Climatic Determinants of Shrimp Yields in Tamil Nadu, India: A Transfer Function Analysis

Abstract

Shrimp aquaculture in Tamil Nadu plays a critical role in supporting livelihoods and contributing to exports but is increasingly vulnerable to climatic variability. This study investigates how seasonal precipitation, extreme temperatures, and lagged production impact shrimp yields in four key districts—Tiruvallur, Cuddalore, Thanjavur, and Nagapattinam—over the period 2015–2023. Using statistical models, we identify major trends and district-specific sensitivities. For instance, excessive summer and winter precipitation coupled with high maximum temperatures reduced yields in Tiruvallur, whereas warmer summer nights boosted production. In Cuddalore, yields were hampered by seasonal precipitation, elevated minimum temperatures, and the lingering effects of previous yields. Thanjavur's production suffered from extreme temperatures and winter rainfall but benefited from milder winter nights. Nagapattinam showed unique dynamics, where winter precipitation and summer maximum temperatures enhanced yields, while summer rainfall and lagged production had adverse effects.These findings highlight the need for tailored, district-specific strategies to manage climate risks and sustain shrimp farming. For example, adaptive measures such as optimizing water management or selecting climate-resilient shrimp varieties could mitigate negative impacts. Future research could integrate factors like water quality and disease outbreaks to strengthen the sector's resilience further.

Keywords: Climate change, Shrimp farming, transfer function model, temperature, precipitation

1. Introduction

Aquaculture is a cornerstone of global food security and economic growth, with shrimp farming recognized as one of the fastest-growing and most lucrative sectors (FAO, 2020). In India, shrimp aquaculture significantly contributes to seafood exports and sustains the livelihoods of millions, particularly in coastal states like Tamil Nadu (Globefish, 2022; Singh *et al.*, 2021). Tamil Nadu's favorable geographic and climatic conditions make it a major hub for shrimp production; however, the sector faces mounting challenges due to climate variability, which disrupts production systems and impacts yields (Do & Ho, 2022).

Key climatic factors such as precipitation and temperature are critical to shrimp farming success. Excessive rainfall can disrupt pond salinity and nutrient balance, while temperature extremes stress shrimp, reducing growth rates and increasing vulnerability to disease (Ahmed & Diana, 2015; Islam *et al.,* 2019). Additionally, lagged effects from previous production cycles complicate yield predictions (Devlin *et al.,* 2017). Despite the recognized importance of these dynamics, limited research has quantitatively explored the specific impacts of climate on shrimp yields at a district level, particularly in Tamil Nadu, where localized climatic and production variations demand tailored analyses.

This study addresses these gaps by examining the effects of key climatic variables—seasonal precipitation and temperature extremes—on shrimp yields across four districts in Tamil Nadu: Thiruvallur, Cuddalore, Thanjavur, and Nagapattinam. Using ARIMA-based regression models, which are well-suited for capturing the temporal and dynamic relationships between climatic factors and production outcomes, we provide a detailed analysis of how these factors influence shrimp production. These models incorporate both lagged and immediate effects, offering robust predictions of climate-yield relationships.The findings of this study aim to equip policymakers and aquaculture practitioners with actionable insights to develop district-specific strategies for mitigating climate risks. By enhancing the resilience of shrimp farming systems to climatic variability, this research contributes to the broader goal of sustaining Tamil Nadu's aquaculture industry in the face of ongoing and future climate challenges

2. Martials and Methods

2.1.Data Collection

Shrimp production data for Whiteleg shrimp across four districts of Tamil Nadu (Thiruvallur, Cuddalore, Thanjavur, and Nagapattinam) were obtained from the Marine Products Export Development Authority (2015–2023). Climatic data on temperature and precipitation for the same period were sourced from the India Meteorological Department. To ensure temporal alignment, all data were structured as time series, with each observation representing an annual time point. This alignment facilitated the analysis of lagged effects and temporal dependencies between climate variables and shrimp production. Missing data, where present, were addressed using interpolation methods to ensure consistency across the dataset.

2.2.Transfer Function Model (ARIMA) Framework

2.2.1. Framework

The Transfer Function Model (TFM) extends the ARIMA model to incorporate exogenous (external) variables, thereby linking time series dynamics with external predictors—climatic factors. The structure of the ARIMA model includes three main components: Autoregressive (AR) component models the influence of past values of the dependent variable on its current production. It captures the temporal dependence within the shrimp production series. The Integrated (I) component accounts for the differencing necessary to achieve stationarity in the data, ensuring that the series is free of trends and remains stable over time. Moving Average (MA) component models the relationship between past forecast errors and the current value of the dependent variable, accounting for noise in the data.

In the TFM, the exogenous climate variables (precipitation and temperature) are integrated into the model, influencing shrimp production alongside the endogenous time series components. The ARIMA and transfer function modeling frameworks are grounded in established methodologies (Box *et al.*, 2008; Wei, 2006), providing a robust basis for analyzing the interplay between climatic variability and shrimp production.The general form of the Transfer Function Model is expressed as:

$$Y_i = \alpha + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-i} + \varepsilon_i$$

$Y_i$represents the dependent variable (log-transformed shrimp production) at time t
X_{t-i} denotes the exogenous climate variables (lagged by
β_i are the coefficients for the climate variables,
ε_i is the residual error term at time
α is the constant term,
p and q represent the orders of the AR and MA components, respectively

Optimal lag lengths for exogenous variables were determined using criteria like Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The choice of

ARIMA and TFM over other models was driven by their suitability for time series with temporal dependencies and the ability to model delayed effects.

2.2.2. Data processing and Model Estimation

Before modeling, the production data were log-transformed to stabilize variance and improve normality. Stationarity was tested using the Augmented Dickey-Fuller test, with differencing applied as needed to achieve stationarity.

The TFM was estimated using Maximum Likelihood Estimation (MLE), which optimizes model parameters for the best fit. The iterative process accounted for both endogenous dynamics (via ARIMA components) and the effects of exogenous climate variables. Diagnostic tests, such as the Ljung-Box test, were applied to residuals to ensure no remaining autocorrelation, confirming model adequacy.

2.2.3. Model Evaluation

Model performance was assessed using AIC and BIC to balance fit and complexity. Significant climatic predictors were identified through t-tests ($p < 0.05$). Predictive accuracy was evaluated using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. High alignment between predicted and actual values validated the model's reliability for forecasting shrimp production.

3. Results and discussion

3.1. Thiruvallur District

The ARIMA regression model for Tiruvallur district provides insightful results about the relationship between the independent variables and the dependent variable Among the predictors, summer precipitation shows a significant negative effect ($p<0.01$), with a 1-unit increase leading to a 0.694 decrease in shrimp production. Similarly, winter precipitation has a significant negative impact ($p<0.01$), with one unit increase reducing he shrimp production by 2.439. Climate change significantly impacts shrimp farming activities in East Java, exemplified by the high rate of production failures during the rainy season, primarily driven by pronounced fluctuations in water parameters (Yuniartik*et al.*, 2022). Summer maximum temperature showed a highly significant and substantial negative relationship ($p<0.01$), while summer minimum temperature has a significant ($p<0.01$) positive effect increasing the shrimp production by 75.921 for every unit of increase. Increase in temperature and changes in precipitation pattern remarkedly affect the water salinity, pH and dissolved oxygen resulting in disease incidence, curtail food intake leads to affect the slow growth (Muralidhar*et al.*, 2012). On the other hand, winter maximum and minimum temperature did not influence statistically.

The lagged term (L) in the model highlights the importance of persistence in the time series data, with a coefficient of -0.929 ($p<0.01$). This indicates a strong negative relationship between current and previous production values. The constant terms in the autoregressive and moving average components further define the model's baseline behavior, with the AR constant showing a value of 106.246. The MA constant is marginally significant at $p<0.1$. The model's fit and performance are robust, as indicated by the chi-square value of 175,461,933 $p<0.01$), which suggests the model is statistically significant overall. The Akaike Information Criterion (AIC) value of 4.155 reflects good performance given the dataset. The dependent variable's mean (8.149) and standard deviation (0.666) further contextualize the results, indicating the consistency of production across the observations. In terms of predictive accuracy, the model performs well. For 2023, the predicted log-transformed production (is 8.110, closely matching the actual value of 8.095. When back-transformed, the predicted production is 3,329.205 compared to the actual production of 3,279.001. The minor deviation of 50.204 units demonstrates the model's reliability in forecasting production.

Figure 1 illustrates the autocorrelations of log-transformed shrimp production at different lags, with 95% confidence intervals derived using Bartlett's formula for an MA(q) model. The points represent the autocorrelation coefficients for each lag, and the shaded region indicates the range within which autocorrelations are not statistically significant at the 95% confidence level. For lag 1, the autocorrelation coefficient lies near the confidence boundary, suggesting it may be significant or borderline significant. In contrast, for lag 2, the autocorrelation falls well within the confidence band, indicating no significant autocorrelation. This pattern implies that the residuals of the transfer function model exhibit minimal serial correlation, which supports the adequacy of the fitted model.

3.2.Cuddalore district

The ARIMA regression model for Cuddalore provides valuable insights into the factors influencing shrimp production in the district. The results highlight several significant predictors that affect shrimp production outcomes. Summer and winter precipitation have significant negative effects on shrimp production, with coefficients of −0.898 and −0.857, respectively. These results indicate that excess precipitation during both the summer and winter periods reduces shrimp yields. The significance of these predictors is confirmed by their p-values (0.000), which are well below the 1% threshold. The analysis also reveals that the summer minimum temperature significantly impacts production, with a coefficient of −39.265 and p-value of 0.000. This suggests that higher minimum temperatures during the summer have a substantial adverse effect on shrimp output. Increase in temperature augment the pH and salinity and low water availability may decline the dissolved oxygen level which ultimately affect the total shrimp production (Benavides *et al.,* 2024; Dey *et al.,* 2016; Muralidhar*et al.,* 2012; Rajath*et al.,* 2023; Rosegrant*et al.,* 2016). Conversely, other temperature-related variables, such as winter minimum temperature and summer and winter maximum temperature are not statistically significant predictors of production, as their p-values exceed the typical significance thresholds.

Lagged production is another significant factor in the model, with a coefficient of −0.971 and a p-value of 0.000. This indicates that past production levels strongly influence current production, emphasizing the persistence of production trends over time. The model also includes a constant term, which captures baseline production levels, but its exact interpretation is limited due to the absence of variability in some components. The model diagnostics suggest a good fit, with a mean shrimp production of 7.797 and a standard deviation of 0.291, indicating relatively low variability in the data. The Akaike Information Criterion (AIC) value of −22.141 further supports the model's efficiency in balancing goodness of fit and complexity. However, the limited number of observations (n=9) may affect the robustness of the findings, and additional data would strengthen the analysis. The model's predictive performance is strong, as evidenced by the close alignment between the actual and predicted production values for 2023. The actual logged production value is 8.157, while the predicted value is 8.162. In production units, the actual value is 3488.501, and the predicted value is 3505.022, demonstrating a high degree of accuracy.

Figure 2 displays the autocorrelations of log-transformed production values across different lags, with confidence intervals determined by Bartlett's formula for MA(q) for Cuddalore district. The shaded gray area represents the 95% confidence bands, indicating the range within which the autocorrelations are statistically insignificant. The blue points signify the calculated autocorrelations for specific lags. From the plot, it is evident that all observed autocorrelations fall within the confidence bands, suggesting no significant autocorrelation at the examined lags. This implies that the residuals of the log-transformed production series exhibit randomness and do not display strong temporal dependence, meeting the assumptions of stationarity in a transfer function model.

3.3.Thanjavur District

The ARIMA regression model for provides valuable insights into the factors influencing shrimp production in the Thanjavur. Winter precipitation has a strong negative effect on shrimp production, with a coefficient of −4.327 and a highly significant p-value (0.000). This suggests that increased winter precipitation is associated with a substantial decline in shrimp yields. Summer and winter maximum temperature also negatively impact production, with coefficients of −61.559 and −144.995, respectively, both significant at the 1% level. These findings indicate that higher summer and winter temperatures adversely affect crop productivity, possibly due to heat stress or adverse growing conditions. Conversely winter minimum temperature show positive effects, with being statistically significant (p=0.000) and a coefficient of 45.954. This suggests that higher extreme temperatures during winter may have benefits in Thanjavur district, potentially indicating the resilience. Lagged production is another important factor, with a coefficient of −0.934 and a p-value of 0.004, indicating that past production levels influence current production negatively. This could reflect delayed effects of adverse conditions or challenges in maintaining productivity year-over-year. The model's constant term (510.445) captures the baseline production levels under average conditions. Prolonged exposure to elevated temperatures can precipitate a decline in dissolved oxygen concentrations, engendering hypoxic conditions, while concurrently fostering the proliferation of deleterious algal blooms that compromise aquatic integrity (Akinnawo, 2023). Torrential precipitation attenuates salinity levels and induces pronounced fluctuations in pH, thereby exacerbating physiological stress and diminishing immunological resilience in shrimp (Millard *et al.*, 2021)

The model diagnostics indicate a good fit, with a mean dependent variable (8.951 and a low standard deviation of 0.261. The Akaike Information Criterion (AIC) value of −6.452 suggests the model is well-specified for the given data. However, the limited number of observations (n=9) may limit the robustness of the conclusions, and additional data would enhance the model's reliability. The model's predictive performance is also strong. For the year 2023, the actual logged production 8.562, while the predicted value was 8.560, indicating a close match. In terms of actual production units, the observed value was 5229.998, and the predicted value was 5217.479, demonstrating high predictive accuracy.

Figure 3 portrays that gray shaded region represents the confidence bands within which the autocorrelation values are not statistically significant for Thanjavur. The autocorrelation values for both lag 1 and lag 2 fall inside the confidence bands. This indicates that there is no significant autocorrelation present at these lags, suggesting the residuals of the model are approximately uncorrelated over time.

3.4.Nagapattinam District

Summer precipitation shows a small but statistically significant negative effect on production in Nagapattinam district ($\beta=-0.061$, $p=0.043$), suggesting that higher summer precipitation may negatively impact productivity. Conversely, winter precipitation has a strong positive influence ($\beta=0.391$, $p=0.010$), indicating that increased precipitation during the winter season benefits shrimp production. Summer maximum temperature has a significant positive effect on production (β=21.185, p=0.000), suggesting that moderate warmth during the growing season is favourable while winter maximum temperature has a marginally significant positive effect (β=7.966, p=0.052), implying that warmer winter conditions are beneficial. In contrast, summer and winter minimum temperature negatively affecting the shrimp production in Nagapattinam but winter is not significantly influenced. Shrimp thrive within specific temperature ranges when its deviations can stress the organisms, slowing growth rates and increasing susceptibility to diseases (Millard *et al.,* 2021). Prolonged heat can lead to reduced dissolved oxygen levels in water, causing hypoxia, while also promoting harmful algal blooms that can degrade water quality (Akinnawo, 2023). Cooler conditions slow shrimp metabolism and feeding activity, leading to stunted growth and delayed harvest cycles (Ren *et al.,* 2021).Heavy rains dilute water salinity and cause fluctuations in pH, which can stress shrimp and compromise their immune systems (Millard *et al.,* 2021). Reduced freshwater availability can increase salinity to levels unsuitable for shrimp, disrupting osmoregulation and hindering survival and growth (Molina *et al.,* 2019)

Lagged production has a highly significant negative effect (β=−0.992, p=0.000), reflecting a strong inverse relationship between the previous year's production and the current year's production. This may be due to factors such as soil nutrient depletion, resource competition, or external shocks like weather variability. The constant term (−44.979) reflects underlying baseline productivity, adjusted for the effects of other variables. The model performs well overall, with a highly significant Chi-square statistic (7217400542.776, p=0.000) and an Akaike Information Criterion (AIC) value of −35.016, indicating a well-specified model. The predicted logged production (production =9.608) for 2023 aligns perfectly with the actual logged production. In real terms, the actual production (14877.495) closely matches the predicted production (14879.724), demonstrating the model's excellent predictive capability.

Figure 4 shows the autocorrelations of the log-transformed production values at different lags, with 95% confidence intervals calculated using Bartlett's formula for MA(q) processes for Nagapattinam district. The gray shaded region represents the confidence bands within which the autocorrelation values are not statistically significant. From the graph, the autocorrelation values for both lag 1 and lag 2 fall inside the confidence bands. This indicates that there is no significant autocorrelation present at these lags, suggesting the residuals of the model are approximately uncorrelated over time. This result supports the assumption that the residuals are white noise, meeting a key requirement for the validity of the transfer function model.

3.5.Comparative Analysis

Across districts, the ARIMA regression models consistently demonstrate the significant influence of climate variables, particularly precipitation and temperature, on shrimp production. Excess precipitation and extreme temperatures generally have negative effects, while moderate warmth and optimal rainfall conditions can be beneficial. Lagged production terms highlight the temporal dependencies and the importance of maintaining stable environmental conditions over time.These findings underscore the need for climate-resilient aquaculture practices, such as improved pond design, water quality monitoring, and adaptive feeding strategies, to mitigate the impacts of climate variability. Policy measures should prioritize capacity-building initiatives for farmers and investments in infrastructure to enhance resilience. Additionally, integrating long-term climate projections into aquaculture planning can support sustainable growth in shrimp farming.

4. Conclusion and implication

Across all districts, precipitation and temperature are critical determinants of shrimp production, with district-specific variations reflecting local climatic and environmental contexts. Lagged production consistently underscores the temporal dependencies inherent in aquaculture systems. The predictive accuracy of the models across districts highlights their robustness and potential utility for forecasting shrimp yields.

These findings emphasize the complex interplay between climatic variables and shrimp production, which varies across districts. Precipitation, temperature, and production history play pivotal roles, reflecting both environmental constraints and adaptive opportunities. The robust predictive performance of these models highlights their utility in forecasting shrimp yields under varying climatic scenarios, providing a valuable tool for policymakers, researchers, and practitioners. These models can guide adaptive strategies, such as optimizing farming practices or implementing climate-resilient measures, to sustain and enhance shrimp production in the face of changing environmental conditions. These findings provide valuable insights for policymakers, aquaculture managers, and researchers, emphasizing the need for district-specific adaptive strategies to mitigate the adverse effects of climatic variability. Integrating additional factors such as water quality, nutrient management, and disease dynamics into future models could further enhance predictive capabilities and inform sustainable aquaculture practices.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Table1: Climate Variables and Lagged Production Coefficients for Tamil Nadu Districts

	Tiruvallur			Cuddalore			Nagapattinam			Thanjavur		
	Coef.	St.Err.	p-value	Coef.	St.Err.	p-value	Coef.	St.Err.	p-value	Coef.	St.Err.	p-value
Summer precipitation	-0.69	0.15	0.000	-0.90	0.07	0.000	-0.06	0.03	0.043	-0.02	0.26	0.940
Winter precipitation	-2.44	0.94	0.009	-0.86	0.11	0.000	0.39	0.15	0.010	-4.33	0.35	0.000
Summer maximum temperature	-117.15	26.13	0.000	4.76	7.72	0.537	21.19	3.61	0.000	-61.56	12.21	0.000
Winter maximum temperature	13.40	10.36	0.196	3.55	3.36	0.290	7.97	4.10	0.052	-145.00	16.63	0.000
Summer minimum tempera rue	75.92	26.65	0.004	-39.27	9.64	0.000	-13.62	3.19	0.000	31.86	.	.
Winter minimum tempera rue	17.29	19.18	0.367	0.97	.	.	-2.27	4.09	0.579	45.95	10.06	0.000
Constant	106.25	.	.	112.60	.	.	-44.98	.	.	510.45	.	.
Lagged production	-0.93	0.18	0.000	-0.97	0.13	0.000	-0.99	0.03	0.000	-0.93	0.32	0.004
Constant	0.09	0.06	0.059	0.02	0.03	0.207	0.01	0.01	0.151	0.06	0.02	0.006
Mean dependent var	8.149			7.797			9.5			8.951		
SD dependent var	0.666			0.291			0.216			0.261		
Chi-square	1.75E+08			4.56E+09			7.22E+09			2.76E+10		
Akaike crit. (AIC)	4.155			-22.141			-35.016			-6.452		

Table 2: Comparison of Predicted and Actual Shrimp Production (Log-Transformed and Actual Values) for Tamil Nadu Districts

	Predicted log-transformed production	Actual log-transformed production	Actual production	Predicted production
Tiruvallur	8.095	8.11	3279.001	3329.205
Cuddalore	8.157	8.162	3488.501	3505.022
Thanjavur	9.608	9.608	14877.5	14879.72
Nagapattinam	8.562	8.56	5229.998	5217.479

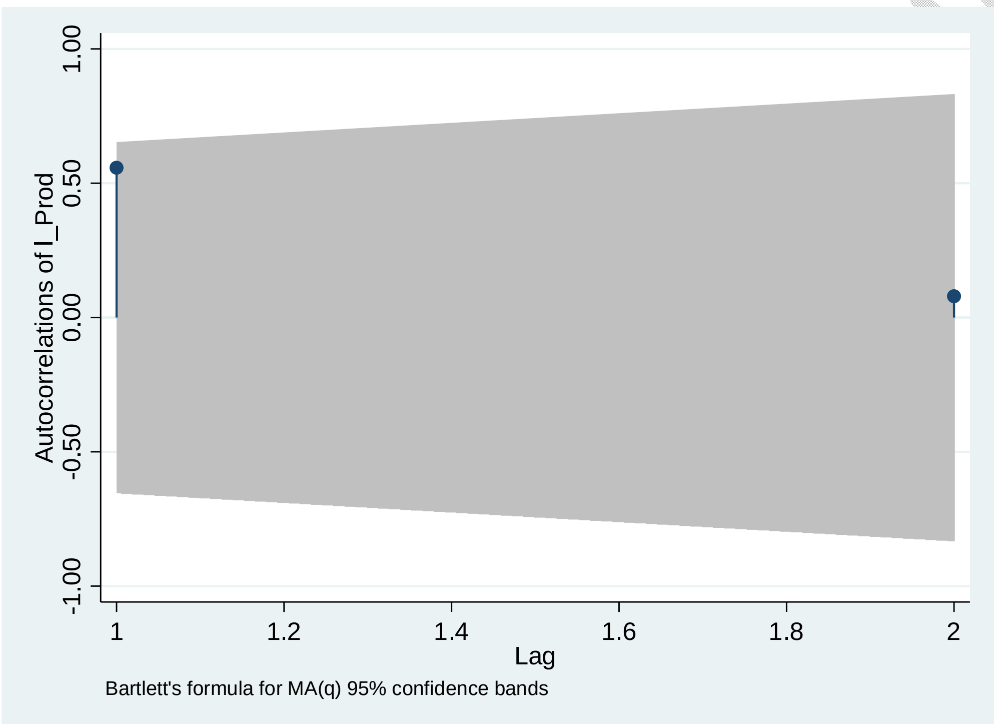

Figure 1. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Tiruvallur

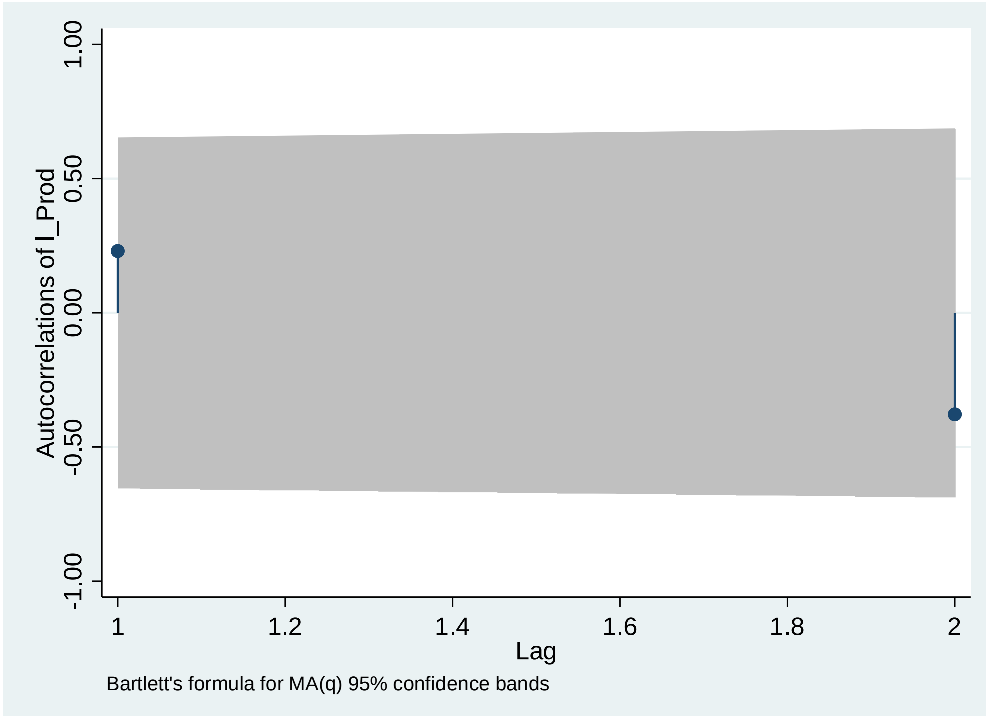

Figure 2. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Cuddalore

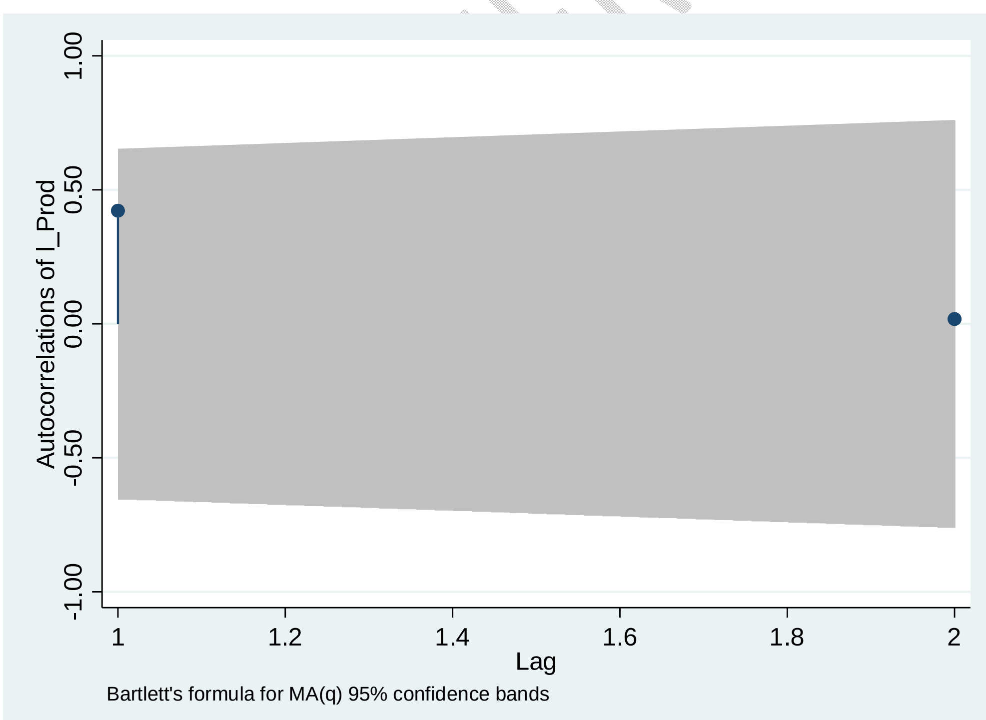

Figure 3. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Thanjavur

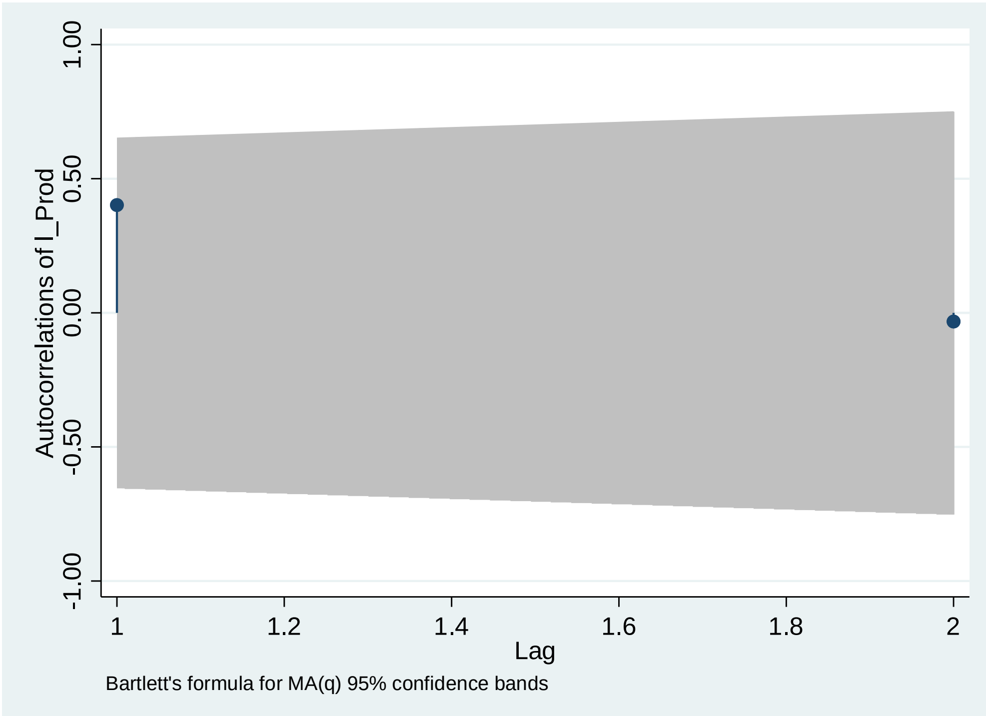

Figure 4. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Nagapattinam