p-ISSN 2338 – 3216
e-ISSN 2528 – 1070

JURNAL STATISTIKA
UNIVERSITAS MUHAMMADIYAH SEMARANG
13(2) 2025: 123-133

HILDRETH-LU METHOD FOR AUTOCORRELATION CORRECTION IN TIME-SERIES REGRESSION OF SHRIMP GROWTH PERFOMANCE

Febriyani Eka Supriatin[1*], Aulia Rahmawati[2], Muhammad Dailami[3]
[1,2,3] Department of Fisheries and Marine Resources Management, Aquaculture Study Program, Faculty of Fisheries and Marine Science, Universitas Brawijaya, Indonesia

***e-mail**: febriyaniekas@ub.ac.id

Article Info:
Received: October, 10th 2025
Accepted: December, 5th 2025
Available Online: December 12th 2025

Keywords:
autocorrelation correction; Hildreth–Lu method; shrimp growth; time-series regression

Abstract: Autocorrelation frequently occurs in time-series regression models, leading to inefficient estimators and biased inference when ignored. This study analyzed the relationship between water quality parameters and shrimp growth performance by applying the Hildreth–Lu iterative method to correct autocorrelation. The iterative procedure evaluates several potential ρ values and selects the one that minimizes the residual sum of squares, allowing efficient correction of autocorrelation without data loss. The dataset consisted of Specific Growth Rate (SGR) as the dependent variable and three water-quality parameters-temperature, pH, and dissolved oxygen (DO)-as explanatory variables, with pond type included as a dummy factor. The initial Ordinary Least Squares (OLS) estimation revealed that temperature and pH significantly affected SGR, while the Durbin–Watson (DW) value of 0.878 indicated positive autocorrelation in the residuals. After applying the Hildreth–Lu correction, the estimated autocorrelation coefficient (ρ) was 0.64, and the DW statistic improved to 2.03, confirming that serial correlation had been successfully removed. The corrected model provided more efficient and unbiased parameter estimates without requiring data transformation or loss of observations. The results confirm that temperature is the most influential factor in shrimp growth, while pH, DO, and pond type showed no significant effects. The study highlights the importance of autocorrelation diagnostics in regression analysis and demonstrates that the Hildreth–Lu method is an effective and reliable approach for improving model efficiency in small-sample time-series data.

1. INTRODUCTION

The linear regression model is one of the most widely used analytical approaches in statistics to describe the relationship between a response variable and one or more predictor variables. The reliability of this model strongly depends on the fulfillment of several classical assumptions, including normality, homoscedasticity, absence of multicollinearity, and particularly, the absence of autocorrelation among residuals. Violation of any of these assumptions can lead to inefficient parameter estimates, biased standard errors, and misleading statistical tests [1], [2].

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

One of the most common violations in time-series data is autocorrelation, which refers to the linear relationship between the residuals of one observation and those of the previous period. When autocorrelation occurs, the Ordinary Least Squares (OLS) method no longer produces efficient estimators because the variance of residuals becomes downward-biased (underestimated). Consequently, t-tests and F-tests derived from these estimates become invalid, leading to erroneous inferential conclusions [3], [4]. Therefore, detecting and correcting autocorrelation is a crucial step in analyzing data with temporal dependence.

In applied research particularly in aquaculture studies data on growth performance and water quality are often collected periodically. Such temporally structured data tend to exhibit autocorrelation because environmental conditions and organismal growth are inherently continuous over time. Moreover, differences in pond type (HDPE-lined and concrete ponds) may contribute to variations in water-quality dynamics, which further amplify temporal dependence between observations [3]. In this context, the primary concern is not the biological influence of these factors, but rather the statistical implication of assumption violations arising from autocorrelation in time-series data.

Several approaches have been developed to address autocorrelation, including the Cochrane Orcutt, Prais Winsten, and Hildreth Lu methods. The Cochrane Orcutt method discards the first observation and transforms the model through quasi-differencing, which reduces sample efficiency. The Prais Winsten method improves upon this by retaining the first observation using a modified transformation. The Hildreth Lu method is applied as an iterative estimation procedure to correct first-order autocorrelation in regression models. Rather than functioning as a standalone statistical model, the Hildreth Lu method identifies the optimal autocorrelation coefficient (ρ) through a grid-search process that minimizes the residual sum of squares, allowing the regression parameters to be re-estimated more efficiently. This approach is computationally simple and particularly effective when the sample size is limited [5], [6], [7].

Recent econometric studies have reaffirmed the importance of iterative correction models such as Hildreth Lu for improving estimation efficiency in small-sample and applied time-series contexts [8], [10]. Furthermore, hybrid estimation techniques have emerged to address more complex data structures. For instance, Badawaire [11] proposed an estimator that integrates LAD, Hildreth Lu, and Kibria Lukman approaches to handle simultaneous issues of autocorrelation, multicollinearity, and heavy-tailed errors. Similarly, Xu [12] developed the MSRC (Maximum Significant ρ Correction) method to model parameter-driven autocorrelation in time-series data. These developments indicate that iterative and robust approaches continue to play a key role in improving regression model efficiency and reliability.

While most previous applications have focused on economic and financial datasets, the current study extends the methodological use of the Hildreth Lu model to environmental and biological time-series. This extension is academically significant because it demonstrates the model's robustness across disciplines, and practically relevant for ensuring reliable decision-making in aquaculture management and environmental monitoring.

This study aims to demonstrate the application of the Hildreth Lu model to correct autocorrelation violations in time-series regression data. As an empirical illustration, time-series observations of water-quality parameters and Litopenaeus vannamei growth performance from two pond systems were analyzed. The analysis focuses on identifying autocorrelation, estimating parameters using the iterative Hildreth Lu approach, and evaluating model efficiency before and after autocorrelation correction. Accordingly, this

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

study contributes methodologically to the application of regression modeling in time-series data and enhances the practical understanding of the importance of autocorrelation correction in applied statistical analysis.

2. LITERATURE REVIEW

2.1. Linear Regression and Autocorrelation

The linear regression model explains the relationship between a dependent variable (Y) and one or more independent variables (X_1, X_2, …, X_k). The general form of the model is:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_k X_{kt} + \varepsilon_t \quad (1)$$

Where ε_t is the error term that should be independent and identically distributed with zero mean and constant variance.

Autocorrelation occurs when errors at time t are correlated with errors at time t–1, i.e.,

$$Cov(\varepsilon_t, \varepsilon_{t-1}) \neq 0 \quad (2)$$

Autocorrelation occurs, causing the Ordinary Least Squares (OLS) estimators to remain unbiased but inefficient [13], [14]. Autocorrelation reduces estimation precision and biases test statistics, necessitating corrective procedures for reliable inference [7].

2.2. Durbin-Watson Test

The Durbin–Watson (DW) test is a diagnostic tool used to detect first-order autocorrelation in time-series regression residuals. The DW statistic is defined as:

$$DW = \frac{\sum_{t=2}^{n}(\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{n} \varepsilon_t^2} \quad (3)$$

A value close to 2 indicates the absence of autocorrelation, while values significantly lower or higher indicate positive or negative autocorrelation, respectively [13], [15].

2.3. Cochrane-Orcutt and Prais-Winsten Methods

Several transformation-based techniques have been developed to address autocorrelation. The Cochrane Orcutt and Prais Winsten procedures estimate the autocorrelation coefficient ρ iteratively and transform the model as follows:

$$Y_t - \rho Y_{t-1} = \beta_0(1-\rho) + \beta_1(X_t - \rho X_{t-1}) + u_t \quad (4)$$

The Cochrane–Orcutt method excludes the first observation, which reduces sample size, whereas Prais–Winsten retains it through a modified transformation. Both rely on iterative estimation until convergence [13], [15].

2.4. Hildreth-Lu Model

The Hildreth–Lu model provides an alternative to transformation methods by directly estimating the autocorrelation coefficient ρ through a grid search that minimizes the residual sum of squares (RSS):

$$RSS(\rho) = \sum_{t=2}^{n}(Y_t - \rho Y_{t-1} - \beta_0 - \beta_1 X_t)^2 \quad (5)$$

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

The ρ value that minimizes RSS(ρ) is selected as the best estimator. This approach is computationally simple, does not remove observations, and is suitable for small samples [5], [10].

2.5. Recent Developments

Modern econometric studies have expanded upon classical autocorrelation correction methods to address increasingly complex data structures. De Blander [16] introduced iterative correction procedures for short-panel models, while Badawaire [17] proposed a hybrid estimator combining the Least Absolute Deviation (LAD) and Hildreth Lu approaches to simultaneously handle autocorrelation and heavy-tailed errors. Xu [18] developed the MSRC (Maximum Significant ρ Correction) method to model parameter-driven autocorrelation in time-series data, demonstrating enhanced estimation accuracy. In addition, Poojari [8] presented a modified least-squares ratio estimator designed to improve computational efficiency for autocorrelated data. These recent advancements highlight the continued relevance of iterative and hybrid approaches for improving model robustness in applied statistics.

3. METHODOLOGY

3.1. Data Source and Variables

The data were collected from 13 vannamei shrimp ponds located in Banyuwangi Regency, East Java Province, Indonesia, during a 30-day production cycle. This study utilized time-series data obtained from shrimp (Litopenaeus vannamei) aquaculture ponds. The dataset comprised water-quality parameters (temperature, pH, and dissolved oxygen) and growth performance indicators, namely Specific Growth Rate (SGR, %/day).

Pond type was included as a dummy variable (D_t), where $D_t = 1$ represents HDPE-lined ponds and $D_t = 0$ represents concrete ponds. This variable was introduced to assess structural differences in pond environments that may influence both growth performance and residual behavior.

3.2. Model Development

A multiple linear regression model was used to describe the relationship between SGR and water-quality parameters, incorporating pond type as an additional explanatory variable. The initial estimation was conducted using the Ordinary Least Squares (OLS) method. Diagnostic testing was performed to verify classical assumptions, including normality, multicollinearity, and autocorrelation. The presence of serial correlation among residuals was examined using the Durbin–Watson statistic as formulated in equation (3).

When autocorrelation was detected, the model was corrected using the Hildreth-Lu iterative approach describe in equation (5). This method was selected because it effectively estimates the autocorrelation coefficient (ρ) through an iterative search without transforming or reducing the dataset, which is especially advantageous for small-sample time-series data.

3.3. Analytical Procedure

The analytical process was conducted in several stages as follows:

1. Preliminary estimation: Perform OLS regression using SGR as the dependent variable and assess residual distribution.

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

2. Autocorrelation diagnosis: Evaluate the Durbin–Watson statistic (Equation 3) to detect first-order autocorrelation.
3. Model correction: Apply the Hildreth Lu iterative procedure (Equation 5) to adjust for autocorrelation and re-estimate model parameters.
4. Refinement: Examine whether the corrected model improves residual independence and parameter efficiency.
5. Comparison and interpretation: Compare model performance before and after correction based on the Durbin Watson value, R^2, and the significance of regression coefficients.

The success of autocorrelation correction was determined by improvements in the Durbin Watson value approaching 2 and the elimination of residual dependency. Model efficiency was evaluated based on the statistical significance of regression coefficients at a 5% level, and the coefficient of determination (R^2) was used to measure explanatory power.

4. RESULTS AND DISCUSSION

4.1. Descriptive Analysis

Descriptive statistics for the observed variables are presented in Table 1. The average Specific Growth Rate (SGR) of shrimp during the observation period was 6.14% per day, with moderate variability (standard deviation of 2.77). Water temperature ranged between 28 and 30°C, which falls within the optimal range for Litopenaeus vannamei culture. The mean pH value (8.08) indicates slightly alkaline conditions favorable for growth, while the mean dissolved oxygen (DO) level of 4.55 mg/L remained above the critical threshold for survival and normal metabolism [19].

Table 1. Descriptive Statistics of Variables

Variable	Mean	Std. Dev.	Min	Max
SGR	6.14	2.77	2.65	12.43
Temperature	28.95	0.54	28.00	30.00
Ph	8.08	0.18	7.70	8.35
Do	4.55	0.37	3.94	5.23

The stable values of temperature and pH suggest effective pond management and provide a good foundation for analyzing the statistical relationship between environmental factors and shrimp growth.

4.2. Preliminary Regression Model

The Ordinary Least Squares (OLS) regression results are summarized in Table 2. The analysis revealed that temperature and pH positively affected SGR, both statistically significant at $\alpha = 0.05$, while DO and pond type showed no significant effects. The model explained approximately 47% of the variation in SGR ($R^2 = 0.471$)

Table 2. OLS Regression Results (Before Correction)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
const	-151.741	31.064	-4.885	0.0
Temperature	3.633	0.724	5.02	0.0
Ph	6.114	2.397	2.55	0.015
Do	0.39	1.154	0.338	0.737
PondDummy	2.026	1.057	1.916	0.064

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

Variable	Coefficient	Std. Error	t-Statistic	p-Value
R-squared	0.471			
Durbin–Watson	0.878			

However, the Durbin–Watson (DW) value of 0.878 indicates positive autocorrelation among residuals, violating the independence assumption [1]. As illustrated in Figure 1, the residuals followed a repetitive pattern rather than a random distribution, confirming the presence of serial dependence. According to Wooldridge [13], such dependence can lead to inefficient parameter estimates and underestimated standard errors, resulting in misleading hypothesis tests.

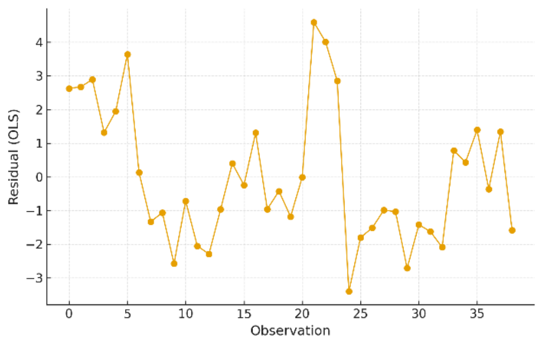

Fig 1. Residual OLS

4.3. Correction of Autocorrelation Using the Hildreth-Lu Method

The Hildreth–Lu iterative correction method was applied to address the autocorrelation problem. The best autocorrelation coefficient (ρ) was estimated at 0.64, reflecting moderate positive correlation among residuals. After correction, the Durbin–Watson statistic increased to 2.03, as shown in Table 3, suggesting that the autocorrelation was successfully removed. As illustrated in Figure 2, the improvement in model diagnostics was evident: the Durbin–Watson (DW) statistic increased from 0.878 to 2.03, while the coefficient of determination (R^2) slightly decreased from 0.471 to 0.456. This indicates that the correction enhanced model efficiency and reduced bias without significantly compromising explanatory power. The residual pattern after correction (Figure 3) appeared random and homoscedastic, confirming the validity of the model assumptions.

The findings of this study are in line with recent research addressing the correction of autocorrelation in regression models. Several studies in the past decade have demonstrated that applying methods such as Cochrane-Orcutt, Hildreth-Lu, or Prais-Winsten effectively increases the Durbin–Watson statistic toward the ideal value of 2, indicating the successful removal of autocorrelation and resulting in more random and homoscedastic residuals [3], [20], [21]. For example, Bimanto [20] found that after applying the Prais-Winsten method, the Durbin–Watson value increased and the residuals became more random, while the coefficient of determination (R^2) decreased only slightly, similar to the pattern observed in this study 18. Likewise, Subhi and Al Azkiya [3] reported that both Cochrane-Orcutt and Hildreth-Lu methods eliminated autocorrelation, with only a minor reduction in R^2, but improved model efficiency and reduced bias. These findings reinforce that correcting for autocorrelation enhances model validity and efficiency without substantially compromising explanatory power, in line with the results presented here.

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

Table 3. Hildreth–Lu Regression Results (After Correction)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Const	-49.869	11.26	-4.429	0.0
Temperature	4.028	0.809	4.976	0.0
Ph	2.863	2.435	1.176	0.248
Do	0.884	0.983	0.9	0.375
PondDummy	0.823	1.288	0.639	0.527
R-squared	0.456			
Durbin–Watson	2.029			
Best rho (ρ)	0.64			

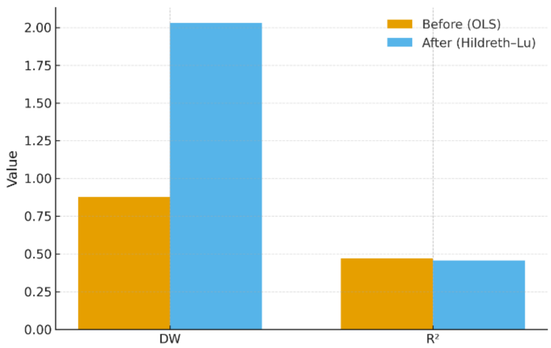

Fig 2. Comparison: DW & R^2 (Before vs After)

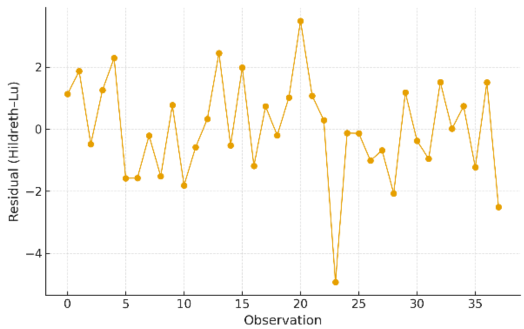

Fig 3. Residuals (Hildreth–Lu)

Compared to the OLS model, the corrected regression showed a slightly lower R^2 (0.456) but yielded more efficient and consistent parameter estimates. The results indicate that temperature remained the dominant variable affecting SGR ($p < 0.01$), while pH, DO, and pond type remained insignificant. This demonstrates the effectiveness of the Hildreth–Lu method in producing reliable estimates for small-sample time-series data [9].

4.4. Interpretation of Parameters

As indicated in Table 3, temperature exhibited a strong and significant positive influence on shrimp SGR. The scatterplot in Figure 4 visually confirms this relationship, showing a clear upward trend. This finding aligns with previous studies by Masqari [22] who reported that water temperature plays a critical role in regulating shrimp metabolism and feed conversion efficiency. Within the optimal range of 28–30°C, metabolic activity increases without triggering stress, thus accelerating growth.

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

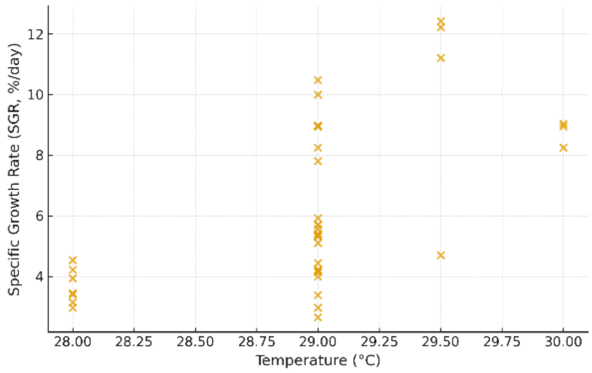

Fig 4. Scatter SGR vs Temperature

The effects of pH and DO were not statistically significant, likely because their variations were minor and within the physiological tolerance range for L. vannamei [23], [24]. Similarly, pond type had no measurable effect on growth, suggesting that both HDPE and concrete ponds provided comparable environmental conditions under proper management.

Although the Hildreth Lu correction slightly reduced the model's explanatory power, the gain in estimator efficiency and unbiasedness was far more critical. The improvement in the DW statistic confirmed that residual independence had been achieved, validating the corrected model for inference. Similar benefits of Hildreth Lu correction in small-sample regression analysis were also noted by Koutsoyiannis (2006) and reaffirmed in recent studies on environmental time-series modeling [9].

4.5. Discussion

The overall findings reinforce the dominant influence of temperature on shrimp growth and the importance of maintaining stable physicochemical conditions. The results are consistent with those of Masqari [22], who reported that temperature fluctuations strongly affect feed utilization and energy allocation in L. vannamei. Meanwhile, the non-significant effects of pH and DO suggest that the system maintained near-optimal conditions throughout the study period, similar to observations by Do [23] and Apresia [24].

From a statistical perspective, the improvement of the Durbin Watson value from 0.878 to 2.03 demonstrates that the Hildreth Lu method effectively eliminates serial correlation without data transformation or loss of observations. This result supports prior findings by [1] and , Poojari [9], who demonstrated that the application of the Hildreth Lu method is effective in reducing first-order autocorrelation while maintaining the original sample structure. Similar to the present study, both studies reported a substantial improvement in the Durbin Watson statistic and the emergence of more random and homoscedastic residual patterns after correction, indicating enhanced model validity. In addition, they noted a slight reduction in R^2, which was interpreted as a natural consequence of removing biased serial dependence from the model rather than a deterioration in explanatory power. The findings of this study reinforce these conclusions by showing that the correction process not only improves model efficiency and reduces estimation bias, but also produces more reliable interpretations of the relationship between water quality parameters and shrimp growth. Therefore, this study provides further empirical evidence supporting the relevance of autocorrelation correction techniques in time-series regression,

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

particularly in aquaculture research where environmental measurements often exhibit temporal dependence.

In summary, the integration of robust statistical correction techniques such as Hildreth Lu in aquaculture research ensures that conclusions drawn from time-dependent data are both valid and reliable. Such methodological rigor contributes to more precise modeling of biological responses, ultimately supporting sustainable and data-driven aquaculture management.

5. CONCLUSION

This study applied the Hildreth Lu iterative correction method to address autocorrelation in time-series regression models of shrimp growth performance. The initial Ordinary Least Squares (OLS) estimation indicated significant positive effects of temperature and pH on Specific Growth Rate (SGR), but the model violated the assumption of error independence, as reflected by a low Durbin Watson (DW) value of 0.878. After applying the Hildreth Lu correction, the autocorrelation coefficient (ρ) was estimated at 0.64, and the DW statistic improved to 2.03, confirming that serial correlation was successfully removed. Although the coefficient of determination (R^2) slightly decreased, the corrected model provided more efficient and reliable parameter estimates without compromising explanatory power. Temperature remained the most influential variable, while pH, dissolved oxygen (DO), and pond type showed no significant effects, highlighting the importance of robust regression diagnostics and autocorrelation correction in aquaculture time-series analysis. Overall, the findings demonstrate that the Hildreth Lu method is an effective alternative for ensuring model efficiency and statistical validity, particularly when dealing with small-sample datasets where transformation-based methods may not be optimal. This study therefore provides valuable methodological insight for future aquaculture research and may serve as a reference for selecting appropriate correction techniques. Future studies should explore the integration of Hildreth Lu with other modern approaches, such as generalized least squares or machine-learning-based corrections, to further enhance model performance and predictive capability in dynamic aquaculture systems.

6. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Faculty of Fisheries and Marine Science, Universitas Brawijaya, for providing financial support through the Faculty Research Grant Scheme of the Faculty of Fisheries and Marine Science in 2023.

REFERENCES

[1] D. N. Gujarati and D. C. Porter, *Basic Econometrics*. McGraw-Hill, 2009.

[2] J. M. Wooldridge, *Introductory Econometrics: A Modern Approach*. Cengage Learning, 2016.

[3] K. T. Subhi and A. A. Azkiya, "Comparison of Cochrane-Orcutt and Hildreth-Lu Methods to Overcome Autocorrelation in Time Series Regression (Case Study of Gorontalo Province HDI 2010-2021)," *Param. J. Stat.*, vol. 2, no. 2, pp. 30–36, 2022, doi: 10.22487/27765660.2022.v2.i2.15913.

[4] R. Davidson and J. G. MacKinnon, *Econometric Theory and Methods*. Oxford University Press, 2004.

[5] W. H. Greene, *Econometric Analysis (8th Edition)*. Pearson Education, 2018.

[6] J. Johnston and J. DiNardo, *Econometric Methods*. McGraw-Hill, 1997.

[7] G. G. Judge, R. C. Hill, W. E. Griffiths, H. Lütkepohl, and T. C. Lee, *Introduction to the Theory and Practice of Econometrics*. Wiley, 1988.

[8] S. Poojari, S. Acharya, V. K. S.G., and V. Serrao, "Modified least squares ratio estimator for autocorrelated data: Estimation and prediction," *J. Comput. Math. Data Sci.*, vol. 14, p. 100109, 2025, doi: https://doi.org/10.1016/j.jcmds.2025.100109.

[9] S. Poojari, "Modified least squares ratio estimator for autocorrelated data," *J. Stat. Model. Appl.*, vol. 10, no. 1, pp. 22–35, 2025.

[10] B. H. Baltagi, *Econometric Analysis of Panel Data*. Springer, 2021.

[11] "Addressing Autocorrelation, Multicollinearity, and Heavy-Tail Errors in the Linear Regression Model," *Asian J. Probab. Stat.*, vol. 26, no. 9 SE-Original Research Article, pp. 61–83, Aug. 2024, doi: 10.9734/ajpas/2024/v26i9646.

[12] Y. Xu, X. Li, and L. Chen, "A novel correction method for modelling parameter-driven autocorrelated time series with count outcome," *BMC Public Health*, vol. 24, p. 18382, 2024.

[13] J. M. Wooldridge, *Introductory Econometrics: A Modern Approach (7th Edition)*. Cengage Learning, 2020.

[14] D. Asteriou and S. G. Hall, *Applied Econometrics*. Palgrave Macmillan, 2015.

[15] R. C. Hill, W. E. Griffiths, and G. C. Lim, *Principles of Econometrics (5th Edition)*. Wiley, 2018.

[16] R. De Blander, "Iterative estimation correcting for error autocorrelation in short panels," *Econom. Stat.*, vol. 15, pp. 1–12, 2020.

[17] A. B. Badawaire, K. Ayinde, and S. O. Olanrewaju, "Addressing autocorrelation, multicollinearity, and heavy-tail errors in the linear regression model," *Asian J. Probab. Stat.*, vol. 18, no. 3, pp. 1–17, 2024.

[18] X. H. Xu, "A novel correction method for modelling parameter-driven autocorrelated time series with count outcomes," *PLoS One*, vol. 19, no. 2, p. e0301385, 2024.

[19] M. A. Rahman, M. M. Hasan, and S. Islam, "Environmental factors affecting vannamei shrimp growth under tropical conditions," *Aquac. Int.*, vol. 28, pp. 1393–1408, 2020, doi: 10.1007/s10499-020-00539-z.

[20] H. Bimanto, H. B. Notobroto, and S. Melaniani, "Application Of The Prais Winsten Method In Overcoming," *J. Biometrika Dan Kependud. (J. Biometrics Popul.)*, vol. 12, no. 1, pp. 32–40, 2023.

[21] S. Adrianto, I. H. N. Balqis, C. Z. N. Soetanto, and M. Ohyver, "Cochrane orcutt method to overcome autocorrelation in modeling factors affecting the number of hotel visitors in Indonesia," *Procedia Comput. Sci.*, vol. 216, pp. 630–638, 2023, doi: https://doi.org/10.1016/j.procs.2022.12.178.

[22] Z. Al-Masqari *et al.*, "Effects of high temperature on water quality, growth performance, enzyme activity, and the gut bacterial community of shrimp (Litopenaeus vannamei)," *Aquac. Res.*, vol. 53, Mar. 2022, doi: 10.1111/are.15836.

[23] D. D. Do, A. H. Le, V. Van Vu, D. P. T. Nguyen, and H. Van Can, "Effects of water quality parameters on growth performance of intensive shrimp pond (Litopenaeus vannamei)," *J. Agric. Dev.*, vol. 23, no. Special Issues 1 SE-, pp. 155–169, Dec. 2024, doi: 10.52997/jad.SI1.14.2024.

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]

[24] F. Apresia, C. Raissa, U. Khansa, and F. Azzura, "The Effect of Water Quality on the Performance Growth of Vannamei Shrimp (Litopenaeus vannamei) at the Center for Brackish Aquaculture Fisheries," vol. 2, no. 3, 2024.

[DOI: 10.14710/JSUNIMUS.13.3.2025.123-133]