Predictive Modelling of Microbial Growth in Stored Fresh-Cut Green Beans

Cicih Sugianti[1*], Dwi Dian Novita[1], Zana Azalia Maktub[1], Dhia Salsabila[1], Wahyu Hidayat[2]

[1]Department of Agriculture Engineering, Agriculture Faculty, University of Lampung, Indonesia 35144
[2]Department of Information System, The Islamic University of Raden Intan Lampung, Indonesia 35131
**Corresponding Author: cicih.sugianti@fp.unila.ac.id*

Received: 30 October 2025

Accepted: 09 December 2025

****Correspondent Email:***
author@email.ac.id

Abstract: *Microbial contamination is a major factor determining the quality and shelf life of fresh-cut vegetables. This study evaluated the microbial growth dynamics of fresh-cut green beans stored at three different temperatures (6°C, 16°C, and 26°C) using the Modified Gompertz and Logistic models. Total microbial counts were assessed using the Total Plate Count (TPC) method, and the data were fitted using nonlinear least squares to obtain key growth parameters. The results showed that both models were able to describe microbial growth trends; however, their performance was strongly influenced by storage temperature. At 6°C, both models exhibited good fit with low RSE values and several significant parameters, indicating a stable sigmoid growth pattern. At 16°C, the modeling performance declined, characterized by higher RSE values and mostly non-significant parameters, suggesting irregular growth dynamics. At 26°C, model accuracy improved again, with the Logistic model showing more stable parameter estimates compared to the Modified Gompertz model. Overall, storage temperature played a crucial role in determining parameter stability and model quality, with the Logistic model demonstrating greater robustness under extreme temperature conditions. These findings provide scientific insights for determining shelf life and developing microbiological quality control strategies for fresh-cut grean bean.*

Keywords: *fresh-cut, green beans, microbial growth model, Logistic, Gompertz.*

1. INTRODUCTION

The consumption of fresh-cut vegetables continues to rise in line with lifestyle changes that prioritize convenience, ease of preparation, and maintained nutritional quality. Although washing, cutting, and packaging processes help preserve freshness, they also cause cellular damage. Such damage triggers increased respiration, ethylene production, and the release of cellular fluids, creating favorable conditions for microbial growth. As a result, fresh-cut vegetables generally have a shorter shelf life compared to intact produce, making microbiological quality control crucial throughout distribution and food safety systems.

Microbial growth in fresh-cut vegetables is influenced by various factors, including sanitation practices, storage temperature, moisture content, packaging type, and commodity physiology. Green beans—widely consumed and commonly marketed in fresh-cut form—are particularly susceptible to physical and chemical alterations after cutting, which accelerates microbial colonization. Therefore, understanding microbial growth patterns during storage is essential for estimating shelf life, determining quality limits, and designing more effective processing interventions.

Mathematical modeling has become an important component of predictive microbiology. Primary models such as the Gompertz and Logistic equations are widely used to describe microbial growth dynamics, encompassing lag, exponential, and stationary phases. These models enable estimation of crucial parameters, including maximum growth rate, initial population, maximum population, and lag duration. Accurate models also support the food industry in optimizing cold chain management, packaging systems, and distribution logistics. However, model performance may vary depending on commodity type and the characteristics of the observed growth data.

This study is motivated by the need to predict microbial growth in efforts to extend the shelf life of fresh-cut foods. Chaturvedi et al. (2023) demonstrated that Logistic, Gompertz, and Baranyi models can effectively characterize microbial growth in Chhana in relation to storage conditions. Other studies have also utilized microbial growth patterns to develop models such as modified Gompertz, Huang, and Baranyi to predict food shelf life (Tsironi et al., 2017; Emtiazi et al., 2023; Hu et al., 2018). Physicochemical-based modeling has likewise been employed to predict quality degradation during storage (Mohd Ali et al., 2022), including zero-order and first-order kinetics commonly applied to vegetables, fruits, and fishery products (Mohd Ali et al., 2022; Li, 2020; Niu, 2020). Li et al. (2024) reported that higher storage temperatures accelerate quality deterioration and increase microbial populations in fresh-cut tubers, while Ruan et al. (2024) integrated quality parameters with microbial growth to predict the shelf life of fresh-cut radishes.

Based on this background, the present study aims to model microbial growth in fresh-cut green beans using the Gompertz and Logistic models and to compare the accuracy and parameter stability of both models. The results are expected to provide a scientific foundation for determining shelf life and designing microbiological quality-control strategies for fresh-cut green bean products.

2. MATERIALS AND METHODS

The equipment used in this study included a Lab Tech autoclave, test tubes, Petri dishes, a colony counter, micropipettes, pipette tips, and beakers. The materials consisted of fresh-cut green beans, Nutrient Agar (NA), and distilled water.

The study began with the preparation of materials followed by the treatment of the fresh-cut vegetable product. The green beans were washed, cut, packaged, and then stored at three different temperatures (6°C, 16°C, and 26°C). During the storage period, samples were taken and analyzed at predetermined intervals. Each treatment was conducted in triplicate.

2.1 Microbial Growth Measurement

All equipment was sterilized prior to use to prevent contamination. Approximately 10 g of sample was homogenized in 90 mL of sterile diluent, followed by serial dilution from 10^{-1} to 10^{-6}. A volume of 1 mL from each dilution was plated onto Petri dishes containing Nutrient Agar (NA) and incubated at 35–37°C for 24–48 hours. All procedures were conducted aseptically to ensure accuracy and avoid contamination. Total Plate Count (TPC) was calculated using Equation (1), and the resulting data were transformed into $\log_{10}$ values.

$$\text{TPC (CFU/g)} = \frac{Average\ colony\ count\ x\ Dilution\ Factor}{Volume\ of\ sample\ plated} \ldots\ldots\ldots(1)$$

2.2 Mathematical model

In this study, microbial growth kinetics of fresh-cut green beans stored at different temperatures were analyzed using two non-linear sigmoidal growth models, namely the Modified Gompertz Model and the Logistic Model. These models were selected due to their widespread application and reliability in describing microbial growth patterns in fresh produce and other perishable food matrices. Both models allow for the estimation of biologically meaningful parameters such as the maximum population density, growth rate, and lag phase duration, which are essential for characterizing microbial behavior under varying storage conditions. Modified Gompertz model and Logistic model are presented in Eq. (2) dan Eq. (3).

$$y(t) = A + C \exp exp \left\{- \exp exp \left[\mu\left(\frac{e}{C}\right)(\lambda - t) + 1\right]\right\} \ldots. (2)$$

A = Initial microbial level
C = maximum increase (asymptotic difference)
$\mu = Maximum\ specific\ growth\ rate$
$\lambda = Lag\ time$

$$y(t) = A + \frac{K - A}{1 + \exp exp\left[-r\left(t - t_0\right)\right]} \ldots\ldots\ldots\ldots(3)$$

A = initial microbial population
K = maximum microbial population
r = specific growth rate
t_0 = inflection point time

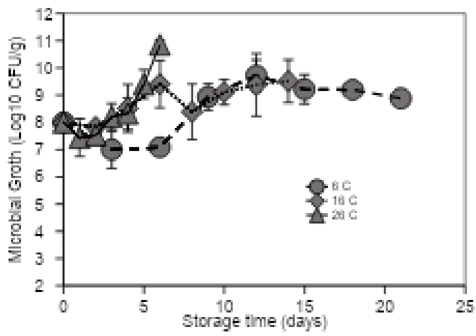
2.3. Model Fitting

The growth model parameters for fresh-cut green beans were estimated using the nonlinear least squares (NLS) approach in R software. The fitting process was performed by incorporating the model equations (Modified Gompertz and Logistic) into the NLS optimization algorithm to obtain parameter estimates that minimize the difference between model predictions and observed data.

The first criterion evaluated was the residual standard error (RSE), which indicates the magnitude of deviation between the observed data and the fitted model. A lower RSE value reflects better model performance in capturing the actual growth pattern. Parameter significance was then assessed to determine whether each estimated parameter contributed meaningfully to the shape of the growth curve. Parameters with low p-values were considered more reliable in describing microbial growth dynamics.

In addition, the number of iterations required for model convergence was used as an indicator of estimation stability; a well-behaved model typically converges within a reasonable number of iterations and does not produce warnings related to singular gradients.

3. RESULT AND DISCUSSION



Available online at https://conference.lppm.unila.ac.id/index.php/icsiger
DOI: https://doi.org/10.23960/icsiger

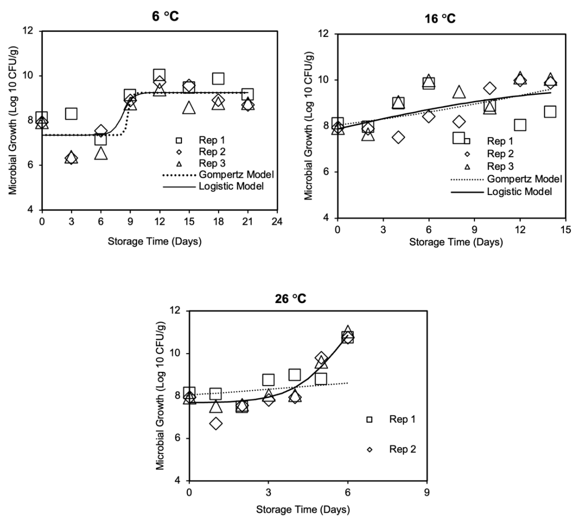
3.1 Microbial Growth Patterns During Storage of Fresh-Cut Green Beans

Figure 1 illustrates that the microbial growth patterns of fresh-cut green beans under all three storage temperatures exhibit a consistent trend—an overall increase in microbial population with increasing storage time. At 6°C, microbial growth progressed the slowest. The lag phase was relatively short, followed by an exponential phase occurring between 6 and 12 hours, before reaching the stationary phase. Minor fluctuations observed after 12 hours may be attributed to microbial adaptation to low-temperature stress or nutrient competition among microbial populations (Ray & Bhunia, 2013).

At 16°C, the growth rate increased more rapidly. The exponential phase emerged earlier, approximately between 4 and 10 hours, with a steeper increase in microbial count compared to low-temperature storage. This moderate temperature likely enhanced enzymatic activity and cellular metabolism, enabling microbes to adapt and proliferate more quickly (McKellar & Lu, 2004). After the 10th hour, microbial growth plateaued, marking the onset of the stationary phase.

At 26°C, microbial proliferation was the fastest, consistent with the characteristics of mesophilic microorganisms whose optimal growth temperature typically ranges from 25 to 37°C. The exponential phase occurred very rapidly—from the 2nd to the 6th hour—followed by a gradual slowdown approaching the stationary phase. This pattern aligns with previous reports on microbial growth kinetics in fresh produce, which show accelerated growth at ambient temperature (Li & Chen, 2021; Zwietering et al., 1990).

Overall, despite some variation among replicates, the microbial growth curves follow a classic sigmoid pattern consisting of lag, exponential, and stationary phases (Wang, 2024). Differences in the rate of transition between these phases at 6°C, 16°C, and 26°C clearly demonstrate that temperature is a dominant factor influencing microbial metabolic activity and growth dynamics.



3.2 Potential Predictive Modeling of Microbial Growth

Microbial growth in food products generally follows a sigmoid pattern characterized by a lag phase, an exponential growth phase, and a stationary phase. To quantitatively describe this pattern, two widely used primary mathematical models are the Modified Gompertz model and the Logistic model. Both models realistically represent microbial growth dynamics and allow estimation of key biological parameters, including maximum growth rate, lag phase duration, and maximum population density.

Figure 2 presents the application of the Modified Gompertz and Logistic models to microbial growth data at storage temperatures of 6°C, 16°C, and 26°C. The modeling results indicate that both the Modified Gompertz and Logistic models were able to describe the microbial growth patterns of fresh-cut green beans; however, the quality of model fit was strongly influenced by storage temperature. The estimated parameters derived from the Modified Gompertz and Logistic models are summarized in Table 1 and Table 2, respectively.

At low temperature (6°C), both the Gompertz and Logistic models produced statistically significant estimates for the key parameters (A and C/K), with low and nearly identical Residual Standard Error (RSE) values. This indicates that microbial growth under low-temperature storage tends to follow a stable sigmoid pattern, consistent with growth behavior commonly observed in fresh horticultural products (Li, 2020). This finding aligns with previous reports demonstrating that low temperatures extend the lag phase and reduce the maximum growth rate, thereby improving the performance of sigmoid-based models such as Gompertz and Logistic (Wang & Guo, 2024). The Logistic model showed slightly greater stability because most of its parameters were statistically significant, supporting literature suggesting that Logistic models often yield more robust estimates under low-variability storage conditions (Zwietering et al., 1990).

In contrast, at moderate temperature (16°C), both models exhibited reduced performance, as indicated by the lack of parameter significance and increased RSE. This suggests that microbial growth at intermediate temperatures may follow a less consistent pattern due to more complex adaptive dynamics, consistent with observations reported for dairy products and other fresh foods (Roy et al., 2023). Previous studies have also noted that transitional temperatures (10–20°C) often produce growth curves that deviate from a clean sigmoid shape, making nonlinear models less stable (McKellar & Lu, 2004). The Logistic model still performed slightly better, with

Tabel 1. Result of estimated parameters from Modified Gompertz model

Model	Temperature	Parameters	Estimate	Std. Error	t value	Pr (>|t|)
Gompertz	6 °C	A	7.358	0.2057	35.77	$<2x10^{-16}$
		C	1.892	0,2908	6.506	$2.43x10^{-6}$
		μ	3.359	$5.277x10^{5}$	0.000	1
		λ	8.44	$8.784x10^{4}$	0.000	1
		RSE	0.617			
	16 °C	A	7.0513	32.2479	0.219	0.829
		C	15.000	1060.2049	0.014	0.989
		μ	0.1685	4.6149	0.037	0.971
		λ	0.000	470.5172	0.000	1.000
		RSE	0.7933			
	26 °C	A	7.6947	0.1828	42.104	$<2x10^{-16}$
		C	15.000	41.8987	0.358	0.725
		μ	1.8105	2.6387	0.686	0.502
		λ	4.3156	3.0865	1.399	0.180
		RSE	0.4628			

Tabel 2. Result of estimated parameters from Logistic model

Model	Temperature	Parameters	Estimate	Std. Error	t value	Pr (>|t|)
Logistic	6 °C	A	7.3531	0.2531	29.053	$<2x10^{-16}$
		K	9.2536	0.1789	51.715	$<2x10^{-16}$
		r	2.0000	6.8884	0.290	0.77454
		t_0	8.2396	2.7036	3.048	0.00636
		RSE	0.6186			
	16 °C	A	5.8358	31.1049	0.188	0.853
		K	9.9183	4.7775	2.076	0.051
		r	0.1467	0.9743	2.076	0.051
		t_0	0.000	87.6126	0.000	1.000
		RSE	0.7864			
	26 °C	A	7.6706	0.2092	36.665	$<2x10^{-16}$
		K	13.3252	5.7341	2.324	0.0327
		r	1.0812	0.7219	1.498	0.15257
		t_0	5.7684	1.9102	3.020	0.00772
		RSE	0.4639			

parameters K and r approaching significance, consistent with evidence that the Logistic model is more tolerant of data noise than the Gompertz model (Baranyi & Roberts, 1994).

At high temperature (26°C), the performance of both models improved again. High temperatures accelerate microbial metabolism, making the growth pattern more pronounced and the sigmoid curve more distinct, as previously reported for fresh vegetables and other perishable commodities (Silva et al., 2017). The low RSE values indicate that both models were able to represent microbial growth effectively under this condition. The Logistic model showed a slight advantage, with a greater number of statistically significant parameters, reinforcing claims that it performs well under conditions of rapid microbial growth (Liang et al., 2022).

Overall, the findings demonstrate that storage temperature strongly influences the stability of parameter estimates in microbial growth modeling. The Logistic model tends to be more stable at extreme temperatures (both low and high), whereas the Modified Gompertz model performs best when the growth pattern follows a clean sigmoid curve with a well-defined lag phase. These results are consistent with theoretical perspectives emphasizing that model selection should be guided by environmental conditions and the nature of the observed data (Wang & Guo, 2024).

4. CONCLUSIONS

In conclusion, the performance of microbial growth models is highly dependent on storage temperature. At 6°C, both the Modified Gompertz and Logistic models accurately described the microbial growth pattern, as indicated by low RSE values and statistically significant key parameters, with the Logistic model showing slightly greater stability. At 16°C, the performance of both models declined, characterized by largely non-significant parameters and higher RSE, suggesting that microbial growth at moderate temperatures is less consistent and more difficult to model. At 26°C, both models again showed good fit, although the Logistic model yielded more significant parameter estimates than the Gompertz model. Overall, the Logistic model demonstrated greater robustness across temperature variations, whereas the Modified Gompertz model was more suitable for datasets exhibiting a stable sigmoid pattern.

ACKNOWLEDGEMENT

This research was supported and funded by the Basic Research Grant from the Institute for Research and Community Service (LPPM), University of Lampung, through the BLU Grant Scheme of 2025.

REFERENCES

Baranyi, J., & Roberts, T. A. (1994). A dynamic approach to predicting bacterial growth in food. International Journal of Food Microbiology, 23(3–4), 277–294. https://doi.org/10.1016/0168-1605(94)90157-0.

Buchanan, R. L., & Whiting, R. C. (1996). Risk assessment and predictive microbiology. Journal of Food Protection, 59(13), 31-36. https://doi.org/10.4315/0362-028X-59.13.31.

Chaturvedi, K., Basu, S., Singha, S., Das, K. (2023). Predictive microbial growth modelling for an effective shelf-life extension strategy of Chhana (Indian cottage cheese). Food Control, 151, 109697. https://doi.org/10.1016/j.foodcont.2023.109697

Emtiazi, G.; Ghoreishi, F.S.; Darani, K.K.; Yücel, Ö.; Tarlak, F. Prediction of Growth Kinetics of Bacillus Tequilensis in Nutrient Broth under Isothermal and Non-Isothermal Conditions. Food Sci. Technol. 2023, 43, e123422. https://doi.org/10.1590/fst.123422.

Hu, J.; Lin, L.; Chen, M.; Yan, W. Modeling for Predicting the Time to Detection of Staphylococcal Enterotoxin A in Cooked Chicken Product. Front. Microbiol. 2018, 9, 1536. doi: 10.3389/fmicb.2018.01536.

Kapetanakou, AE., Taoukis, P., Skandamis, PN., 2019. Model development for microbial spoilage of packaged fresh–cut salad products using temperature and in-package CO2 levels as predictor variables. LWT, 113, 108285. https://doi.org/10.1016/j.lwt.2019.108285.

Li, Z., Wen, Y., Yan, Y., Ning, Y., Xie, M., Zhu, Y., & Wang, H. (2024). The kinetic study on key quality and microbial content of fresh-cutting Chinese yams (Dioscorea opposita Thunb.) at different storage temperatures. Journal of

Stored Products Research, 102251. https://doi.org/10.1016/j.jspr.2024.102251.

Li, Z.; Li, L.; Zhang, Y.; He, Q. Frozen Kinetics Models for Sensory, Chemical, and Microbial Spoilage of Preserved Razor Clam (Sinonovacula Constricta) at Different Temperatures. Int. J. Food Eng. 2020, 16, 20190288. https://doi.org/10.1515/ijfe-2019-0288.

McKellar, R. C., & Lu, X. (2004). Modeling microbial responses in food. CRC Press.

Mohd Ali, M.; Hashim, N.; Abd Aziz, S.; Lasekan, O. Shelf Life Prediction and Kinetics of Quality Changes in Pineapple (Ananas Comosus) Varieties at Different Storage Temperatures. Horticulturae 2022, 8, 992. https://doi.org/10.3390/horticulturae8110992.

Niu, Y.; Yun, J.; Bi, Y.; Wang, T.; Zhang, Y.; Liu, H.; Zhao, F. Predicting the Shelf Life of Postharvest Flammulina Velutipes at Various Temperatures Based on Mushroom Quality and Specific Spoilage Organisms. Postharvest Biol. Technol. 2020, 167, 111235. https://doi.org/10.1016/j.postharvbio.2020.111235.

Ray, B., & Bhunia, A. (2013). Fundamental food microbiology (5th ed.). CRC Press.

Ruan S, Zhu T, Zuo C, Peng J, Liu L, Lan W, Pan L, Tu K. Storage Properties and Shelf-Life Prediction of Fresh-Cut Radishes Treated by Photodynamic Technology. Foods. 2024 Jul 26;13(15):2367. doi: 10.3390/foods13152367. PMID: 39123557; PMCID: PMC11311309.

Tsironi, T.; Dermesonlouoglou, E.; Giannoglou, M.; Gogou, E.; Katsaros, G.; Taoukis, P. Shelf-Life Prediction Models for Ready-to-Eat Fresh Cut Salads: Testing in Real Cold Chain. Int. J. Food Microbiol. 2017, 240, 131–140. https://doi.org/10.1016/j.ijfoodmicro.2016.09.032.

Wang, J., and Guo, X. (2024). The Gompertz model and its applications in microbial growth and bioproduction kinetics: Past, present and future. Biotechnology Advances, 72, 108335. https://doi.org/10.1016/j.biotechadv.2024.108335.

Zwietering, M. H., Jongenburger, I., Rombouts, F. M., & van 't Riet, K. (1990). Modeling of the bacterial growth curve. Applied and Environmental Microbiology, 56(6), 1875–1881. https://doi.org/10.1128/aem.56.6.1875-1881.1990.