day. A marked increase in growth rate was observed at the optimal temperatures of 25°C and 27°C, registering 0.244 g/day and 0.282 g/day, respectively. These temperatures likely provided the ideal thermal conditions for physiological processes, resulting in the most vigorous growth. The difference in growth rate between 27°C and 15°C was 1558.8%. As temperatures rose to 30°C and 35°C, the growth rates diminished to 0.148 g/day and 0.118 g/day, respectively. This decline indicated higher temperatures began to exert stresses on the plants (Table 4).

ANOVA was performed to determine the statistical significance of temperature effect on plant growth using the fresh mass as an indicator. The results showed that the temperature effect was significant ($p<0.05$) (see Appendix A for details of ANOVA).

These findings underscored the critical impact of temperature on plant development. The optimal growth range was found between 25°C to 27°C. This observation offers valuable insights into agricultural practices, especially in controlled environment agriculture where temperature can be precisely regulated to maximize plant growth and productivity, beyond which further increases in temperature lead to a reduction in growth parameters.

4.3 Effects of Lighting Duration

There were visually noticeably differences in plant size among three lighting periods (Fig. 20). Specifically, the plants were bigger for longer lighting durations. As the light exposure increased from 7 to 14 hours, there was a notable enhancement in growth metrics (Tables 5 and 6). The number of leaves increased marginally with longer light durations, rising from an average of 3.08 leaves for 7 hours of lighting to 3.33 leaves for 14 hours, a modest increase of

approximately 7.1%. However, more pronounced effects were observed in leaf dimensions. When the light duration was extended from 7 hours to 14 hours, the average leaf length surged by 125.2% from 41 mm to 93 mm, and leaf width increased by 167.7% from 43 mm to 114 mm. Plant height also significantly increased with longer light durations, from an average height of 125 mm for 7 hours to 251 mm for 14 hours, or 101.1% (Table 5).

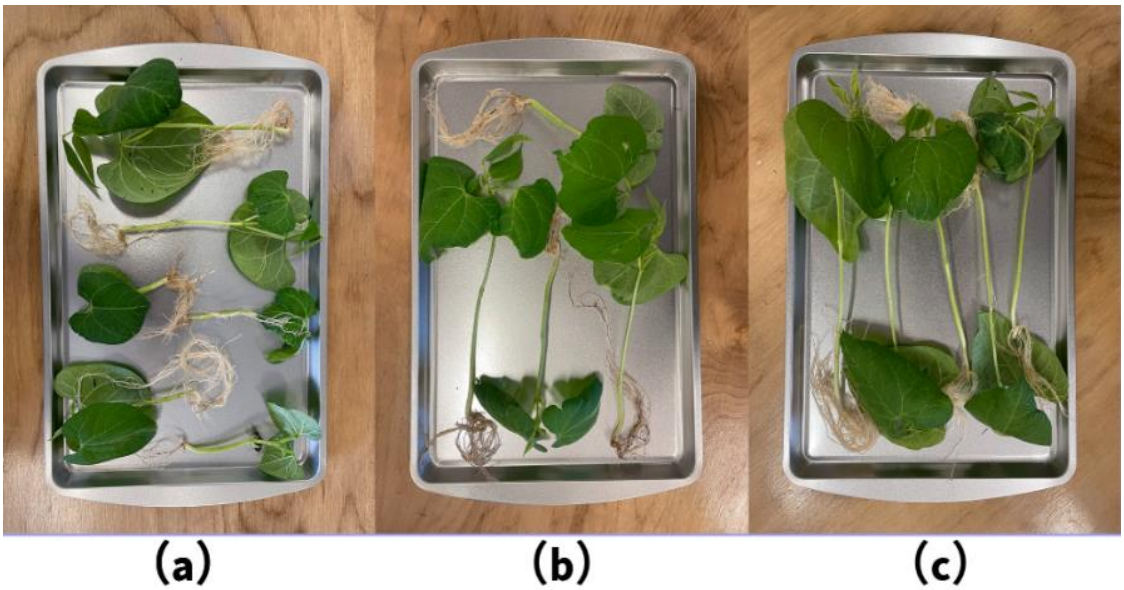

Figure 20. Plant samples before drying at three different light period settings. (a) 7 hours, (b) 10 hours, (c) 14 hours.

Table 5. Leaf and plant height measurements at different light durations for 27°C air temperature and 150 mol/s.m^2, with Standard Error of the Mean (SEM)

Lighting duration (h)	Leaf number (N)	Leaf Length (mm)	Leaf Width (mm)	Final height (with root) (mm)
7	3.08 (0.32)	41 (3)	43 (2)	125 (4)
10	3.04 (0.30)	61 (3)	74 (5)	174 (8)
14	3.33 (0.20)	93 (3)	114 (5)	251 (5)

Table 6. Biomass and water content measurements at different light durations for 27°C air temperature and 150 mol/s.m^2, with Standard Error of the Mean (SEM)

Lighting duration (h)	Fresh mass (g)	Dry mass (g)	Water Content (%)	Growth Rate g/day
7	1.95 (0.20)	0.21 (0.02)	88.50 (0.31)	0.095 (0.013)
10	3.68 (0.24)	0.40 (0.03)	89.22 (0.57)	0.186 (0.009)
14	7.32 (0.27)	1.00 (0.03)	86.10 (0.54)	0.282 (0.005)

Fresh mass and dry mass of the plants demonstrated a pronounced sensitivity to light duration. The fresh mass saw a remarkable ascent of 275.4%, from 1.95 g for 7 hours to 7.32 g for 14 hours of light exposure (Table 6). Similarly, the dry mass increased by 376.2%, from 0.21 g to 1.00 g. The water content showed some variations when the lighting duration changed, with the highest level recorded at 10 hours of light exposure (89.2%), and a minor decrease of 3.5% when the duration was increased to 14 hours (86.1%) (Table 6).

A comparative analysis of the growth rates under different light durations revealed a compelling pattern of plant responsiveness to lighting duration (Table 6). When increasing from a light duration of 7 hours to 10 hours, the growth rate exhibited a relative increase of 95.8% (from 0.095 to 0.186 g). The impact of light duration became even more pronounced when comparing the growth rates between 7 hours and 14 hours of light exposure, a remarkable 196.8% increase from 0.095 to 0.282 g/day. This near tripling of the growth rate with extended light duration underscored a logarithmic relationship between light availability and plant growth, up to a certain threshold, beyond which the rate of growth would level off. Taking the fresh mass as an example, the correlation could be presented by a logarithmic function with $R^2 = 0.95$ (Fig. 21). It suggested a nonlinear relationship between light duration and biomass. The positive coefficient of the logarithmic term indicates that biomass accumulation rates increase as light duration extends, but the rate of increase slowed down as the duration continued to extend.

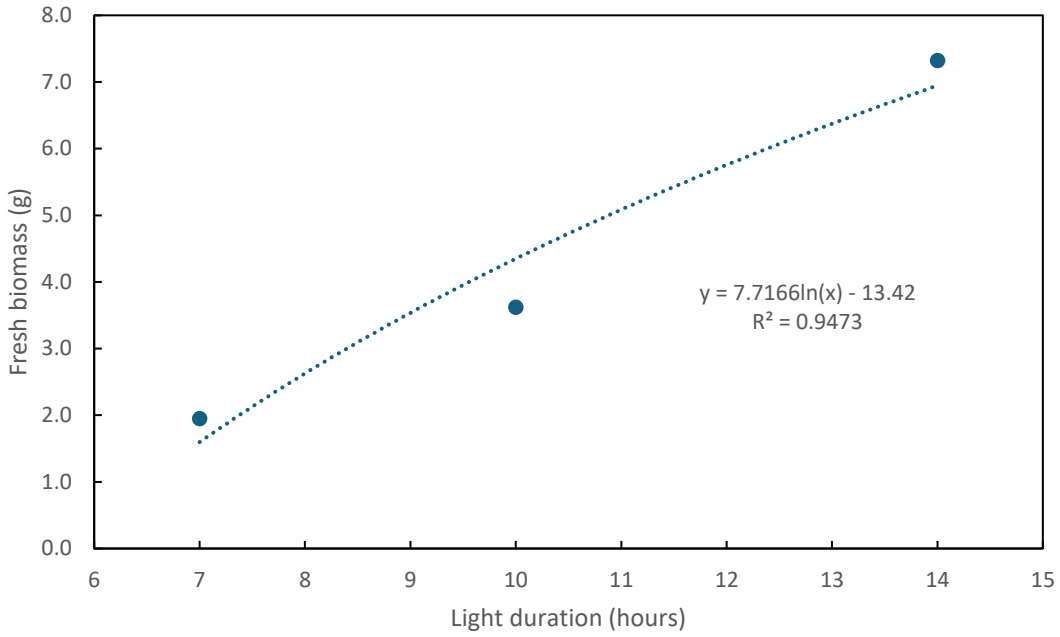

Figure 21. Variation of fresh mass with light duration for lighting intensity of 150 μmol/s.m^2 and temperature of 27°C

The progression of growth rates with increasing light duration reflected a dose-dependent response of plant growth to light availability. These findings were consistent with the understanding that photosynthesis, the process by which plants convert light energy into chemical energy, is a driving force for growth. The implications of these results are particularly relevant in the context of optimizing controlled environment agriculture. By adjusting light duration, growers can potentially influence and augment plant growth rates, optimizing crop yields and efficiency.

ANOVA was performed to determine the statistical significance of differences in plant growth (using the fresh mass as an indicator) among three lighting durations. The results showed that the light duration effect was significant ($p<0.05$) (see Appendix A for details of ANOVA).

4.4 Effect of Light Intensity

Visual inspection of plant samples did not reveal significant differences in plant size

between two light intensity levels (Fig. 22). Further analysis was performed on plant growth metrics to explore the light intensity effects. At 100 μmol/m²/s, the average leaf number was 3.60, which decreased slightly to 3.33 under the higher light intensity of 150 μmol/m²/s. The leaf length and width measurements at the higher intensity showed increases of 25.5% and 52.4%, respectively, when compared to the lower intensity (Table 7). The final height of the plants exhibited a moderate increase of 6.5%.

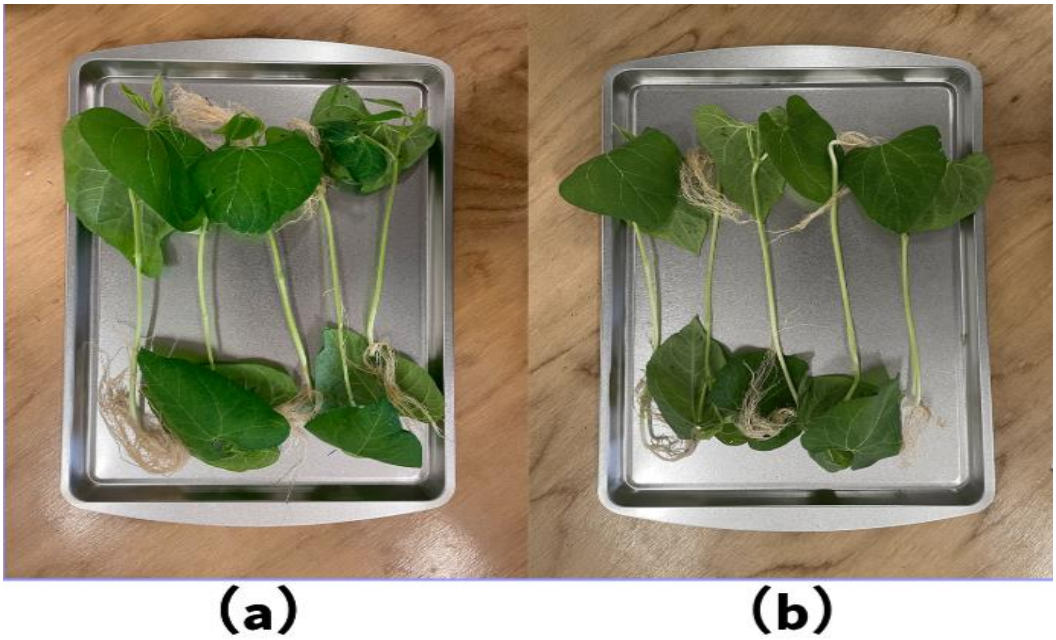

Figure 22. Plant samples after 7 days of testing (growth) at light intensities of: (a) 150 μ mol/s.m^2, (b) 100 μmol/s.m^2. The lighting duration was 14 h.

Table 7. Leaf and plant height measurements at different light intensities for 27°C air temperature and 14 hours of light duration, with Standard Error of the Mean (SEM)

Light Intensity μmol/s.m^2	Leaf number (N)	Leaf Length (mm)	Leaf Width (mm)	Final height (with root) (mm)
100	3.60 (0.58)	74 (3)	75 (2)	236 (8)
150	3.33 (0.20)	93 (3)	114 (5)	251 (5)

The fresh mass of the plants increased by 53.5%, from 4.58 g at the lower intensity to 7.00 g at the higher intensity (Table 8). Dry mass also followed this trend, with an increase of

137.5%, from 0.40 g to 0.95 g, suggesting that light intensity profoundly affected biomass accumulation, while its effect on linear growth was less pronounced (e.g., plant height increased only 6.5%). Water content showed a slight decrease of 5.3%, from 91.1% to 86.3%, potentially indicating a higher transpiration rate at increased light intensities. The growth rate paralleled these changes, increased from 0.217 g/day at the lower intensity to 0.278 g/day at the higher intensity, representing an increase of 28.1% in growth rate.

Table 8. Biomass and water content measurements at different light intensities for 27°C air temperature and 14 hours of light duration, with Standard Error of the Mean (SEM)

Light Intensity µmol/s.m^2	**Fresh mass (g)**	**Dry mass (g)**	**Water Content (%)**	**Growth Rate g/day**
100	4.58 (0.37)	0.40 (0.03)	91.12 (0.17)	0.217 (0.012)
150	7.00 (0.33)	0.95 (0.05)	86.30 (0.55)	0.278 (0.008)

The data suggested that a higher light intensity could substantially improve certain growth parameters, such as biomass accumulation. However, the effect on some plant growth metrics, such as leaf development was not significant. These findings highlighted the nuanced relationship between light intensity and plant growth and suggested that while increased light intensity could drive photosynthesis and growth, it might also induce physiological changes that could impact overall plant health and water-use efficiency. The interplay of light and temperature showed a significant impact. Longer light durations combined with higher intensity resulted in increased fresh and dry mass, pointing towards enhanced photosynthetic activity. However, this benefit seemed to plateau or even reverse at the highest temperature conditions. Statistical analysis revealed that the impact of light intensity on fresh mass was significant ($p<0.05$) (details in APPENDIX A).

4.5 Further Data Analysis

Understanding the combined effects of multiple environmental factors on plant growth is critical in establishing strategies for smart environmental control in CEA. There are many methods for assessing and predicting the combined effects of multiple factors, such as multivariate regression analysis and machine learning. Given that the data collected in this study was not sufficient for developing and training machine learning models, two less data-demanding methods of data analysis were used to explore their potential of fusing multiple sensor data for smart environmental control in CEA. Regression analysis was applied to quantify the interactive impact of temperature and daily light integral on plant growth. K-means clustering was used to identify natural groupings of different combinations of temperature and lighting, offering an intuitive understanding of how various combinations of environmental factors could yield similar growth patterns.

4.5.1 Regression Analysis

Multivariate regression analysis was attempted to assess the relationships between the plant growth and three environmental factors (temperature, light duration, and light intensity). Fresh mass was selected as the plant growth indicator in regression analysis mainly because it was measured directly with a high-precision scale, but it should be noted that other plant growth metrics could be used too, such as dry mass which is more commonly used (it was calculated from two measured parameters in this study, fresh mass and moisture content). Given that these plant growth metrics were highly correlated (e.g., dry mass was correlated to fresh mass with a Pearson correlation of 0.91 in this study), fresh mass served as a good indicator of the plant growth in this study. Previous discussion (Fig. 19 and 21) showed that the fresh mass varied nonlinearly with temperature and light duration, but there were not enough data points to

determine the pattern of variation with light intensity because only two levels (data points) were tested for light intensity. However, there is a common way of combining the effect of light duration and intensity by using the daily light integral (DLI), which was calculated as follows:

$$DLI\ (mol/m^2.day) = Light\ intensity\ (PPFD)\ (\mu mol/m^2.s) \times Light\ duration\ (s) \times 10^{-6} \quad (3)$$

Once the DLI was calculated from the light duration and intensity, regression analyses were performed to explore the correlation between the plant fresh biomass and two environmental factors (temperature and DLI). A linear model was first tested, resulting in an R-squared value of 0.61, which was considered not satisfactory. A second order polynomial was then tested, with an R-squared value of 0.86. By removing the cross term (T×C) from the second-degree polynomial model, a markedly better fit to the data was found, with an R-squared value of 0.92.

$$m = -28.92 + 1.93T + 3.81D - 0.04T^2 - 0.27D^2 \quad (4)$$

where: m = fresh mass (biomass production) (g)

D = Daily Light Integral (mol/m^2.day)

T = temperature (°C)

The contributions of temperature and Daily Light Integral in the regression equation were assessed by examining the standardized coefficients for each predictor. First, the standardized coefficients of terms T, D, T^2 and D^2 were determined (5.3, 3.0, -5.0, and -2.6, respectively), and then the contribution of each term was calculated as the percentage of the sum of the absolute values of these standardized coefficients, resulting in 33%, 19%, 32%, 16% for T, D, T^2 and D^2, respectively. It appeared the temperature contributed more to the plant growth in the range of

conditions tested in this study. The total contribution by temperature (terms T and T^2) was 65%, and by DLI (D and D^2) 35%.

Model (Eqn. (4)) predictions showed a clear pattern of how temperature and DLI would jointly affect the plant growth (fresh mass) (Fig. 23). Specifically, i) fresh mass increased with temperature when temperature was lower, peaked at an optimal temperature, and then started to decrease; and ii) the rate of increase and the peak (maximum) of fresh mass were higher for higher LDI. Another interest observation was that the optimal temperature for biomass production increased with DLI, specifically the optimal temperature increased from 24°C to 27°C when DLI increased from 3.8 and 7.6 mol/m^2.day. This information is important for optimizing the environmental conditions for plants while minimizing energy consumption. For example, if a producer (farmer) decides to set lighting at 3.8 mol/m^2.day in a crop production facility, he/she could use the regression equation to predict the optimal temperature (24°C) to achieve the best plant growth without wasting heating energy to raise the temperature beyond 24°C.

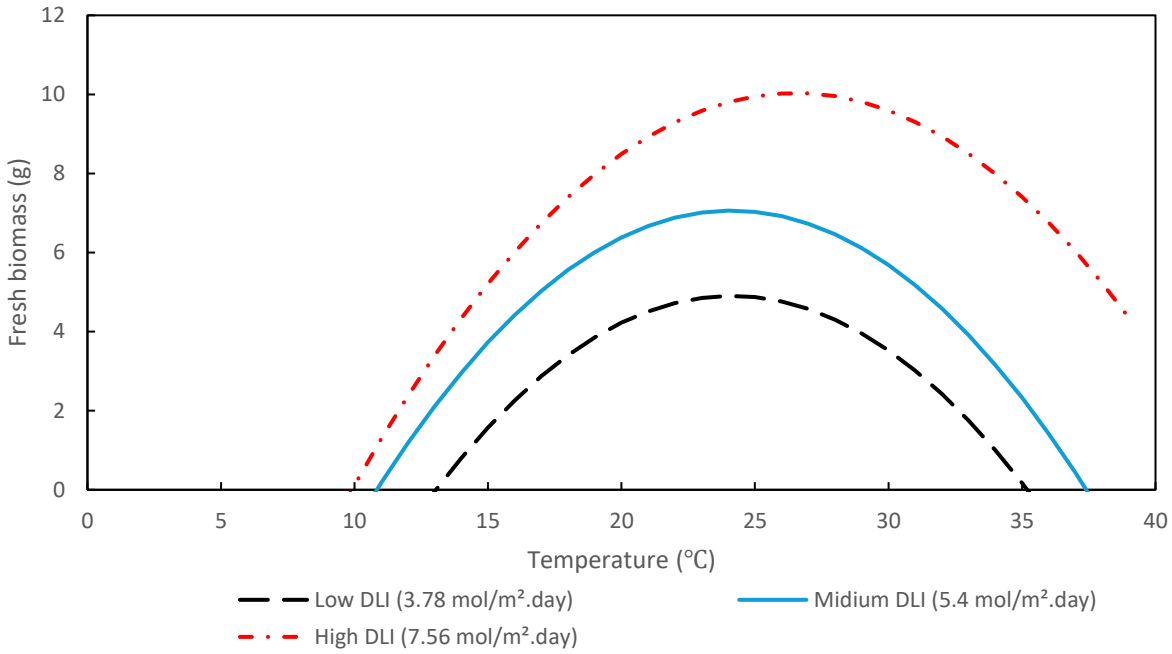

Figure 23. Predicted effects of temperature and daily light integral (DLI) on plant biomass production (fresh mass).

4.5.2 K-means Clustering Analysis

Because of the interactive effects of different environmental factors, different combinations of environmental factors (e.g., temperature and lighting) may result in similar outcomes in terms of plant growth. K-means clustering analysis was performed to group different combinations of temperature and DLI. It should be noted that the datasets in this study were limited and the purpose of performing K-means clustering was to demonstrate the potential of different data analytics techniques to interpret the multiple sensor data for smart environmental control in CEA for crop production.

A total of 27 combinations of temperature and DLI were clustered (details of datasets are presented in APPENDIX B) and the cluster plot illustrated the segmentation of datasets into three distinct clusters (Fig. 24). Cluster 1 **(**Blue Circles**)** represented plants that experienced high lighting conditions at high moderate temperatures, with moderate fresh mass (Appendix B). Cluster 2 (Green Triangles) represented the conditions of low light levels and low temperatures,

which was suboptimal, potentially leading to slower plant growth rates or lower biomass production compared to the other clusters. Cluster 3 (Red Squares) covered a large of DLI values at the middle range of temperature values, suggesting a wide range of lighting conditions would yield similar outcomes.

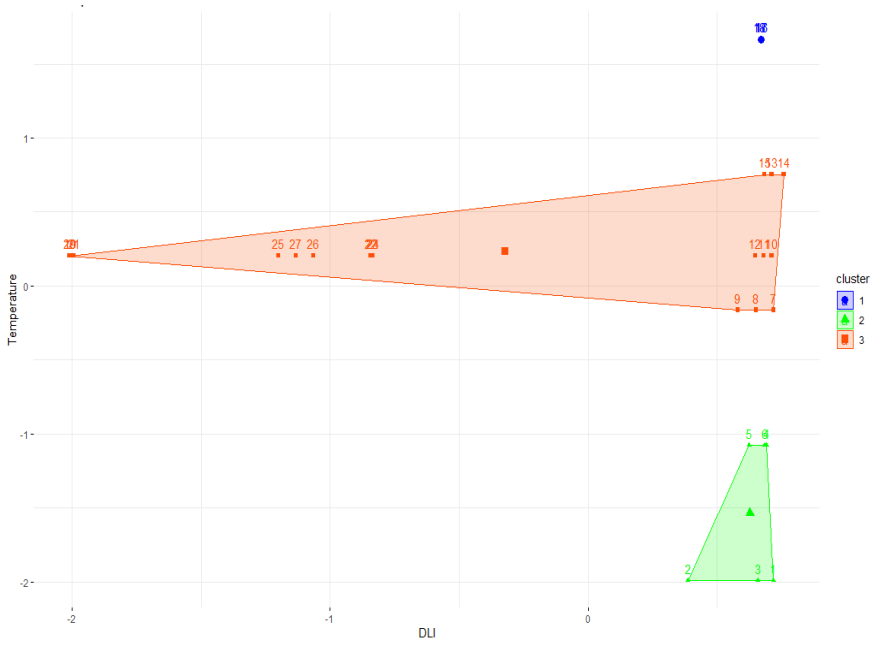

Figure 24. K-means cluster plot based on combinations of temperature and DLI.

CHAPTER 5. CONCLUSIONS

This thesis presented an experimental study to explore the use of smart sensors in monitoring the environmental conditions and their effects on plant development in a small-scale controlled environment facility. Wireless smart sensors were used to remotely monitor/collect various environmental data, including air temperatures, humidity, CO_2 concentration, light intensity, soil temperature and moisture, and barometric pressure. A set of metrics was established to quantify plant development, including leaf morphology, plant height, fresh biomass production, and dry biomass production. Several methods were used to analyze the multiple sensor data to quantify the effect of each environmental factor on the plant growth

metrics, as well as interplays between the environmental factors. The following conclusions were drawn from the study:

1) Smart sensors were effective in monitoring the environmental conditions in controlled environment crop production facilities. The sensors and associated WSN (wireless sensor network) collected reliable data that could be used for developing smart control strategies for environmental control.
2) The three tested environmental variables (temperature, light duration, and light intensity) all had significant effects on plant growth and their interactions were significant. This justified the necessity of using multiple smart sensors for monitoring environment in controlled environment facility for crop production.
3) The combined effect of temperature and DLI (daily light integral) on plant growth (fresh biomass) could be adequately described by a second order polynomial model, and this model could be potentially used to fuse sensor data of temperature and light to achieve optimal plant growth with minimum energy use.
4) Multivariate analysis tools, such as K-means clustering analysis, have the potential of being used to analyze multiple sensor data for developing smart control strategies for controlled environment systems for crop production.

CHAPTER 6. RECOMMENDATIONS

The study presented in this thesis was a small-scale experimental study using a test chamber to simulate controlled environment systems for crop production. This study was exploratory in nature and could be improved in many aspects. The following are some recommendations for future studies:

1) Experimental Design Enhancement

Future studies should consider implementing a randomized complete block design (RCBD) to mitigate the variability within experimental units and enhance the reliability of the results. This design would better account for the influence of uncontrolled variables that might affect the outcome.

It is advisable to collect a larger dataset to strengthen the statistical power of the analyses. The current study's dataset was relatively small, which may limit the application of certain data analytics such as machine learning algorithms that require robust datasets to detect complex patterns effectively. Exploring a wider range of variables, including soil quality, humidity, and genetic factors, may reveal other important influences on plant growth. A multifaceted approach to data collection could uncover more intricate relationships that were not evident in this study.

2) Large Scale Testing

Conducting the experiments on a commercial scale, or at least a larger scale, controlled environment facility would be beneficial, which could provide insights into the scalability of the findings and their applicability in practical agricultural settings.

3) Robust Models

When more data is available, more sophisticated models/techniques, such as machine learning, could be employed to capture complex, non-linear relationships more accurately. When

employing methods like Generalized Additive Models (GAM), using cross-validation techniques (e.g., k-fold cross-validation) can improve model validation.

APPENDIX A. ANOVA SINGLE FACTOR DETAILS

Table A1. One Factor ANOVA for temperature effect on fresh mass

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
15	3	3.387733	1.129244	0.017916713
20	3	4.383444	1.461148	0.000262473
25	3	16.74308	5.581026	0.019792367
27	3	21.00358	7.001194	0.128012806
30	3	8.467902	2.822634	0.041159275
35	3	6.869079	2.289693	0.026364727

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	84.61465	5	16.92293	434.8348536	3.98E-13	3.105875
Within Groups	0.467017	12	0.038918			
Total	85.08166	17				

Table A2. Single Factor ANOVA for light duration effect on fresh mass

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
7	3	5.851079	1.95036	0.001168
10	3	11.04172	3.680572	0.058013
14	3	21.00358	7.001194	0.128013

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	39.5311	2	19.76555	316.7654	8.26E-07	5.143253
Within Groups	0.374388	6	0.062398			
Total	39.90549	8				

Table A3. Single Factor ANOVA for light intensity effect on fresh mass

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
100	3	13.736	4.578667	0.07835
150	3	21.00358	7.001194	0.128013

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	8.802961	1	8.802961	85.31525	0.000764	7.708647
Within Groups	0.412726	4	0.103182			
Total	9.215688	5				

APPENDIX B. DATA SHEET FOR K-MEANS CLUSTER PLOT

Table B. Data sheet of 27 data combinations for K-meanis cluster plot

Data Point Number	Temperature ((°C)	DLI (mol/m^2.day)	Fresh Biomass (g)
1	15	7.56	1.28
2	15	7.56	1.02
3	15	7.56	1.09
4	20	7.56	1.47
5	20	7.56	1.48
6	20	7.56	1.44
7	25	7.56	5.44
8	25	7.56	5.72
9	25	7.56	5.58
10	27	7.56	6.79
11	27	7.56	7.41
12	27	7.56	6.79
13	30	7.56	2.82
14	30	7.56	3.02
15	30	7.56	2.62
16	35	7.56	2.48
17	35	7.56	2.18
18	35	7.56	2.21
19	27	3.78	1.98
20	27	3.78	1.92
21	27	3.78	1.95
22	27	5.40	3.90
23	27	5.40	3.72
24	27	5.40	3.42
25	27	5.04	4.62
26	27	5.04	4.84
27	27	5.04	4.28

Note: Three clusters are color coded: Cluster 1 blue; Cluster 2 green; Cluster 3 red

APPENDIX C. RSTUDIO CODE OF POLYNOMIAL REGRESSION MODEL

```r
library(readxl)
library(caret)
library(Metrics)

data <- read_excel("D:/dry mass.xlsx")
data <- data[, c("Temperature", "DLI", "WetBiomass")]

data <- na.omit(data)

if (nrow(data) > 1) {
  set.seed(123)
  index <- createDataPartition(data$WetBiomass, p=0.8, list=FALSE)
  trainData <- data[index, ]
  testData <- data[-index, ]

  poly_model <- lm(WetBiomass ~ poly(DLI, 2, raw = TRUE) +
                     poly(Temperature, 2, raw = TRUE), data=trainData)
  predictions <- predict(poly_model, newdata=testData)
  rsq <- R2(predictions, testData$WetBiomass)
  cat("R-squared value for the testing set:", rsq, "\n")
  coefficients <- coef(poly_model)
  print(coefficients)
  equation <- paste("WetBiomass = ", round(coefficients[1], 2),
                    " + ", round(coefficients[2], 2), "* DLI",
                    " + ", round(coefficients[3], 2), "* I(DLI^2)",
                    " + ", round(coefficients[4], 2), "* Temperature",
                    " + ", round(coefficients[5], 2), "* I(Temperature^2)")
  print(equation)
} else {
  cat("Not enough data points to perform the analysis.\n")
}

```

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