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Comparative Analysis of Exponential and Logistic Models on Population Growth (Case Study: Ogan Komering Ulu Regency)

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Abstract

Population growth is an important indicator in regional development planning because it is closely related to resource requirements, public service provision, and the formulation of socioeconomic policies. This study aims to analyze and compare the performance of the exponential and logistic models in projecting the population growth of Ogan Komering Ulu (OKU) Regency and to determine the most appropriate model based on the Mean Absolute Percentage Error (MAPE) criterion. This research employed a quantitative approach with a comparative descriptive method using secondary population data for the period 2014–2025 obtained from the Central Bureau of Statistics (BPS) of Ogan Komering Ulu Regency. Model parameter estimation was performed using the Generalized Reduced Gradient (GRG) optimization method through the Solver feature in Microsoft Excel, with the objective function of minimizing the MAPE value. The results indicate that both models exhibit a very high level of accuracy in representing the observed population dynamics. The exponential model produced a MAPE value of 0.4% with an estimated growth rate parameter of $r = 0.01$, whereas the logistic model yielded a MAPE value of 0.3% with estimated parameters of $r = 0.038$ and an optimized carrying capacity parameter (K). Although both models were classified as very accurate, the logistic model demonstrated slightly superior performance due to its lower prediction error and its ability to incorporate environmental carrying capacity into the population growth mechanism. Therefore, the logistic model was identified as the most suitable model for representing population growth in OKU Regency and is recommended for long-term population projections and regional development planning over future planning horizons extending beyond the observation period.

Keywords: Population Growth, Logistic Model, Exponential Model, Population Projection, Mathematical Modeling

1. Introduction

Population growth is an essential indicator in the development planning of a region, as it is closely related to resource needs, public services, and the formulation of economic and social policies. The dynamics of population size that occur over time are influenced by various factors, including birth rates, death rates, migration, environmental conditions, and resource availability. Therefore, a mathematical approach is required that can accurately represent population growth patterns to support effective decision-making, ensuring that formulated policies are more precisely targeted.

Mathematical modeling has proven to be an effective approach in analyzing and predicting population growth. Through mathematical modeling, the complex interactions between population dynamics and environmental factors can be represented systematically, thereby providing a clearer picture of the mechanisms underlying population growth. Among various mathematical approaches, the exponential model and the logistic model remain the most widely used methods in population growth analysis because they are able to describe both unrestricted and resource-limited population dynamics (Di & Xu, 2021; Al Mahkya et al., 2026).

The exponential model is a population growth model that describes ideal population development under environmental conditions that continue to increase without resource limitations (Kusuma Wardhana & Muhtadin, 2024). Projections using the exponential model indicate the potential for over-population in the long term. This model is more suitable for short-term projections and does not consider the maximum capacity of an area (Marbun et al., 2024). As an alternative, the logistic model was developed by incorporating the concept of carrying capacity, which limits population growth.

The logistic model accommodates the existence of population growth limits influenced by inhibiting factors, so that the population size does not undergo infinite growth. To date, the logistic model is still considered the model that most closely approximates empirical conditions or actual states (Anggreini, 2020). Determining the best model in population growth analysis requires objective evaluation measures. One widely used measure is the Mean Absolute Percentage Error (MAPE), because it can measure the prediction error rate in the form of a percentage, making it easy to interpret. A smaller MAPE value indicates that the model has a better level of accuracy in representing actual data (Kim & Kim, 2016).

Based on previous research, the comparison of exponential and logistic models reviewed from MAPE values shows that the logistic model produces lower prediction error rates. Research by Sulma and Nursamsi (2023) on population growth estimation in Bulukumba Regency shows that the logistic model is more accurate than the exponential model because its error value is smaller and its estimation results are closer to actual data. Similar results were also found in population projection research in the Special Region of Yogyakarta. Anggreini et al. (2023) showed that the carrying capacity based on the logistic model was 10,652,814 people, with a population growth rate of 0.02048. Based on the evaluation results using the MAPE value, the logistic model was deemed more suitable for describing population growth in the long term.

Research by Suryani and Khasanah (2022) on population projections for Riau Province shows that the logistic model produces a smaller error value compared to the exponential model, which is 1.91629, so the logistic model is considered better at representing long-term population growth. More recent studies have also consistently reported that logistic models outperform exponential models in long-term population projections. Al Mahkya et al. (2026), in their study of population growth in Central Lampung Regency, demonstrated that the logistic model optimized using the Generalized Reduced Gradient (GRG) method yielded lower prediction errors and more realistic projections than the exponential model. Comparative analyses conducted in several regions further indicated that logistic growth models generally provide predictions that are closer to empirical population data because they incorporate environmental carrying capacity constraints (Di & Xu, 2021; Anggreini et al., 2023). These findings strengthen the argument that logistic models are more appropriate for long-term demographic forecasting.

Population growth analysis and modeling are very important to support data-based decision-making processes, particularly at the regional level. Ogan Komering Ulu (OKU) Regency is one of the regions in South Sumatra Province that experiences year-to-year population growth dynamics that need to be analyzed quantitatively. Changes in population size in this region are influenced by various factors, such as birth rates, death rates, and population migration. To date, studies comparing the accuracy of exponential and logistic models in projecting population growth in this region are still limited.

OKU Regency is one of the strategic regencies in South Sumatra Province with demographic dynamics that continue to develop over time. Based on data from the Central Bureau of Statistics, the population of OKU Regency in 2025 was recorded at 386,816 people, which provides a significant contribution to the total population of South Sumatra Province. As a region with economic characteristics based on the agriculture, trade, and service sectors, OKU Regency shows demographic dynamics influenced by natural population growth, population mobility, as well as urban and rural development. These conditions make OKU Regency a relevant study area to be analyzed using a mathematical modeling approach.

Although population growth modeling studies have been conducted in several regions of Indonesia, most previous studies have focused on provinces or large urban areas, such as the Special Region of Yogyakarta, Riau Province, and Central Lampung Regency (Anggreini et al., 2023; Suryani & Khasanah, 2022; Al Mahkya et al., 2026). A preliminary literature search conducted through Google Scholar and indexed national journals using the keywords "population growth model", "exponential model", "logistic model", and "Ogan Komering Ulu Regency" did not identify any published studies specifically comparing exponential and logistic models for population projection in OKU Regency using data from 2014–2025. Therefore, empirical evidence regarding the most appropriate population growth model for this region remains unavailable, indicating a clear research gap.

Accordingly, this study addresses the following research questions: (1) How well do the exponential and logistic models represent the population growth pattern of OKU Regency during the 2014–2025 period? and (2) Which model provides the highest prediction accuracy based on the Mean Absolute Percentage Error (MAPE) criterion?

Therefore, this study aims to analyze and compare the exponential model and the logistic model in modeling the population growth of OKU Regency, as well as determining the most accurate model based on the MAPE value. The results of this study are expected to contribute to the development of population growth modeling methods and serve as a consideration for local governments in more effective development planning.

2. Methods

This research is a quantitative study with a comparative descriptive approach. The data used are secondary data in the form of the population of OKU Regency from 2014–2025 obtained from the Central Bureau of Statistics. Data analysis was carried out by comparing two population growth models, namely the exponential model and the logistic model, to determine the most suitable model in representing the population growth pattern of OKU Regency.

2.1 Exponential Model

The population growth model according to Malthus is known as the exponential growth model. This model is based on the assumption that the population growth rate is directly proportional to the population size at a certain time and is not influenced by environmental limiting factors, such as resource limitations, living space, or competition among individuals. Thus, the population is assumed to grow continuously following an exponential pattern over time. The concept of exponential population growth was first proposed by Thomas Robert Malthus in 1798, stating that population growth will increase geometrically if there are no environmental constraints (Siti Nurkholipah et al., 2017).

According to Irma Suryani & Nur Khasanah (2022), the population size at time t is denoted by N(t), then the population size at time t_0 is N_0, with constant birth and death rates b and d, and the population growth rate is denoted by r, where k = b − d, then the exponential model is written as follows:

$$\frac{dN(t)}{dt} = rN(t)$$

The solution of Equation (1) is as follows:

$$N(t) = N_0 e^{rt}$$

2.2 Logistic Model

The logistic model is an improvement of the exponential model and was first introduced by Pierre Verhulst in 1838. Verhulst showed that the population growth rate depends not only on the current population size but also on how close the population is to the upper limit that can be supported by the environment, known as the carrying capacity (Siti Nurkholipah et al., 2017). The logistic equation is as follows:

$$\frac{dN(t)}{dt} = rN\left(1 - \frac{N}{K}\right)$$

The particular solution of Equation (3) is:

$$N = \frac{K}{e^{-rt}\left(\frac{K}{N_0} - 1\right) + 1}$$

Equation (4) represents a simplified form of the particular solution of the logistic model that will be used as the basic model in projecting the population.

2.3 Determination of Carrying Capacity (K)

In the logistic model, the carrying capacity parameter (K) represents the maximum population that can be sustainably supported by the environment under existing socioeconomic and environmental conditions. The determination of K is an important stage because it strongly influences the shape of the population growth curve and the estimated intrinsic growth rate.

In this study, the carrying capacity parameter was not determined arbitrarily. Instead, K was estimated simultaneously with the intrinsic growth rate parameter (r) using the Generalized Reduced Gradient (GRG) Nonlinear optimization method available in Microsoft Excel Solver. This approach allows the optimization process to identify the combination of parameter values that minimizes the Mean Absolute Percentage Error (MAPE) between the observed population data and the model predictions.

The simultaneous estimation of r and K through nonlinear optimization has been widely applied in demographic and ecological studies because it provides more objective parameter estimates and reduces subjectivity in specifying carrying capacity values (Tjørve & Tjørve, 2017; Kumar & Kostina, 2024). The optimization process was constrained such that K must always be greater than the maximum observed population during the study period, ensuring biological and demographic plausibility.

To evaluate the robustness of the logistic model, a sensitivity analysis was conducted by varying the carrying capacity parameter around the optimal value obtained from the GRG optimization. Specifically, K values within ±10% and ±20% of the optimal estimate were tested, and the resulting MAPE values were compared. This analysis was performed to examine the stability of the model predictions against changes in carrying capacity and to ensure that the model conclusions were not highly sensitive to a single parameter value.

2.4 Parameter Estimation and GRG Optimization

Parameter estimation in this study was carried out using the Generalized Reduced Gradient (GRG) Nonlinear method through the Solver feature in Microsoft Excel. This method is one of the gradient-based nonlinear optimization techniques used to obtain optimal parameter values by minimizing the objective function, which in this study is the Mean Absolute Percentage Error (MAPE). The solver-based parameter optimization approach is still widely used in recent studies because it has good capability in handling nonlinear models and differential equations (Kumar & Kostina, 2024). The optimization process was carried out using the Solver feature in Microsoft Excel, which has been widely applied in estimating nonlinear model parameters (Barati, 2013).

For the exponential model, only the intrinsic growth rate parameter (r) was estimated. In contrast, for the logistic model, both the intrinsic growth rate parameter (r) and the carrying capacity parameter (K) were estimated simultaneously during the optimization process. This simultaneous estimation allows the model to determine the most appropriate carrying capacity directly from the observed population data by minimizing the MAPE value.

The initial value of the growth rate parameter (r) in the exponential model was obtained based on actual population data. The exponential model assumes that the rate of change of the population is proportional to the population at a certain time, which is expressed as:

$$\frac{dN(t)}{dt} = rN(t)$$

From Equation (5), the parameter r can be expressed as:

$$r = \frac{\frac{dN}{dt}}{N(t)}$$

Since the data used are annual data, the first derivative with respect to time is approximated using the finite difference method, namely:

$$\frac{dN}{dt} \approx \frac{N_{(t)} - N_{(t-1)}}{\Delta t}$$

Thus, Equation (6) can be written as:

$$r = \frac{\frac{N_{(t)} - N_{(t-1)}}{\Delta t}}{N(t)}$$

Since the time interval used is one year, then $\Delta t = 1$, so it is obtained:

$$r = \frac{N_{(t)} - N_{(t-1)}}{N(t)}$$

Furthermore, for the logistic model, the estimation of the initial value of parameter r is calculated based on the logistic growth model that considers the value of K, namely:

$$\frac{dN}{dt} = rN(1 - \frac{N}{K})$$

Based on Equation (10), the parameter r can be written as:

$$r = \frac{\frac{dN}{dt}}{N_{(t)}\,(1 - \frac{N_{(t)}}{K})}$$

By using the finite difference approach for annual data, it is obtained:

$$r = \frac{\frac{N_{(t)} - N_{(t-1)}}{\Delta t}}{N_{(t)}\,(1 - \frac{N_{(t)}}{K})}$$

Since Δt = 1, then Equation (12) is simplified to:

$$r = \frac{N_{(t)} - N_{(t-1)}}{N_{(t)}\,(1 - \frac{N_{(t)}}{K})}$$

The values of r obtained in each period are then averaged and used as initial values in the parameter optimization process using the GRG Nonlinear method through the Solver feature in Microsoft Excel. The optimization is carried out by minimizing the MAPE value, which is formulated as:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{N_{(t)} - \bar{N}_{(t)}}{N_{(t)}}\right| \times 100\%$$

where (N_t) is the actual population at time (t), and (\hat{N}_t) is the predicted population obtained from the model.

To evaluate the robustness of the logistic model, a sensitivity analysis was conducted on the carrying capacity parameter (K). After obtaining the optimal value of (K), additional simulations were performed by varying (K) within ±10% and ±20% of its optimal estimate. The resulting MAPE values were then compared to assess the stability of the model predictions and to ensure that the conclusions were not highly sensitive to a single carrying capacity value.

The comparison of the two models was based on the level of agreement between the predicted and actual population values. Model performance was evaluated using MAPE, which measures the magnitude of deviation between model predictions and actual observations in percentage form. The interpretation of MAPE values is presented in Table 1.

Table 1. MAPE Interpretation

MAPE Value	MAPE Interpretation
$\text{MAPE} < 10\%$	Very Accurate
$10\% \leq \text{MAPE} < 15\%$	Very Good
$15\% \leq \text{MAPE} < 20\%$	Good
$20\% \leq \text{MAPE} < 50\%$	Reasonable
$\text{MAPE} > 50\%$	Not Accurate

The smaller the MAPE value obtained, the higher the accuracy level of the model. Therefore, the model with the smallest MAPE value was selected as the best model for representing the population growth pattern of OKU Regency.

2.5 Research Stages

The research stages are carried out systematically as follows:

1) Data collection. Population data of OKU Regency from 2014–2025 are obtained from BPS OKU Regency as actual data.
2) Data preparation and processing. The data are arranged and processed in the form of a time series using Microsoft Excel software.
3) Calculation of actual growth rate. The annual growth rate value (r_i) is obtained from two consecutive years of data using Equation (9) for the exponential model and Equation (12) for the logistic model. Then, the values are averaged as the initial value of parameter r in the optimization process.
4) Parameter optimization with Excel Solver GRG. The initial value of r is used as the starting point in the Solver feature of Microsoft Excel. For the exponential model, parameter r is optimized by minimizing the MAPE value. For the logistic model, both parameters r and K are simultaneously optimized using the GRG Nonlinear method with the objective function of minimizing the MAPE value. The optimization is constrained so that the carrying capacity parameter K remains greater than the maximum observed population value.
5) Sensitivity analysis of carrying capacity. After obtaining the optimal value of K, a sensitivity analysis is performed by varying K within ±10% and ±20% of its optimal value. The corresponding MAPE values are then compared to evaluate the robustness and stability of the logistic model.
6) Calculation of population based on the model. The optimal parameter values resulting from the optimization process are substituted into Equation (2) for the exponential model and Equation (4) for the logistic model to obtain population projection results.
7) Model evaluation and comparison. The performance comparison of the two models is evaluated using the MAPE value based on the criteria in Table 1. The model with the smallest MAPE value is selected as the best model.

3. Result and Discussion

Based on secondary data obtained from the Central Bureau of Statistics of OKU Regency, the population during the period 2014–2025 is presented in Table 2, with the population at time t, calculated starting from 2014, denoted as N(t). Furthermore, modeling was carried out to identify the population growth pattern and to compare the level of suitability of the exponential model and the logistic model to the available actual data.

Table 2. Population Data of Ogan Komering Ulu Regency for the Years 2014–2025

Year	t-th Year	$N(t)(population)$
2014	0	344.932
2015	1	349.787
2016	2	354.488
2017	3	359.092
2018	4	364.260
2019	5	368.756
2020	6	367.603
2021	7	371.106
2022	8	375.538
2023	9	379.130
2024	10	383.039
2025	11	386.816

Based on Table 2, the population of OKU Regency during the period 2014–2025 shows a relatively increasing growth pattern. The population increased gradually from 344,932 people in 2014 to 386,816 people in 2025. However, in 2020 there was a slight decrease compared to the previous year, from 368,756 people to 367,603 people. This small decrease in 2020 does not change the general trend of population growth. After this period, the population again shows a relatively stable pattern until the end of the observation period, with an average increase of around 4,000–5,000 people per year. This pattern indicates that the data have a trend suitable for analysis using exponential and logistic models.

3.1 Exponential Model

Before the optimization process was carried out, the initial value of parameter r was first calculated based on the data in Table 2 using Equation (9). The results of this calculation are presented in the following table.

Table 3. Values of r from the exponential model equation

Year	$N(t)(population)$	$r_{\text{exponential Model}}$
2014	344.932	0
2015	349.787	0,01388
2016	354.488	0,01326
2017	359.092	0,01282
2018	364.260	0,01419
2019	368.756	0,01219
2020	367.603	-0,00314
2021	371.106	0,00944

2022	375.538	0,01180
2023	379.130	0,00947
2024	383.039	0,01021
2025	386.816	0,00976
	r rata-rata =	0,01

The average value of r obtained was then used as the initial value in the parameter optimization process using the GRG method. The optimization results using the Solver feature in Microsoft Excel show that the optimal growth rate value is r = 0.01 per year, with a MAPE value of 0.4%. Based on this parameter value, the exponential model equation for OKU Regency with base year 2014 can be written as follows:

$$N(t) = 344.932\, e^{0,01t}$$

The comparison between the actual data from BPS and the prediction results of the exponential model is presented in Table 4.

Table 4. Comparison between Actual Data and Exponential Model Prediction Results

Year	BPS Data (Population)	Model Prediction (Population)	Difference
2014	344.932	344.932	0,00
2015	349.787	348.574	1.212,90
2016	354.488	352.255	2.233,34
2017	359.092	355.974	3.117,92
2018	364.260	359.733	4.527,22
2019	368.756	363.531	5.224,84
2020	367.603	367.370	233,35
2021	371.106	371.249	142,67
2022	375.538	375.169	369,35
2023	379.130	379.130	0,01
2024	383.039	383.133	94,21
2025	386.816	387.179	362,67

Furthermore, the actual data and the predicted values of the exponential model are plotted in graphical form to evaluate the level of model suitability to the observed data. The plot results are shown in Figure 1.

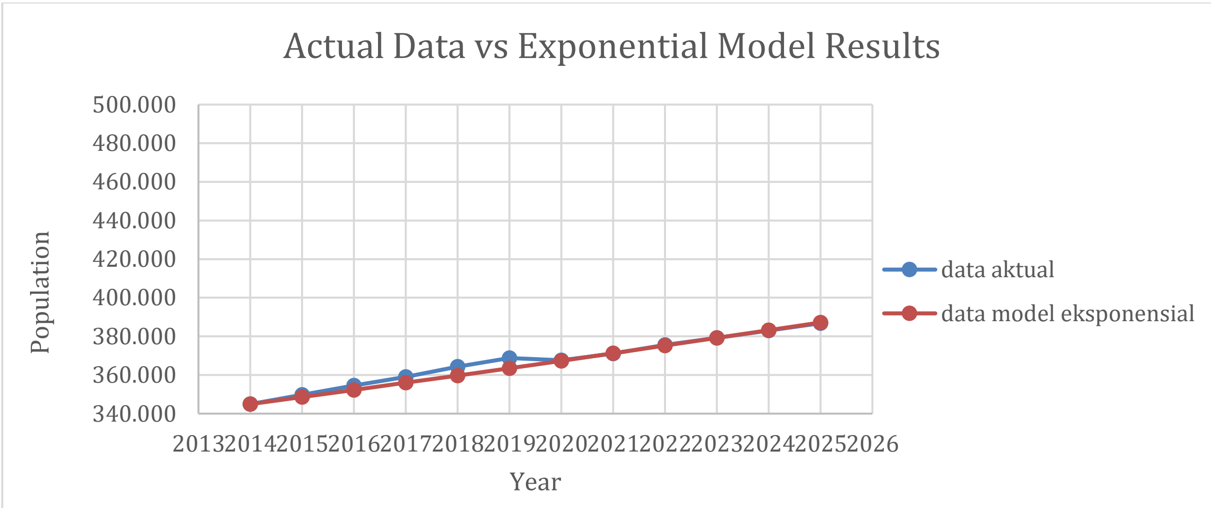

Figure 1. Comparison between Actual Data and Exponential Model Prediction Results

Based on Figure 1, the exponential model shows a very high level of agreement with the observed population data, as indicated by the MAPE value of 0.4%, which is categorized as very accurate according to the criteria in Table 1. The predicted and observed curves almost overlap throughout the observation period, indicating that the model adequately captures the short-term growth trend. This finding is consistent with previous studies reporting that exponential models may provide satisfactory performance for short- to medium-term projections when population growth remains relatively stable and environmental constraints have not yet become dominant (Marbun et al., 2024).

However, the exponential model assumes a constant growth rate and unlimited resource availability, implying that population growth continues indefinitely. Such assumptions may become unrealistic in long-term demographic projections because population growth is generally influenced by environmental, socioeconomic, and infrastructural constraints. Consequently, although the exponential model performs well within the observed period, its applicability may decrease for long-term forecasting where carrying capacity effects become increasingly important.

3.2 Logistic Model

As in the exponential model, the initial step in the logistic model is to determine the value of parameter r based on actual data using Equation (12). The results of these calculations are presented in the following table.

Table 5. Values of r from the logistic model equation

Year	$N(t)(Population)$	r logistic model
2014	344.932	0
2015	349.787	0,04620
2016	354.488	0,04557
2017	359.092	0,04550
2018	364.260	0,05226
2019	368.756	0,04645
2020	367.603	-0,01185
2021	371.106	0,03662
2022	375.538	0,04741
2023	379.130	0,03919
2024	383.039	0,04363
2025	386.816	0,04313
	r mean =	0,039

Based on Table 5, a decline in population occurred during the 2019–2020 period, as indicated by the negative growth rate value (r = -0.01185). The population decreased from 368,756 people in 2019 to 367,603 people in 2020. This decline coincides with the global COVID-19 pandemic, which significantly affected demographic dynamics in many regions, including Indonesia. The pandemic potentially contributed to increased mortality rates, reduced birth rates, restrictions on population mobility, and changes in migration patterns. Therefore, the temporary decline observed in 2020 may not solely reflect normal demographic fluctuations but also extraordinary external disturbances associated with the pandemic.

The inclusion of this anomalous period in the dataset provides an opportunity to evaluate the robustness of both models under non-normal demographic conditions. Despite the population decline in 2020, both models were still able to maintain high predictive accuracy, indicating that the estimated parameters remain sufficiently robust in representing the overall population growth pattern of OKU Regency.

Based on these results, the logistic model equation representing the dynamics of population growth in OKU Regency can be formulated as follows:

$$N(t) = \frac{500.000}{1{,}449e^{-0.038t} + 1}$$

The comparison between the actual data from BPS and the prediction results of the logistic model is presented in Table 6 below.

Table 6. Comparison of Actual Data and Logistic Model Results

Year	BPS Data (Population)	Model Prediction (Population)	Difference
2014	344.932	344.932	0,00
2015	349.787	349.039	747,74
2016	354.488	353.084	1.403,93
2017	359.092	357.065	2.027,12
2018	364.260	360.980	3.279,70
2019	368.756	364.829	3.926,93
2020	367.603	368.610	1.007,07
2021	371.106	372.322	1.216,32
2022	375.538	375.965	426,97
2023	379.130	379.537	407,33
2024	383.039	383.039	0,19
2025	386.816	386.469	347,05

Furthermore, the actual data and the predicted values of the logistic model are plotted in graphical form to evaluate the level of model suitability to the observed data. The plot results are shown in Figure 2.

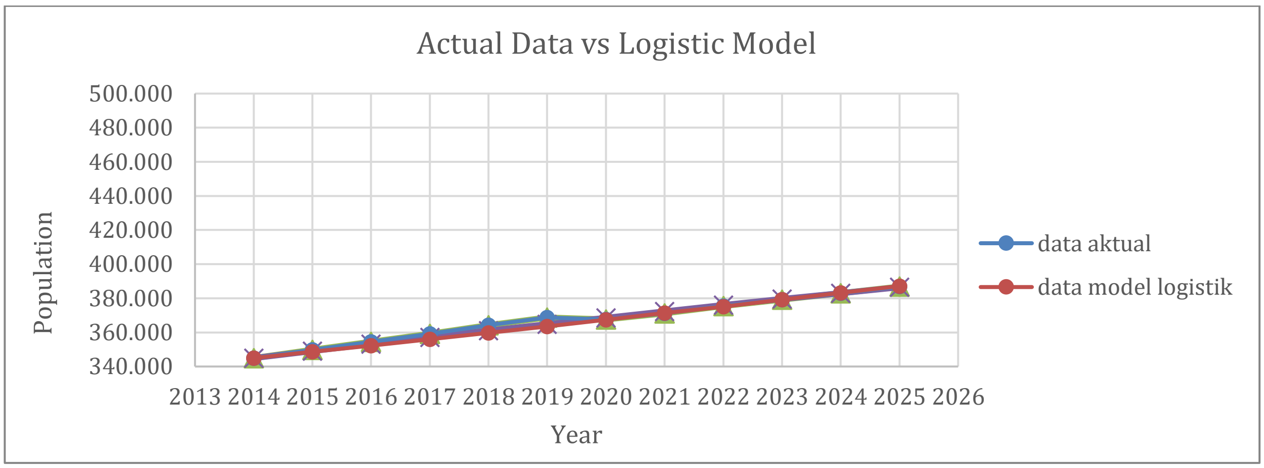

Figure 2. Comparison of Actual Data and Logistic Model Results

Based on Table 6, the logistic model produces a MAPE value of 0.3%, which is categorized as very accurate according to the criteria in Table 1. Figure 2 also demonstrates that the logistic curve closely follows the observed population trajectory throughout the study period. The superior performance of the logistic model is not merely reflected by its lower MAPE value but can also be explained mechanistically.

Unlike the exponential model, the logistic model incorporates the carrying capacity parameter (K), which represents environmental and socioeconomic limitations affecting population growth. As the population size approaches the carrying capacity, the growth rate gradually decreases, resulting in a sigmoidal growth pattern. This mechanism allows the logistic model to adapt more effectively to changes in growth trends and to represent decelerating population growth. Consequently, the logistic model can better capture realistic demographic processes, particularly when population growth begins to slow due to limitations in resources, infrastructure, land availability, or other environmental constraints.

The leveling-off pattern observed at the end of the study period suggests that the population growth rate in OKU Regency has started to decelerate. Therefore, incorporating carrying capacity into the model provides a more realistic representation of long-term population dynamics.

3.3 Comparison between Exponential Model and Logistic Model Results

After data processing, different results were obtained between the exponential model and the logistic model. The differences between the two models are presented in the following table.

Table 7. Comparison of Parameter Values and Accuracy Levels of Exponential and Logistic Models

Parameter/Indicator	Exponential Model	Logistic Model
Growth Rate (r)	0.01 per year	0.038 per year
Carrying Capacity (K)	Does not consider carrying capacity	500,000 population
MAPE	0.4%	0.3%
Accuracy Criteria	Very Accurate	Very Accurate
Long-Term Growth Trend	Growth increases without limit	Growth slows as it approaches carrying capacity (K)

Based on Table 7, both models exhibit very high levels of accuracy, with MAPE values of 0.4% for the exponential model and 0.3% for the logistic model. According to the criteria presented in Table 1, both models are categorized as very accurate in representing the population growth pattern of OKU Regency. Nevertheless, the logistic model demonstrates a slightly lower MAPE value, indicating a better fit to the observed population data.

The superior performance of the logistic model cannot be explained solely by the difference in MAPE values. Mechanistically, the logistic model incorporates the carrying capacity parameter (K), which reflects environmental and socioeconomic constraints affecting population growth. Consequently, the logistic model allows the growth rate to gradually decrease as the population approaches the carrying capacity, producing a sigmoidal growth pattern that is more consistent with real demographic processes. In contrast, the exponential model assumes unlimited resources and a constant growth rate, resulting in continuous population growth without upper limits. Such assumptions may become unrealistic in long-term demographic projections because population growth is generally constrained by factors such as land availability, infrastructure capacity, economic conditions, and environmental resources.

The difference between the estimated growth rate parameters in the exponential and logistic models should not be interpreted as a direct numerical comparison because the two parameters have fundamentally different mathematical meanings. In the exponential model, parameter r represents a constant per-capita growth rate under the assumption of unlimited environmental resources. Conversely, in the logistic model, parameter r denotes the intrinsic maximum growth rate that occurs when population size is far below the carrying capacity. As the population approaches K, the effective growth rate decreases due to the term $(1 - N/K)$ in the logistic equation. Therefore, the larger value of r obtained in the logistic model (0.038) does not necessarily imply faster actual population growth compared with the exponential model (0.01). Instead, it represents the maximum growth potential of the population under ideal conditions before environmental constraints become significant.

The findings of this study are consistent with previous studies reporting that logistic models generally outperform exponential models in long-term population projections because they account for carrying capacity limitations (Anggreini et al., 2023; Al Mahkya et al., 2026). However, several studies have also shown that exponential models may provide comparable or even superior performance for short- to medium-term projections, particularly when population growth remains relatively stable and environmental constraints are not yet dominant (Marbun et al., 2024). Therefore, model selection should not rely solely on statistical indicators but should also consider the projection horizon, demographic characteristics, and theoretical assumptions underlying each model.

Although both models demonstrate high predictive accuracy, this study did not incorporate confidence intervals or uncertainty bounds in the model predictions. Consequently, the projected values should be interpreted as point estimates rather than exact forecasts. Future studies are recommended to employ statistical approaches such as bootstrap resampling, Monte Carlo simulation, or Bayesian parameter estimation to quantify uncertainty and generate prediction intervals. Incorporating uncertainty analysis would improve the scientific robustness and reliability of demographic projections.

Overall, the results indicate that the logistic model provides a more realistic representation of the population dynamics of OKU Regency because it not only produces the smallest prediction error but also incorporates environmental carrying capacity into the population growth mechanism. Considering the observed tendency of population growth to gradually decelerate during the study period, the logistic model is recommended for long-term population projection and regional development planning in OKU Regency.

4. Conclusion

This study compared the performance of exponential and logistic models in representing the population growth of Ogan Komering Ulu (OKU) Regency during the period 2014–2025. The findings indicate that both models are capable of accurately describing the observed population dynamics, as evidenced by MAPE values below 1%, namely 0.4% for the exponential model and 0.3% for the logistic model. Although both models are classified as very accurate, the logistic model provides a slightly better fit to the observed data.

The superior performance of the logistic model is not only reflected in its lower prediction error but also in its ability to incorporate environmental carrying capacity into the population growth mechanism. Consequently, the logistic model offers a more realistic representation of long-term demographic dynamics, particularly when population growth tends to decelerate as environmental and socioeconomic constraints become increasingly important. Therefore, the logistic model is considered more appropriate for supporting long-term population projections and regional development planning in OKU Regency.

Nevertheless, this study has several limitations. First, although the carrying capacity parameter (K) was estimated through GRG optimization, the estimation relied solely on historical population data and did not explicitly incorporate environmental, land-use, or resource availability indicators. Second, the model evaluation was limited to in-sample data using MAPE, without performing out-of-sample validation to assess predictive performance under future conditions. Third, the parameter estimation process employed only the Microsoft Excel Solver with the GRG Nonlinear algorithm, whereas alternative optimization techniques may provide different parameter estimates and uncertainty characteristics. In addition, uncertainty bounds or confidence intervals were not included in the population projections.

Future research is recommended to integrate demographic components such as migration, fertility, and mortality into population growth models to obtain more comprehensive projections. Further studies may also employ stochastic or Bayesian modeling approaches to quantify prediction uncertainty, conduct out-of-sample validation, and compare various optimization techniques. Moreover, extending the analysis to the sub-district level within OKU Regency would provide more detailed information to support localized development planning and population policy formulation.

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