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Comparative Analysis of Growth Models for Lettuce (*Lactuca sativa*) in a Plant Factory under Red-Blue LED Treatment

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ABSTRACT

The growth of lettuce (Lactuca sativa) in controlled environments such as Plant Factories is highly influenced by lighting, particularly under red-blue (RB) LED treatment. Accurate growth prediction models are essential for optimizing yield. This study compared four models linear, polynomial, logistic, and Gompertz to determine the best predictor of leaf area expansion. Leaf area measurements over 30 days were analyzed using Easy Leaf Area software. Results showed that the Gompertz model consistently outperformed others with the lowest Mean Absolute Percentage Error (MAPE) of 14.55% (slow), 39.51% (medium), and 29.13% (high), and the highest R^2 values of 0.99 across all growth categories. In contrast, linear and polynomial models exhibited extremely high MAPE values, exceeding 300% in most cases. The study concludes that the Gompertz model is the most accurate and biologically realistic for modeling lettuce growth in Plant Factory systems, offering robust predictive capability for sustainable precision agriculture.

1. INTRODUCTION

The growth of lettuce (*Lactuca sativa*) plants is influenced by a complex range of environmental factors, including temperature, humidity, light, and nutrients. Research shows that variations in climate and soil conditions can significantly affect the yield and quality of lettuce crops (Lee *et al*., 2015; Wallace *et al*., 2012). For example, excessively high or low temperatures can cause plant stress, which impacts growth and yield (Wallace *et al*., 2012). In addition, lettuce can be grown using an indoor farming concept called Plant Factory. Plant Factory is a controlled indoor farming system that uses LED (Light Emitting Diode) lighting to substitute solar energy for photosynthesis. The advantages of Plant Factory are the ease of controlling the environment and nutrients, and the absence of pests or pesticides. LED lighting has been shown to affect lettuce growth, where the right combination of light spectra can increase biomass and chlorophyll content (Han *et al*., 2017; Sukhova *et al*., 2023; Talib *et al*., 2020). Understanding the growth of plants is very important to increase the productivity of lettuce plants.

In relation to plant growth, mathematical modeling has been developed as a tool to predict plant growth. Various models have been designed to describe the mechanism of plant growth, including linear regression models that have been used by (Bakhshandeh *et al*., 2012; Harfenmeister *et al*., 2019; Zhou & Yin, 2014) Polynomial models done by (Putra *et al*., 2022) A logistic model published by (Ghasiani *et al*., 2021; Kurniawan *et al*., 2022), Gompertz model (Purwanti *et al*., 2014; Jane *et al*., 2020; Ribeiro *et al*., 2018), and the ANN model (Çelik *et al*., 2023; Dada & Laseinde, 2024; Moreira *et al*., 2023). It is not yet known exactly which model is best for predicting plant growth, so research is needed to use the best model to accurately describe the development of lettuce plants.

Plant growth modeling is essential for precision agriculture, especially under controlled environments like Plant Factories. Despite numerous models available, including regression and non-linear models, the best predictive model for lettuce growth under LED lighting remains unclear. This study aims to compare different models and determine the most accurate one for describing leaf area development in lettuce.

2. RESEARCH MATERIALS AND METHODS

The materials used in this study were Grand Rapids lettuce seeds, AB mix nutrition brand Usaha Tani, rockwool, and water. The tools used in this research are TDS and EC meters (0-5000 ppm, 0-9990 uS/cm, accuracy ±2%), Xingweiqiang brand pH meter (0.00-14.00 pH), Fultrum brand LED grow light 120 cm long (18 W, wavelength 450 nm and 650 nm), thermohygrometer brand HTC-1 (10-50 ºC accuracy ±1 ºC, 10-99% accuracy ±5%), pump brand Yamano WP-105, lux meter AS803, measuring cup, digital scale WH-B30 and 30 cm ruler.

2.1. Plant Factory Preparation

Plant Factory is a closed plant cultivation system used to cultivate lettuce plants, artificially maintaining an optimal environment with optimal environmental parameters. Figure 1 shows the layout of the plant factory used in this study. There are three racks, and each rack contains three DFT (Deep Flow Technique) hydroponic channels and three LED lights for plant growth. Each rack consisted of 18 plants, and six plants are used as samples exposed to full LED light on the middle rack. In this case, the upper and lower shelves were identical to the middle shelf, so data collection was not collected. Environmental variables in this study include temperature, relative humidity, and light intensity. Nutrient solution values are constant, ranging from 400 ppm (vegetative phase) to 1200 ppm (generative phase). The nutrient solution tank is placed at the bottom of the rack. Each gutter is connected to a pipe that serves as a channel for nutrient circulation from the water tank to the gutter. The nutrient solution consists of solutions A and B. Each was made into a concentrated solution of 1 liter. Concentrated solutions A and B will provide nutrients to the plants as needed.

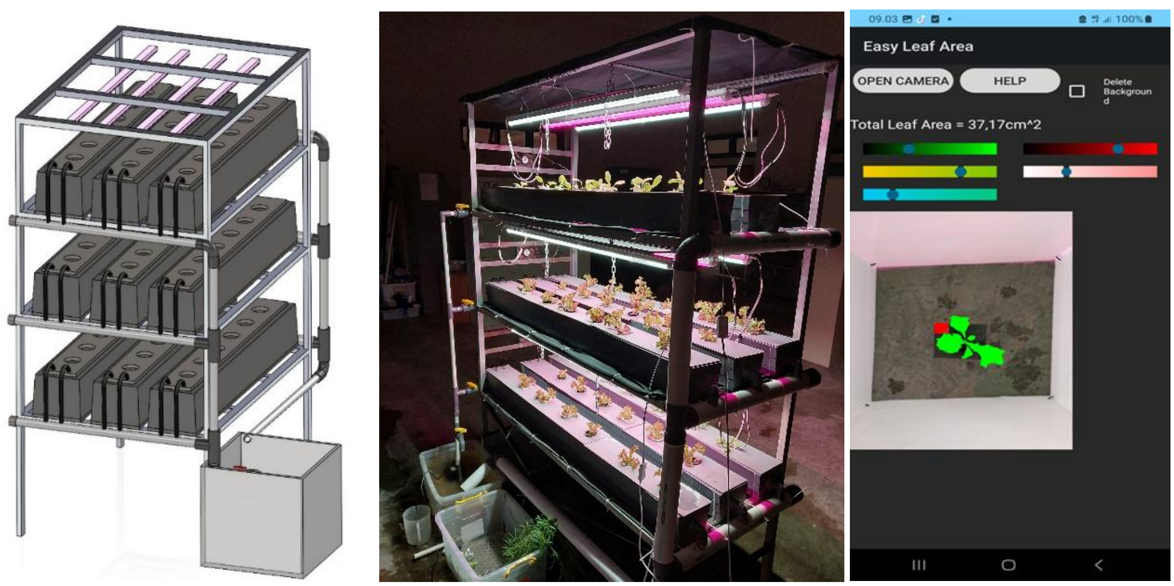

Figure 1. (a & b) Laboratory scale plant factory, (c) Leaf area measurement using Easy Leaf Area software

2.2. Plant Growth Environment Preparation

Grand Rapids lettuce seeds were sown in the greenhouse using rockwool media for 25 days. On the first day, the seeds were planted in dark conditions, on the second day, when they started to break, they were placed in the sun. Rockwool is kept wet during sowing. When the seeds were 25 days old or had 4 or 5 leaves, they were transferred to hydroponic gutters filled with water and 400 ppm nutrient solution.

Environmental parameters were adjusted to the growth of plants, the temperature of the environment was maintained in the range of 25–28 °C, pH was kept constant between 6 and 7, and irradiation using an artificial light type LED growth light lamp, which was turned on for 18 hours of light and 6 hours of darkness. Data collection of environmental parameters was carried out every day in the morning (08.00), noon (12.00), and evening (17.00).

2.3. Measurement of crop area

Easy Leaf Area software (Figure 1c) is an open-source application (https://www.quantitative-plant.org/) based on the Arabidopsis algorithm that uses a combination of thresholding, color ratio, and connected component analysis to measure leaf area in images quickly. The Arabidopsis algorithm-based image set calculates the automatic selection criteria using the following equations (Easlon & Bloom, 2014):

$$green\ threshold\ G = 1{,}223\ \times\ (greenest\ mean\ G) - 111 \quad (1)$$

$$\frac{G}{R} = 0{,}360\ \times\ \left(greenest\ mean\frac{G}{r}\right) + 0{,}589 \quad (2)$$

$$\frac{G}{B} = 0{,}334\ \times\ \left(greenest\ mean\frac{G}{B}\right) + 0{,}534 \quad (3)$$

Easy Leaf uses the red area to calibrate the known area in each image as a scale to calibrate the leaf area estimate. The area reading is independent of the image source, camera distance, and focus. The total number of green leaf pixels and red area calibration pixels is used to estimate the leaf area. The calibration system in the Easy Leaf Area application uses red color to accurately and non-destructively determine the measurement scale of leaf area. The process begins by placing a red calibration object (2×2 cm) alongside the leaf to be measured. The application then uses digital image processing algorithms to identify red pixels (calibration object) and green pixels (leaf), and calculates the number of each. Based on the ratio of these pixels to the actual area of the calibration object, the application automatically converts the number of leaf pixels into units of area (e.g., cm^2), ensuring precise measurements. In other words:

$$\text{Leaf area} = (\text{number of green pixels}) \times (\text{calibration area/number of red pixels}) \quad (4)$$

The leaf and calibration areas should also be placed in the same area to minimize errors due to camera distortion.

2.4. Mathematical Model

2.4.1. Regression Models

Regression modeling is one of the techniques that can be used for forecasting and prediction. Besides that, regression analysis can be used in some cases to determine the causal relationship between independent and dependent variables (Wu *et al*., 2019). In a regression model, independent variables predict dependent variables (Roopa & Asha, 2019). Regression analysis estimates the value of the dependent variable 'y due to a range of values of the independent variable 'x' (Seber & Lee, 2012). In this study, linear regression and polynomial regression models were used.

Linear regression is a mathematical model with one independent variable (Abdulazeez *et al*., 2020). Linear regression distinguishes the effect of independent variables from the interaction of dependent variables. The equation used is $y_t = \beta_0 + \beta_1 t + \varepsilon$ where y_t is a variable measured or observed at the time (*t*), β is an unknown parameter to be estimated, and ε is error value w, which is also time dependent and follows the probability distribution of y (Acharya *et al*., 2019).

Polynomial regression (Prasad *et al*., 2015; Roziqin *et al*., 2016) It is a type of regression analysis in nth degree polynomial modeling of the relationship between independent and dependent variables. Polynomial regression is a special case of multiple regression, with only one independent variable t (Ostertagová, 2012), with dependent variable yt that depends linearly on the powers of a single independent variable (t, t^2, ..., t^k). A one-variable polynomial regression model of kth order can be expressed as:

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \cdots + \beta_k t^k + \varepsilon \quad (5)$$

2.4.2. Logistic and Gompertz Models

It is known that plant growth follows a sigmoidal growth curve (Damgaard & Weiner, 2008; Vanclay, 1994). Several sigmoidal growth models, such as the logistic model and the Gompertz model (Karadavut *et al*., 2008; Karadavut *et al*., 2010) It can be used to make plant growth predictions. These advances in plant growth modeling allow a better understanding of the relationship between plant growth parameters (Paine *et al*., 2012).

Therefore, leaf canopy area data were used to derive the growth curves of the Logistic (L) and Gompertz (G) models using RStudio software. Predicted canopy area (L_t), inflection weight (L_i), inflection time (t_i), and maximum growth rate (*MGR*) for both models were calculated as follows (Selvaggi *et al*., 2015):

Logistic : $$L_t = \frac{A}{1+Be^{-kt}} \qquad W_i = A/2 \qquad t_i = (Ln.B)/k \qquad MGR = (W_i x k)/2 \tag{6}$$

Gompertz : $$L_t = Ae^{-e^{(b-kt)}} \qquad W_i = A/e \qquad t_i B/k \qquad MGR = W_i x k \tag{7}$$

where A is the final area asymptote of the canopy (cm²), B is a constant of integration, k is the growth rate of canopy area (cm²/day), e is a constant (2.72), t is time (days). The canopy area change curve with coefficient of determination value (R^2) and low standard error (MAPE) shows that the curve is accurate for leaf canopy area prediction. The formula for obtaining the coefficient of determination using the correlation coefficient (Chicco *et al*., 2021):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\overline{y_i})^2} \tag{8}$$

where y_i is value of observation i, $\widehat{y_i}$ is estimated value i, $\overline{y_i}$ is average observation value, n is the number of observation. The model was validated by comparing the output with field data corresponding to the simulated scenario. Model validation is also beneficial in reducing costs, finding more errors, and improving scalability, flexibility, and model quality (Bustomi & Yulianti, 2013). Model validation was determined using Mean Absolute Percentage Error (MAPE) calculated as the following:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-y_i}{y_i}\right| x100\% \tag{9}$$

3. RESULTS AND DISCUSSIONS

3.1. Leaf Area Measurement Using Easy Leaf Area Application

Plant or canopy area measurements are measured using the Easy Leaf Area application. Measurements were taken for 30 days in the plant factory, resulting in different leaf areas in each treatment. The growth in Figure 3 shows a pattern of increasing plant area. The study found that the leaf area continued to increase every day and formed a sigmoid curve. Samples T1 to T6 showed variations in plant growth. Plant samples in the center (T2, T3, T4) tend to have the highest growth compared to those on the edge (T1, T5, T6). The difference in plant growth is due to the uneven light received by the plants. According to (Zhu *et al*., 2013). Plants with optimal access to light and nutrients tend to have higher photosynthetic rates, producing more biomass, which is reflected in increased area. These results are also supported by recent research showing that the amount of light received by plants can increase photosynthetic efficiency and biomass growth, especially in controlled environments such as plant factories (Smith *et al*., 2023). When creating the mathematical model, slow growth (T2 and T6), medium growth (T1 and T5), and fast growth (T3 and T4) groups were created.

Based on Figure 3 from day 1 to day 15, the dominant phenomenon was the early vegetative growth phase with a relatively slow and gradual increase in plant area for all treatments (T1-T6). This process was a period of adaptation, root formation, and primary leaf growth that was not yet massive. However, from day 16 to day 30, there is a significant acceleration in the growth of plant area, showing exponential increase, indicating the transition from the active vegetative growth phase to the generative phase. This process involves the optimization of photosynthesis, leading to faster plant growth in terms of height, number of leaves, and root length.

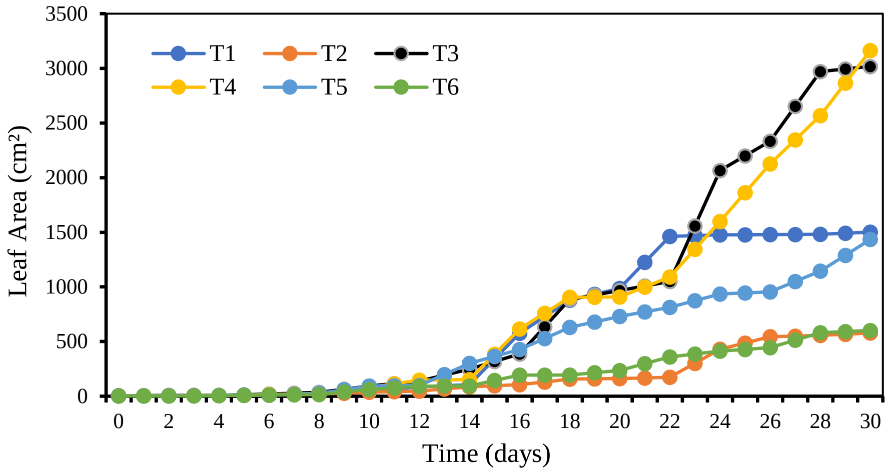

Figure 3. Leaf area of lettuce during growth

The RB (Blue-red) LED light treatment has an average area of 592.23 cm² (Figure 3). One of the main reasons why red and blue combination lights (RB LEDs) are so good for plant growth is that both spectra directly affect the photosynthesis process. Red (R) and blue (B) light are the two most effective wavelengths for photosynthesis in the absorption of chlorophyll (Li *et al*., 2020). Studies conducted by Seyedi found that *Lactuca sativa* plants exposed to a combination of red and blue light showed a significant increase in fresh weight compared to other light treatments (Seyedi *et al*., 2024). Furthermore, the study showed that the correct proportion of red and blue light can optimize root growth and increase plant resistance to stress conditions (Malekzadeh *et al*., 2024).

3.2. Leaf Area Estimation Using Mathematical Models

3.2.1. Leaf Area Estimation Using Regression Models

The linear model for low-growth plants is expressed as $y = 20.22x - 133.54$, where y denotes plant height and x represents days. This model suggests a constant growth rate of approximately 20.22 units per time interval. However, the exceptionally high MAPE of 330.86% indicates substantial deviation from observed values, revealing poor accuracy in representing real growth behavior. Although the R^2 value of 0.85 implies medium fit, this is insufficient for precise modeling. In contrast, the polynomial model of order two is given by $y = 1.01x^2 - 11.07x + 32.78$. This equation represents a parabolic growth trend, where growth accelerates over time after an initial decline. The second-order term (x^2) captures the non-linear nature of plant development more effectively. This is corroborated by a significantly reduced MAPE of 43.30% and an improved R^2 value of 0.98, indicating high predictive reliability and goodness of fit. According to (Faaris *et al*., 2023) the value of the coefficient of determination ranges from 0 to 1, the closer to 1. Therefore, quadratic modeling better reflects the early slow growth and subsequent acceleration phase typical of young plant development.

The medium-growth plants demonstrate a linear growth pattern defined by $y = 56.94x - 363.76$, implying a higher constant growth rate than low-growth plants. However, the model's predictive performance is very poor, as indicated by a highly high MAPE of 785.42%, suggesting that the model grossly misestimates actual values. Despite an R^2 of 0.90, this inconsistency signals that the linear model fails to capture key growth dynamics. The second-order polynomial model for medium-growth plants, $y = 1.7x^2 + 4.29x - 82.97$y, incorporates acceleration in growth rate over time. This is evident from the positive quadratic term (1.7), implying an upward-opening parabola. The model fits the data better, as seen from the reduced MAPE of 247.63% and improved R^2 of 0.95. While still not optimal, this polynomial formulation aligns more closely with biological growth patterns, which often exhibit phases of rapid acceleration after an initial lag period. In the fast growth category, the linear model is described by $y = 95.53x - 714.08$, denoting a very rapid and constant growth rate. Despite a seemingly strong R^2 value of 0.817, the MAPE of 1886.55% signals catastrophic inaccuracy, rendering the linear model ineffective for practical use in this case.

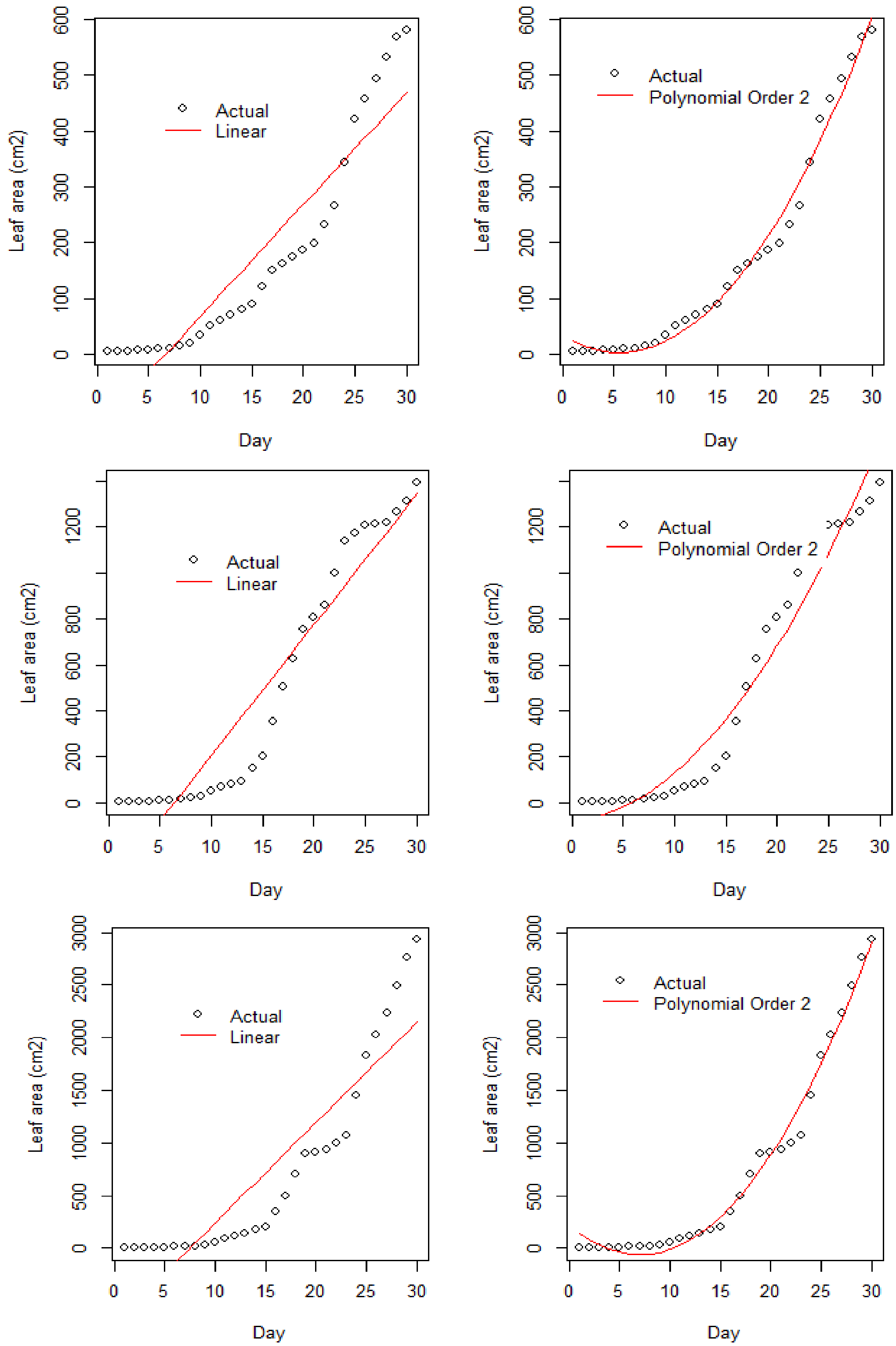

Figure 4. Comparison of lettuce plant area in RB LED treatment with (a) linear and (b) polynomial methods: (top) slow growth, (middle) medium growth, and (bottom) fast growth

The quadratic model, $y = 5.65x^2 - 79.54x + 219.63$, captures a more nuanced pattern of early decline followed by exponential-like growth, as evidenced by the significant coefficient on the x^2 term. This model significantly enhances the fit, with an MAPE reduced to 333.73% and a substantially higher R^2 of 0.9885. Although the error rate is still relatively high, the model structure is more reflective of the biologically plausible scenario in which fast growth plants undergo a delayed exponential phase due to physiological or environmental constraints.

3.2.2. Leaf Area Estimation Using Gompertz and Logistic Models

In the case of slow-growth plants, both the Gompertz and Logistic models exhibit a clear sigmoidal trend, accurately simulating the initial lag phase, a period of exponential increase, and eventual plateau in leaf area. The actual data points (circles) align closely with the predicted curves (solid lines) in both models. The Gompertz model slightly outperforms the Logistic model, as confirmed by a lower MAPE (14.55% vs. 29.2%) and marginally higher R^2 (0.99 vs. 0.99, but with slightly better fit observed in residuals). This indicates that the Gompertz model more precisely captures the asymmetrical nature of biological growth, where the acceleration phase is sharper and the saturation phase is more gradual. Both models effectively describe the slow-growth scenario, but the Gompertz model better matches actual data, especially near the inflection point. The Gompertz model is a non-linear growth equation that is often used to model biological growth, including plant area (Chatterjee *et al*., 2015).

The actual growth pattern for medium-growth plants displays a more dynamic and expansive trend, with a more pronounced growth phase between days 15 and 30. Gompertz and Logistic models successfully follow the observed data, though the Logistic model demonstrates a slightly more consistent alignment throughout the growth trajectory. This is also supported by a lower MAPE value for the Logistic model (13.53%) than Gompertz (39.51%), suggesting higher accuracy. However, the R^2 values remain very close (0.94 for both models), which indicates that both models explain a similar proportion of variance in the data. The visual inspection confirms that both models represent the S-shaped growth accurately, but the Logistic model may better accommodate the symmetric nature of growth transition in this medium category. In addition to using the Gompertz model, crop area prediction is accomplished using the Logistic equation. This model is based on a differential equation that describes how the growth rate is initially fast, then slows down as it approaches maximum capacity (West, 2015).

In the rapid-growth scenario, characterized by an explosive increase in leaf area beyond 2000 cm², both the Gompertz and Logistic models exhibit reliable predictive capacity. The observed data points remain closely clustered along the predicted curves, confirming both models' appropriateness. Nevertheless, the Gompertz model appears to have a tighter fit in the later stages of growth (post day 25), while the Logistic model slightly underestimates the final surge. This is reflected in the MAPE values, where the Gompertz model records a lower error rate (29.13%) than the Logistic (106.1%). The R^2 values are high in both cases (0.99 for Gompertz and 0.98 for Logistic). However, the Gompertz model is better suited for modeling growth patterns that feature an earlier and steeper inflection followed by a gentler deceleration, common in high-vigor plant species. The Gompertz model reflects the biological constraints in plant growth, particularly the saturation phase due to resource limitations, which cannot be captured by polynomial regression.

Both Gompertz and Logistic models are highly effective in modeling plant growth, particularly due to their sigmoidal structure that mirrors biological reality. However, model performance varies with growth intensity: the Gompertz model is more suitable for slow and rapid growth due to its asymmetrical flexibility, while the Logistic model offers a marginal advantage in medium-growth conditions where symmetric S-curves prevail. This underscores the importance of choosing the appropriate model based on the specific physiological dynamics and developmental phases of the plant under observation. This difference is due to the different model structure, response to baseline data, slowing of growth in the late phase, and different parameter estimates (Gachoki *et al*., 2022; Maity *et al*., 2019).

Based on the comparative performance metrics presented in Table 1, the Gompertz model consistently offers the most accurate representation for predicting plant growth across all categories slow, medium, and fast growth. This conclusion is derived from the model's superior Mean Absolute Percentage Error (MAPE) and high coefficient of determination (R^2) values compared to other models, such as linear, second-order polynomial, and logistic models.

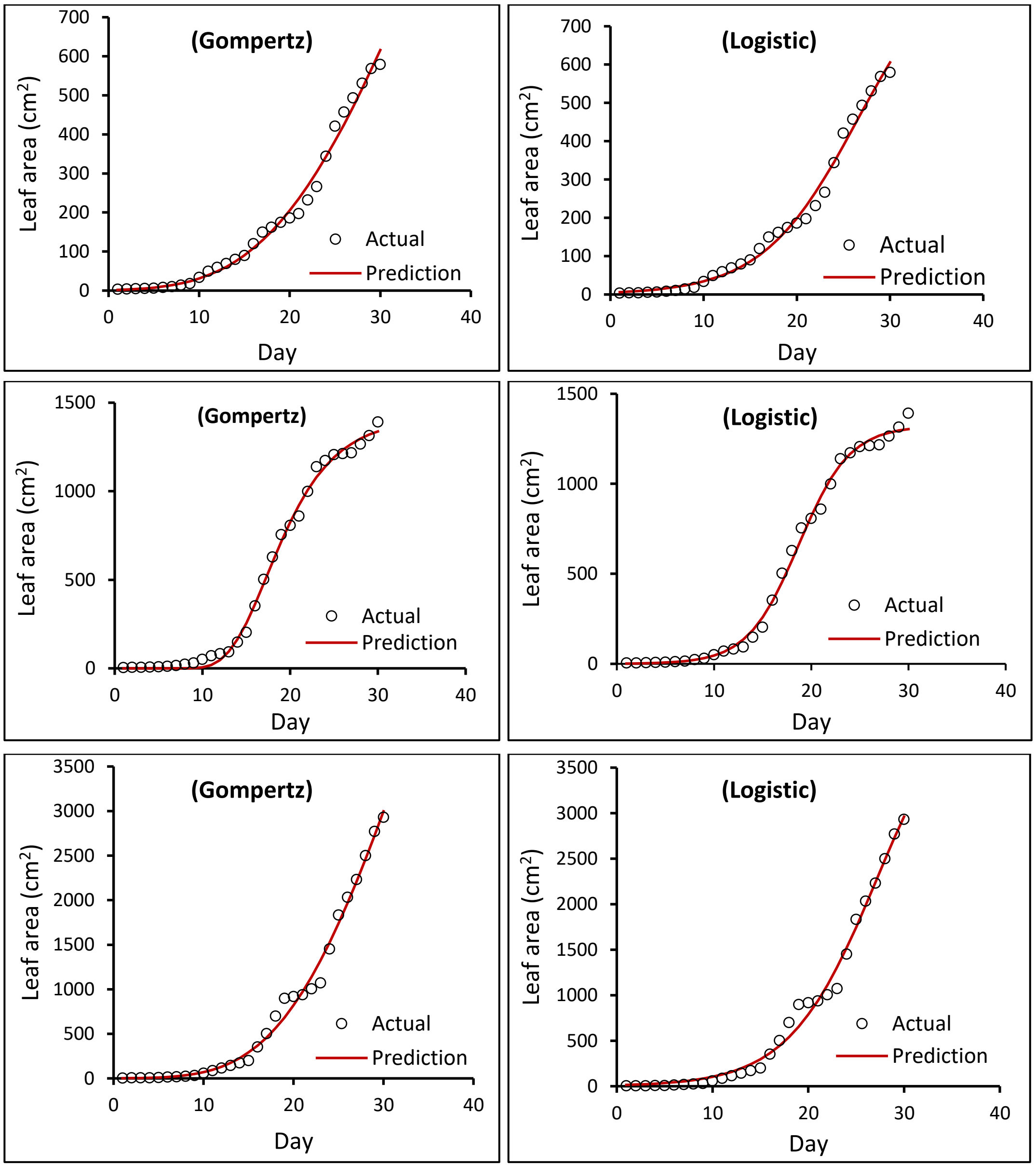

Figure 5. Comparison of the leaf area of lettuce plants using Gompertz and Logistic methods: (top) Slow growth; (middle) medium growth; (bottom) fast growth

For slow-growing plants, the Gompertz model achieved a notably low MAPE of 14.55% with an R^2 of 0.99, outperforming other models, which exhibited either significantly higher error rates or lower predictive reliability. Similarly, in medium growth scenarios, the Gompertz model maintained robustness with an MAPE of 39.51% and an R^2 of 0.94, slightly surpassed in error by the logistic model (MAPE 13.53%), yet demonstrating strong overall consistency and generalizability. For fast growth plants, the Gompertz model once again yielded the best balance of predictive accuracy (MAPE 29.13%) and fit (R^2 0.99), while other models like the polynomial and logistic alternatives suffered from either inflated error values or reduced reliability in extreme growth conditions. Therefore, considering both the error minimization and the strength of correlation across all growth types, the Gompertz model emerges as the most reliable and generalized mathematical approach for modeling diverse patterns of plant growth dynamics. This makes it a highly suitable choice for applications in precision agriculture, plant factory management, and growth forecasting systems.

Table 1. Comparison of leaf area models for lettuce plant

	Slow growth			
	Linear	Polynomial Orde 2	Gomperzt	Logistic
Equation	$y = 20.22x - 133.54$	$y = 1.01x^2 - 11.07x + 32.78$	$y = 2842.68 exp\{-e^{(2,05-0,05x)}\}$	$y = \frac{908.71}{(1+181.44e^{-0,19x})}$
MAPE	330.86%	43.299%	14.55	29.2
R^2	0.85	0.98	0.99	0.99
Pattern	Lines (constant)	Squared (non-linear)	Sigmoid	Sigmoid

	Medium growth			
	Linear	Polynomial Orde 2	Gomperzt	Logistic
Equation	$y = 56.94x - 363.76$	$y = 1.7x^2 + 4.29x - 82.97$	$y = 1410.57\ exp\{-e^{(4.00-0.23x)}\}$	$y = \frac{1321.37}{(1+1245.51e^{-0.38x})}$
MAPE%	785,422%	247.625%	39.51	13.53
R^2	0.90	0.95	0.94	0.94
Pattern	Lines (constant)	Squared (non-linear)	Sigmoid	Sigmoid

	Fast growth			
	Linear	Polynomial Orde 2	Gomperzt	Logistic
Equation	$y = 95.53x - 714.08$	$y = 5.65x^2 - 79.54x + 219.63$	$y = 12681.49\ exp\{-e^{(2.29-0.06x)}\}$	$y = \frac{4539.65}{(1+383.10e^{-0.21x})}$
MAPE	1886,55%	333.728%	29.13	106.1
R^2	0.817	0.9885	0.99	0.98
Pattern	Lines (constant)	Squared (non-linear)	Sigmoid	Sigmoid

Note : y = leaf area (cm^2), x = plant age (day)

4. CONCLUSION

The Gompertz model performs better in predicting lettuce leaf area within a Plant Factory system under red-blue (RB) LED illumination. It consistently outperforms linear, polynomial, and logistic models regarding accuracy and biological plausibility. With the lowest MAPE (0.79%) and high coefficient of determination ($R^2 = 0.99$), the Gompertz model accurately captures the sigmoidal growth trajectory, including early lag, exponential rise, and plateau phases. Its ability to reflect real physiological processes makes it the most suitable model for reliable growth prediction and long-term planning in controlled environment agriculture.

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CONFLICT OF INTEREST

The authors declare no conflict of interest

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