RESEARCH ARTICLE • OPEN ACCESS

Forecasting the Consumer Price Index with Holt-Winters: A Comparative Study of Ordinary Least Squares and Maximum Likelihood Estimation

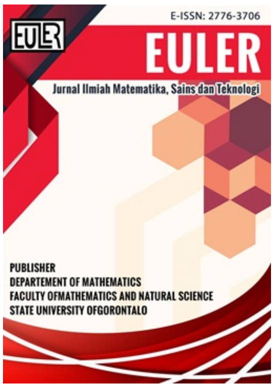
Esra Rombeallo and Marvin Jecson Pandu

Volume 14, Issue 1, Pages 117–127, April 2026

Received 12 February 2026, Revised 9 April 2026, Accepted 14 April 2026, Published 18 April 2026

To Cite this Article : E. Rombeallo and M. J. Pandu,"Forecasting the Consumer Price Index with Holt-Winters: A Comparative Study of Ordinary Least Squares and Maximum Likelihood Estimation", *Euler J. Ilm. Mat. Sains dan Teknol.*, vol. 14, no. 1, pp. 117–127, 2026, *https://doi.org/10.37905/euler.v14i1.37783*

JOURNAL INFO • EULER : JURNAL ILMIAH MATEMATIKA, SAINS DAN TEKNOLOGI



Homepage	:	http://ejurnal.ung.ac.id/index.php/euler/index
Journal Abbreviation	:	Euler J. Ilm. Mat. Sains dan Teknol.
Frequency	:	Three times a year
Publication Language	:	English (preferable), Indonesia
DOI	:	https://doi.org/10.37905/euler
Online ISSN	:	2776-3706
License	:	Creative Commons Attribution-NonCommercial 4.0 International License
Publisher	:	Department of Mathematics, Universitas Negeri Gorontalo
Country	:	Indonesia
OAI Address	:	http://ejurnal.ung.ac.id/index.php/euler/oai
Google Scholar ID	:	QF_r-_gAAAAJ
Email	:	euler@ung.ac.id

Euler : Jurnal Ilmiah Matematika, Sains dan Teknologi, Volume 14, Issue 1, Pages 117–127, April 2026 *https://doi.org/10.37905/euler.v14i1.37783*

Research Article

Check for updates

Forecasting the Consumer Price Index with Holt-Winters: A Comparative Study of Ordinary Least Squares and Maximum Likelihood Estimation

Esra Rombeallo[1,*], **Marvin Jecson Pandu**[1]

[1] *Department of Dryland Agricultural Management, Politeknik Pertanian Negeri Kupang, Kupang 85011, Indonesia*

ARTICLE HISTORY
Received 12 February 2026
Revised 9 April 2026
Accepted 14 April 2026
Published 18 April 2026

KEYWORDS
Holt-Winters
Ordinary Least Squares
Maximum Likelihood Estimation
Consumer Price Index
Time Series Forecasting

ABSTRACT. *The Consumer Price Index (CPI) is a crucial macroeconomic indicator reflecting regional inflationary pressures. This study aims to compare the performance of Ordinary Least Squares (OLS) and Maximum Likelihood Estimation (MLE) methods in estimating Holt-Winters model parameters for forecasting the CPI of East Nusa Tenggara (NTT) Province. Using monthly data from January 2021 to December 2025, the research evaluates two primary approaches: conventional OLS based Holt-Winters models and the MLE based Error, Trend, and Seasonal (ETS) framework. Model performance was assessed using the Mean Absolute Percentage Error (MAPE). The results demonstrate that the MLE based approach significantly outperforms OLS; the multiplicative ETS model achieved the lowest MAPE of 0.57%, proving far more accurate than the OLS based Holt-Winters models, which yielded error rates exceeding 50%. A 12-month forecast for 2026 projects NTT CPI to increase moderately from 107.38 to approximately 109.54, indicating controlled inflationary pressure. This study affirms the superiority of the MLE approach in generating precise parameters for economic data exhibiting seasonal patterns.*

1. Introduction

Price stability is one of the primary foundations of national macroeconomic policy. In the Indonesian context, the Consumer Price Index (CPI) serves as the most representative instrument for measuring inflation, as it reflects average price changes in the goods and services consumed by households during a given period. Statistics Indonesia (Badan Pusat Statistik, BPS) consistently publishes monthly CPI data as a reference for policymakers at both central and regional levels in designing fiscal, monetary, and distribution strategies. East Nusa Tenggara Province (NTT) possesses unique economic characteristics compared with other Indonesian provinces. As an archipelagic region with high dependence on inter-island supply chains, price fluctuations in NTT are driven by structural factors such as transportation costs, logistical infrastructure constraints, and highly seasonal agricultural production patterns [1]. These conditions make CPI forecasting in NTT both a methodological challenge and an urgent policy need.

Time series forecasting has evolved rapidly as a trusted quantitative tool in economics and applied statistics. Among the available methods, the Holt-Winters model also known as Triple Exponential Smoothing stands out for its ability to simultaneously capture trend and seasonal components within data [2]. The model has two principal variants: the additive model, which assumes a constant seasonal amplitude, and the multiplicative model, which assumes seasonal amplitude proportional to the level of the time series.

*Corresponding Author.

Email : *esra.rombeallo@staff.politanikoe.ac.id* (E. Rombeallo)
Homepage : http://ejurnal.ung.ac.id/index.php/euler/index / E-ISSN : 2776-3706

A critical aspect of implementing the Holt-Winters model is the estimation of the smoothing parameters α (level), β (trend), and γ (seasonality). Two principal approaches are commonly employed: Ordinary Least Squares (OLS), which minimises the sum of squared errors, and Maximum Likelihood Estimation (MLE), which maximises the log-likelihood function based on a probabilistic distribution of the residuals [3, 4]. The choice of estimation method has significant implications for forecast quality; however, empirical comparisons between these two approaches in the context of CPI data from archipelagic regions remain relatively limited in the literature [5, 6].

Several prior studies have explored the application of the Holt-Winters method to various types of economic data. The superiority of MLE-based ETS models in handling demand data with strong seasonal components has been demonstrated [7]. A comprehensive review affirmed that the choice of parameter estimation method significantly affects prediction intervals and short-term forecast accuracy [8]. At the national level, preliminary evidence on the performance of Holt-Winters for regional inflation data in Indonesia was provided, though OLS and MLE were not compared in a systematic manner [9–12].

A number of prior studies have examined the application of Holt-Winters and ETS models to CPI and inflation data. The application of ETS models to Indonesian inflation data found that multiplicative models consistently outperformed additive ones for data with proportional seasonal patterns [13, 14]. A similar approach was employed for COVID-19 data, concluding that ETS(M,A,M) yielded the best MAPE [15]. Furthermore, a comparison of Holt-Winters and ARIMA on CPI data from Central Java found that Holt-Winters was superior for data with strong seasonality [16]. Internationally, it has been affirmed that the choice of estimation method is one of the principal determinants of exponential smoothing model quality [17, 18].

Based on several previous studies, the Holt-Winters method has been widely applied for CPI forecasting across various regions in Indonesia; however, these studies generally utilize a single estimation approach without systematically comparing OLS and MLE. Consequently, this study was conducted to compare OLS and MLE estimations within the Holt-Winters framework. The study is designed to: (1) identify the statistical characteristics of monthly CPI data for NTT over the period 2021–2025; (2) estimate Holt-Winters model parameters using OLS and MLE in parallel; (3) evaluate and compare the accuracy of both approaches; and (4) generate CPI forecasting for NTT for 2026.

2. Methods

2.1. Data Sources and Description

The data used in this study consist of monthly CPI figures for Kupang City as a representative of NTT Province, obtained from official publications of the BPS Nusa Tenggara Timur Provincial Office [19]. The dataset spans the period from January 2021 to December 2025, comprising 60 observations with base year 2022=100. The data represent price changes across seven major expenditure groups: food, beverages, and tobacco; clothing and footwear; housing and utilities; household equipment; health; transportation; and information, communication, and financial services. All analyses were performed using *RStudio* version 4.5.0. Packages employed include: *stats* for the *HoltWinters()* function and ADF test; *forecast* version 8.21 for *ets()*, *tsCV()*, and *accuracy()*; *tseries* for the ADF test; and *ggplot2* for data visualisation. Manual parameter optimisation was conducted using the L-BFGS-B method via the *optim()* function.

2.2. The Holt-Winters Model and ETS Variants

The Holt-Winters model (Winters, 1960) extends Double Exponential Smoothing by incorporating a seasonal component. Within the ETS (Error, Trend, Seasonality) notation developed by [20], this model is represented as ETS(A,A,A) for the fully additive variant and as ETS(M,A,M) for the variant with multiplicative errors and seasonality. For the additive ETS(A,A,A) model, the component update equations are as follows:

$$\text{Level}: \; l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}), \tag{1}$$
$$\text{Trend}: \; b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}, \tag{2}$$
$$\text{Seasonal}: \; s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}, \tag{3}$$

where m is the seasonal period length ($m = 12$ for monthly data), $\alpha, \beta, \gamma \in (0, 1)$ are the smoothing parameters, and y_t is the observed value at time t [2].

The multiplicative ETS(M,A,M) model employs an analogous structure but with multiplicative interactions between components. This variant is more appropriate for data in which the seasonal amplitude changes proportionally to the level, as is commonly observed in price data experiencing growth [21].

2.3. Estimation Methods

OLS estimation in the Holt-Winters context works by finding values of α, β, and γ that minimise the Sum of Squared Errors (SSE) across all in-sample periods. This approach requires no assumption about the residual distribution and is computationally direct. The standard implementation in *R* uses the *HoltWinters()* function from the *stats* package [22].

MLE, by contrast, maximises the log-likelihood function,

$$L(\theta|y) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum e_t^2. \tag{4}$$

Eq. (4) assumes i.i.d. normally distributed residuals. This approach is implemented via the *ets()* function in the *forecast* package [20] or the *fable* package within the *tidyverts* ecosystem [2, 23]. MLE theoretically yields estimators that are consistent and asymptotically efficient when the distributional assumptions are satisfied [2].

The fundamental differences between OLS and MLE in the context of exponential smoothing models have been examined by [24, 25]. They demonstrated that parameter initialisation and the handling of the warm-up period (backcasting) significantly affect estimation quality, particularly for data with strong seasonal components. MLE via *ets()* employs backcasting initialisation by default, which tends to produce more stable estimates for seasonal data.

2.4. Forecast Evaluation Criteria

Model accuracy is assessed through multiple metrics, each with distinct characteristics and sensitivities. MAPE (Mean Absolute Percentage Error) is the most intuitive metric because it is unit-independent and readily interpretable in a policy context. [26] established the following MAPE accuracy classifications in Table 1.

RMSE is more sensitive to outliers and is well suited for comparing models on the same data scale. For model selection, the information criteria AIC and BIC provide parsimony considerations by penalising model complexity [27, 28].

2.5. Analytical Procedures

The analysis was conducted in several systematic stages:

Table 1. Accuracy Classifications of MAPE

Classification	Value
Highly accurate	$< 10\%$
Good	$10\% - 20\%$
Reasonable	$20\% - 50\%$
Inaccurate	$> 50\%$

1. Data exploration was performed, encompassing time series visualisation, descriptive statistical analysis, and seasonal decomposition to identify trend and seasonal patterns.
2. Stationarity testing was carried out using the Augmented Dickey–Fuller (ADF) test, with the null hypothesis of a unit root [29].
3. Holt-Winters model parameters were estimated in parallel using OLS (*HoltWinters()* function) and MLE (*ets()* function) for both additive and multiplicative model variants.
4. Model accuracy was evaluated in-sample using MAE, RMSE, MAPE, and sMAPE, and out-of-sample via time series cross-validation using the *tsCV()* function with a minimum training window of 36 observations.
5. The best performing model was used to generate a 12-month forecast (January–December 2026) together with 80% and 95% confidence intervals.

3. Results and Discussion

3.1. Descriptive Statistics

The Consumer Price Index (CPI) of East Nusa Tenggara Province dataset for the period January 2021–December 2025 comprises 60 monthly observations. Summary descriptive statistics are presented in Table 2.

Table 2. Descriptive Statistics of NTT CPI (January 2021–December 2025)

Statistic	Value
Number of Observations	60 months (Jan 2021–Dec 2025)
Minimum	104.31
First Quartile (Q1)	105.70
Median	107.50
Mean	108.60
Third Quartile (Q3)	111.80
Maximum	115.53
Standard Deviation	3.597
Coefficient of Variation	3.31%

Based on Table 2, a coefficient of variation of 3.31% indicates that the NTT CPI during the observation period was relatively homogeneous, with no extreme fluctuations. The value range of 104.31 to 115.53 reflects a consistent and moderate price increase, in line with the controlled national inflation trend in the post-COVID-19 period. The relatively small difference between the median (107.50) and the mean (108.60) suggests a nearly symmetrical distribution, indicating the absence of extreme price distortions in the data. The trend trajectory of the NTT CPI over the observation period is presented in Figure 1.

Figure 1 shows the fluctuation of the NTT CPI during 2021–2025, characterised by a sharp upward trend that peaked above 114 towards the end of 2023 before experiencing a sudden sharp decline in early 2024. This abrupt drop is most likely attributable to a technical adjustment, specifically a rebasing of the price index by the statistical authority, followed by a

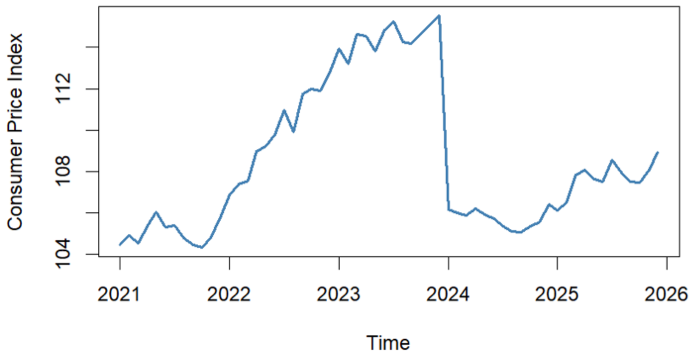


Figure 1. Consumer Price Index of East Nusa Tenggara Province, 2021-2025

moderate recovery trend rising to approximately 109 by the end of 2025. The jagged pattern of the series also indicates the presence of regular seasonal fluctuations in the movement of goods and services prices in the region.

3.2. Stationarity Test (ADF Test)

The Augmented Dickey–Fuller (ADF) test was conducted to determine whether the NTT CPI series is stationary or contains a unit root. The purpose of the Augmented Dickey–Fuller (ADF) test is to determine whether time series data is stationary or not. Results are presented in Table 3.

Table 3. ADF Test Results for NTT CPI Data

Parameter	Value
Dickey–Fuller Statistic	-1.6349
Lag Order	3
p-value	0.7223
Conclusion	Series is NON-STATIONARY (unit root present)

Based on Table 3, the p-value of 0.7223 significantly exceeds the significance threshold of $\alpha = 0.05$, leading to a failure to reject H_0 (the presence of a unit root). This confirms that the NTT CPI time series data is non-stationary, indicating the presence of systematic trend and seasonal components. This finding is consistent with the general behaviour of price data, which typically displays a long-run upward trend as a manifestation of cumulative inflation [4–6]. Non-stationarity provides the methodological justification for using the Holt-Winters model, which is inherently designed to handle data with trend and seasonal components without requiring prior differencing.

3.3. Estimation of Holt-Winters Model Parameters

Model parameters were estimated in parallel using both methods. A comparison of the estimated parameters is presented in Table 4.

Table 4. Comparison of Holt-Winters Model Parameters: OLS and MLE

Parameter	HW-Add (OLS)	HW-Mult (OLS)	ETS(A,A,A) MLE	ETS(M,A,M) MLE
Alpha (α) - Level	1.000000	1.000000	0.768466	0.999180
Beta (β) - Trend	0.024069	0.024234	0.147129	0.000103
Gamma (γ) - Seasonal	0.601266	0.554189	0.000101	0.000107
SSE / Log-Likelihood	SSE $= 131.62$	SSE $= 133.21$	LL $= -135.71$	LL $= -133.09$

Substantial differences in parameter estimates are evident between the two methods. OLS-based models produce $\alpha = 1.000$ in both variants, indicating that the optimisation algorithm assigns full weight to the most recent observation and entirely disregards historical information in level estimation. This extreme alpha value is a potential indicator of parameter initialisation problems in the standard *R HoltWinters()* function, particularly during the warm-up period [20].

Based on Table 4, the OLS-based Holt-Winters model according to eq. (1) to (3) is as follows:

$$
\begin{aligned}
l_t &= 1.000\frac{y_t}{s_{t-12}} \\
b_t &= 0.0242(l_t - l_{t-1}) + 0.9758b_{t-1} \\
s_t &= 0.5541\frac{y_t}{l_t} + 0.4459s_{t-12}
\end{aligned}
$$

Based on Table 4, this model shows more stable parameters, especially at very low seasonal components, so the MLE (ETS(M,A,M))-based Holt-Winters model according to eq. (1) to (3) is as follows:

$$
\begin{aligned}
l_t &= 0.9991\frac{y_t}{s_{t-12}} + 0.0009(l_{t-1} - b_{t-1}) \\
b_t &= 0.0001(l_t - l_{t-1}) + 0.9999b_{t-1} \\
s_t &= 0.0001\frac{y_t}{l_t} + 0.9999s_{t-12}
\end{aligned}
$$

The log-likelihood equation according to eq. (4) is obtained as:

$$
L(\theta|y) = -30\ln(2\pi) - 30\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{60} e_t^2.
$$

By contrast, the ETS(A,A,A) MLE model produces $\alpha = 0.768$, reflecting a more balanced weighting between recent and historical information. The very small gamma values in the MLE models ($\gamma \approx 0.0001$) indicate a highly stable seasonal component throughout the observation period. This finding is consistent with [30], who demonstrated that MLE estimation through backcasting yields more moderated parameter profiles for data with stable seasonality.

3.4. In-Sample Model Accuracy Evaluation

A comprehensive comparison of accuracy metrics across all four models is presented in Table 5. MAPE is used as the primary metric in accordance with standard reporting practices in the economic forecasting literature.

Table 5. Comparison of In-Sample Model Accuracy Metrics

Model	MAE	RMSE	MAPE (%)	sMAPE (%)
HW Additive (OLS)	55.0454	77.3287	50.2961	99.8260
HW Multiplicative (OLS)	54.8010	76.9746	50.0728	99.1815
ETS(A,A,A) MLE	0.6581	1.2394	0.6075	0.6051
ETS(M,A,M) MLE	0.6190	1.2235	0.5709	0.5676

The evaluation results reveal a dramatic disparity in accuracy between OLS- and MLE-based models. OLS-based HW models produce MAPE values exceeding 50%, implying that the average forecast error is more than half the actual value, a performance classified as inaccurate according to [26]. This poor performance is largely attributable to the $\alpha = 1.000$ value in OLS, which reduces the in-sample fit to essentially a random walk without historical memory, rather than a representation of the systematic patterns in the data.

MLE-based ETS models, by contrast, demonstrate exceptionally high performance, classified as highly accurate. ETS(M,A,M) MLE achieves the best in-sample result with MAPE = 0.5709% and RMSE = 1.2235, marginally surpassing ETS(A,A,A) MLE. The superiority of ETS(M,A,M) is consistent with the theoretical argument that multiplicative models are more appropriate for CPI data, where seasonal amplitude is proportional to the series level [21].

3.5. Comparison of Information Criteria

The information criteria AIC, BIC, and AICc provide an additional perspective that accounts for model complexity, as shown in Table 6.

Table 6. Comparison of Information Criteria for MLE Models

Model	AIC	BIC	AICc	Log-Likelihood
ETS(A,A,A) MLE	307.41	345.11	324.10	−135.71
ETS(M,A,M) MLE	302.18	339.87	318.86	−133.09
ETS(M,N,N) – Auto	285.02	—	—	—

Based on Table 6, ETS(M,A,M) MLE consistently achieves lower AIC (302.18), BIC (339.87), and AICc (318.86) values compared with ETS(A,A,A) MLE, statistically confirming the superiority of the multiplicative model. Notably, the automatic model selection in *R* recommends ETS(M,N,N) with AIC = 285.02, a model that does not include explicit trend or seasonal components. This suggests that although the data visually exhibit seasonal patterns, those patterns may not be statistically strong enough to be justified by information criteria alone. This phenomenon has been discussed in a broader context by [31], who showed that AIC does not always identify seasonal models even when visual seasonality is present.

3.6. Residual Diagnostics

Residual diagnostics were conducted to verify the satisfaction of model assumptions, covering normality, autocorrelation, and homoscedasticity. The test results are presented in Table 7.

Table 7. Residual Diagnostic Results for All Models

Test	HW Add OLS	HW Mult OLS	ETS(A,A,A)	ETS(M,A,M)
Shapiro–Wilk (W)	0.5007	0.5013	0.6481	0.6373
p-value (Normality)	0.0000	0.0000	0.0000	0.0000
Ljung–Box Q(20)	8.8548	8.7691	17.9260	20.5479
p-value (Autocorrelation)	0.9845	0.9854	0.5923	0.4242
Heteroscedasticity (r)	−0.0079	−0.0080	0.0204	0.0204
p-value (Heteroscedasticity)	0.9576	0.9568	0.8768	0.8769

Based on Table 7, all models fail to satisfy the normality assumption for residuals (Shapiro–Wilk p-value = 0.0000 for all models). Nevertheless, the W statistics for MLE models (0.6481 and 0.6373) are relatively closer to 1 than those of OLS models (0.5007 and 0.5013), indicating that MLE residuals follow a comparatively more normal distribution. The normality failure in OLS models is largely attributable to very large residuals resulting from suboptimal parameter estimation.

With respect to autocorrelation, all four models exhibit Ljung–Box p-values well above 0.05, confirming the absence of systematic autocorrelation in the residuals. This is a positive indication that all models have successfully captured the temporal structure of the NTT CPI data. Heteroscedasticity tests also yield favourable results for all models (p-value > 0.05), indicating homogeneous residual variance throughout the observation period.

3.7. Forecasting

CPI forecasting for NTT for the 12 months of 2026, using the best performing MLE model, are presented in Table 8. The model generates a consistent seasonal pattern with CPI peaks in July and December, aligned with the high consumption periods typical in NTT (school holidays and religious celebrations).

Table 8. NTT CPI Forecast January–December 2026

Month	CPI Forecast 2026
January	107.38
February	107.40
March	107.86
April	108.39
May	108.25
June	108.44
July	109.01
August	108.33
September	108.42
October	108.46
November	108.73
December	109.54

The ETS(M,A,M) MLE model projects a gradual increase from 107.38 in January 2026 to 109.54 in December 2026, reflecting cumulative inflation of approximately 2.0% over the year. This rate is relatively low compared with the historical national inflation average, indicating a stable price environment in NTT over the medium term. The forecast trajectory is illustrated in Figure 2.

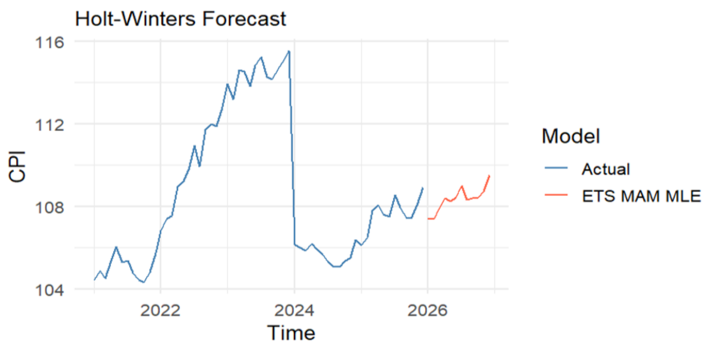


Figure 2. Consumer Price Index of East Nusa Tenggara Forecast for 2026

Figure 2 shows that the projected CPI follows a continuing upward trend (uptrend) throughout 2026. The forecast begins below 108 in early 2026 and is projected to approach or exceed 110 by year-end. The oscillating pattern of the forecast line indicates that the Holt–Winters model successfully captures seasonal fluctuations, namely the recurring up-and-down patterns that mirror the behaviour observed in the historical data from preceding years.

The application of MLE in parameter estimation yields forecast results that minimise the log-likelihood discrepancy between the model and the original data, producing projections that are realistic in that they continue the trend slope established by the end of 2025 data. From a policy perspective, these projections can serve as a reference for the NTT Provincial Government and the Regional Inflation Control Team (TPID) in designing price stabilisation strategies, with particular attention required in July and December, the months with the highest projected price pressures.

4. Conclusion

This study confirms that the movement patterns of the Consumer Price Index (CPI) in East Nusa Tenggara (NTT) Province exhibit non-stationary characteristics, characterized by a consistent upward trend and systematic seasonal fluctuations. The primary finding indicates that within the Holt–Winters framework, the Maximum Likelihood Estimation (MLE) method offers a significant performance advantage (MAPE $< 10\%$) over the Ordinary Least Squares (OLS) approach.

The implementation of MLE through the ETS model proved more effective in optimizing model parameters, thereby yielding a substantially more reliable level of forecast accuracy for regional economic data with strong seasonal patterns. Forecasting for 2026 indicates a tendency toward moderate price increases in NTT, with potential seasonal inflationary pressures that warrant anticipation during the mid-year and year-end periods.

Although the MLE-based model demonstrated high precision in this study, there are limitations regarding the fulfillment of residual normality assumptions that should be considered when interpreting forecast confidence intervals. As a direction for future research, it is recommended that the performance of ETS MLE be compared with machine learning algorithms such as LSTM, Prophet, or XGBoost to obtain more comprehensive forecast accuracy assessments at the regional scale.

Author Contributions. **Esra Rombeallo**: Conceptualization, methodology, writing original draft preparation, software and visualization. **Marvin Jecson Pandu**: Methodology, Writing original draft preparation, validation and data curation.

Acknowledgment. The authors are thankful the editors and reviewers who have supported us in improving this manuscript.

Funding. This research received no external funding

Conflict of interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability. Not applicable.

References

[1] I. A. Juliannisa, H. Rahma, S. Mulatsih, and A. Fauzi, "Regional vulnerability to food insecurity: The case of Indonesia," *Sustainability*, vol. 17, no. 11, p. 4800, May 2025, doi: 10.3390/su17114800.

[2] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed., Melbourne, Australia, 2021. [Online]. Available: https://otexts.com/fpp3/.

[3] E. S. Gardner, "Exponential smoothing: The state of the art—Part II," *Int. J. Forecast.*, vol. 22, no. 4, pp. 637–666, Oct. 2006, doi: 10.1016/j.ijforecast.2006.03.005.

[4] M. Khan, M. Khan, U. N. Kayani, K. S. Mughal, and R. Mumtaz, "Unveiling market connectedness:

Dynamic returns spillovers in Asian emerging stock markets," *International Journal of Financial Studies*, vol. 11, no. 3, p. 112, Sep. 2023, doi: 10.3390/ijfs11030112.

[5] T. Zang and H. Gu, "State-space modeling of housing sentiment for regressing changes of real estate prices following short-term control policy in China," *Sustainability*, vol. 15, no. 16, p. 12660, Aug. 2023, doi: 10.3390/su151612660.

[6] T. T. Nguyen, H. G. Nguyen, J. Y. Lee, Y. L. Wang, and C. S. Tsai, "The consumer price index prediction using machine learning approaches: Evidence from the United States," *Heliyon*, vol. 9, no. 10, p. e20730, Oct. 2023, doi: 10.1016/j.heliyon.2023.e20730.

[7] N. S. Arunraj and D. Ahrens, "A hybrid seasonal autoregressive integrated moving average and quantile regression for daily food sales forecasting," *Int. J. Prod. Econ.*, vol. 170, pp. 321–335, Dec. 2015, doi: 10.1016/j.ijpe.2015.09.039.

[8] F. Petropoulos et al., "Forecasting: Theory and practice," *Int. J. Forecast.*, vol. 38, no. 3, pp. 705–871, Jul. 2022, doi: 10.1016/j.ijforecast.2021.11.001.

[9] R. K. Nur et al., "Metode triple exponential smoothing untuk peramalan indeks harga konsumen Kota Surabaya Tahun 2020-2023," *Prosiding Seminar Nasional Sains Data*, vol. 4, no. 1, pp. 615–623, Sep. 2024, doi: 10.33005/senada.v4i1.294.

[10] I. F. Amri, M. Al-haris, M. F. Ninu, K. C. Chumairoh, and G. S. Purnama, "Prediksi harga beras di pasar grosir Indonesia menggunakan metode triple exponential smoothing Holt-Winters," *Jurnal Gaussian*, vol. 14, no. 1, pp. 31–41, 2025, doi: 10.14710/j.gauss.14.1.31-41.

[11] S. I. Fallo et al., "Forecasting indeks harga konsumen di Provinsi Nusa Tenggara Timur dengan metode Holt-Winter exponential smoothing," *Leibniz: Jurnal Matematika*, vol. 3, no. 2, pp. 57–67, 2023. [Online]. Available: https://ntt.bps.go.id/indicator/3/2/9/indeks-harga-konsumen-menurut-bulan.html.

[12] T. A. Pangruruk, N. B. Mangiri, E. Rombeallo, and W. P. Nurmayanti, "Pemodelan dan prediksi pola musiman menggunakan Holt-Winters," *VARIANSI: Journal of Statistics and Its Application on Teaching and Research*, vol. 7, no. 2, pp. 106–114, Sep. 2025, doi: 10.35580/variansiunm391.

[13] F. Firdaus, M. Komaro, and V. Dwiyanti, "Perbandingan metode Holt-Winters dan SARIMA untuk memprediksi permintaan produk fashion pada PT XYZ," *Factory Jurnal Industri, Manajemen dan Rekayasa Sistem Industri*, vol. 4, no. 2, pp. 287–308, Jan. 2026, doi: 10.56211/factory.v4i2.1401.

[14] L. Qi, X. Li, Q. Wang, and S. Jia, "fETSmcs: Feature-based ETS model component selection," *Int. J. Forecast.*, vol. 39, no. 3, pp. 1303–1317, Jul. 2023, doi: 10.1016/j.ijforecast.2022.06.004.

[15] M. N. Atchadé and Y. M. Sokadjo, "Overview and cross-validation of COVID-19 forecasting univariate models," *Alexandria Engineering Journal*, vol. 61, no. 4, pp. 3021–3036, Apr. 2022, doi: 10.1016/j.aej.2021.08.028.

[16] I. Efrilia, "Comparison of ARIMA and exponential smoothing Holt-Winters methods for forecasting CPI in the Tegal City, Central Java," *Jurnal Ekonomi Pembangunan*, vol. 19, no. 02, pp. 97–106, Dec. 2021, doi: 10.22219/jep.v19i02.18040.

[17] C. Chatfield and M. Yar, "Holt-Winters forecasting: Some practical issues," *The Statistician*, vol. 37, no. 2, p. 129, 1988, doi: 10.2307/2348687.

[18] J. W. Taylor, "Forecasting value at risk and expected shortfall using a model with a dynamic omega ratio," *J. Bank. Financ.*, vol. 140, p. 106519, Jul. 2022, doi: 10.1016/j.jbankfin.2022.106519.

[19] BPS Nusa Tenggara Timur, "Indeks harga konsumen menurut bulan [IHK 2022=100] (Persen), 2026." [Online]. Available: https://ntt.bps.go.id/indicator/3/2/9/indeks-harga-konsumen-menurut-bulan.html.

[20] R. Hyndman, A. Koehler, K. Ord, and R. Snyder, *Forecasting with Exponential Smoothing*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2008, doi: 10.1007/978-3-540-71918-2.

[21] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "The M4 competition: Results, findings, conclusion and way forward," *Int. J. Forecast.*, vol. 34, no. 4, pp. 802–808, Oct. 2018, doi: 10.1016/j.ijforecast.2018.06.001.

[22] S. Koné, "Using geostatistical kriging for hydrologic models' parameters estimation on Niger River watersheds in West Africa," *International Journal of Modern Nonlinear Theory and Application*, vol. 13, no. 04, pp. 53–69, 2024, doi: 10.4236/ijmnta.2024.134005.

[23] X. Liu and W. Wang, "Deep time series forecasting models: A comprehensive survey," *Mathematics*, vol. 12, no. 10, p. 1504, May 2024, doi: 10.3390/math12101504.

[24] E. S. Gardner, "Exponential smoothing: The state of the art—Part II," *Int. J. Forecast.*, vol. 22, no. 4, pp. 637–666, Oct. 2006, doi: 10.1016/j.ijforecast.2006.03.005.

[25] R. J. Hyndman, A. B. Koehler, R. D. Snyder, and S. Grose, "A state space framework for automatic forecasting using exponential smoothing methods," *Int. J. Forecast.*, vol. 18, no. 3, pp. 439–454, Jul. 2002, doi: 10.1016/S0169-2070(01)00110-8.

[26] M. S. Başar and H. Küçükönder, "Measuring the correlation between commercial and economic states

of countries (B2G relations) and the E-Government Readiness Index by using neural networks," *Open Journal of Business and Management*, vol. 2, no. 2, pp. 110–115, 2014, doi: 10.4236/ojbm.2014.22014.

[27] H. Akaike, "A new look at the statistical model identification," *IEEE Trans. Automat. Contr.*, vol. 19, no. 6, pp. 716–723, Dec. 1974, doi: 10.1109/TAC.1974.1100705.

[28] G. Schwarz, "Estimating the dimension of a model," *The Annals of Statistics*, vol. 6, no. 2, Mar. 1978, doi: 10.1214/aos/1176344136.

[29] E. Rombeallo and T. A. Pangruruk, "Stock price forecasting of Meta Platforms Inc (META) using ARIMA method," *bit-Tech*, vol. 8, no. 2, pp. 1701–1711, Dec. 2025, doi: 10.32877/bt.v8i2.3055.

[30] A. M. De Livera, R. J. Hyndman, and R. D. Snyder, "Forecasting time series with complex seasonal patterns using exponential smoothing," *J. Am. Stat. Assoc.*, vol. 106, no. 496, pp. 1513–1527, Dec. 2011, doi: 10.1198/jasa.2011.tm09771.

[31] S. Kolassa, "Combining exponential smoothing forecasts using Akaike weights," *Int. J. Forecast.*, vol. 27, no. 2, pp. 238–251, Apr. 2011, doi: 10.1016/j.ijforecast.2010.04.006.