

Climatic Determinants of Shrimp Yields in Tamil Nadu, India: Insights from Transfer Function Models

Abstract

Shrimp aquaculture in Tamil Nadu is vital to livelihoods and exports but faces significant risks from climatic variability. This study evaluates the effects of summer and winter precipitation, maximum and minimum temperatures, and lagged production on shrimp yields across four districts—Tiruvallur, Cuddalore, Thanjavur, and Nagapattinam—using ARIMA-based transfer function models (2015–2023). In Tiruvallur, excessive summer and winter precipitation, coupled with elevated summer maximum temperatures, exhibited pronounced negative effects on yields, whereas summer minimum temperatures significantly enhanced production. In Cuddalore, shrimp yields were adversely impacted by both summer and winter precipitation, as well as elevated summer minimum temperatures, with lagged production exerting a strong inhibitory influence. Thanjavur revealed a marked sensitivity to winter precipitation and extreme summer and winter maximum temperatures, both of which suppressed yields, whereas winter minimum temperatures had a beneficial effect. Nagapattinam presented distinct dynamics, where winter precipitation and summer maximum temperatures positively influenced yields, while summer precipitation and lagged production exerted deleterious effects. The models demonstrated high predictive accuracy for 2023, highlighting their robustness. These findings underscore the importance of district-specific strategies to mitigate climate risks and sustain shrimp production. Future research integrating water quality and disease dynamics could further enhance the resilience of Tamil Nadu's shrimp aquaculture.

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

1. Introduction

Aquaculture plays a pivotal role in global food security and economic development, with shrimp farming emerging as one of the most lucrative and rapidly expanding sectors (FAO, 2014, 2016, 2020). In India, shrimp aquaculture contributes significantly to the nation's seafood exports, supporting the livelihoods of millions (Globefish, 2022; Singh et al., 2021). Tamil Nadu, a coastal state in southern India, is a major hub for shrimp production due to its favorable geographic and climatic conditions (Krishnan & Babu, 2022). However, the sector is increasingly vulnerable to the effects of climate variability and change, which can disrupt production systems and impact yields (Do & Ho, 2022). Understanding the intricate relationship between climatic variables and shrimp production is, therefore, essential for developing resilient aquaculture systems.

Climate variables, such as precipitation and temperature, are critical determinants of shrimp farming success (Do & Ho, 2022; Islam et al., 2019; Kais & Islam, 2019; Shameem et al., 2015). Excessive precipitation can alter pond salinity, nutrient levels, and water quality, while temperature extremes can stress shrimp, reducing growth and increasing susceptibility to diseases (Ahmed & Diana, 2015; Do & Ho, 2022; Muralidhar et al., 2012; Shameem et al., 2015). Moreover, temporal dynamics, including lagged effects from previous production cycles, add complexity to predicting shrimp yields (Devlin et al., 2017; Montoya et al., 1999). Despite the acknowledged importance of these factors, limited research has quantitatively

explored their impacts using robust statistical models at the regional level. This gap is particularly pronounced for Tamil Nadu, where district-level variations in climate and production systems demand localized analyses.

The present study aims to address this gap by employing transfer function models, specifically ARIMA-based regression models, to quantify the effects of key climatic variables—summer and winter precipitation, summer and winter maximum and minimum temperatures—on shrimp production across four districts of Tamil Nadu: Thiruvallur, Cuddalore, Thanjavur, and Nagapattinam. Transfer function models are well-suited for capturing the temporal and climatic dynamics of aquaculture systems, as they incorporate both lagged and contemporaneous relationships between independent variables and production outcomes.

By integrating district-level data and applying a rigorous statistical approach, this study provides actionable insights into the climatic determinants of shrimp yields. The findings aim to inform policymakers, aquaculture practitioners, and researchers on the implications of climate variability for sustainable shrimp farming in Tamil Nadu. Furthermore, the study underscores the importance of region-specific strategies to mitigate climate risks and enhance the resilience of shrimp aquaculture in the face of ongoing and future climatic challenges.

2. Materials and methods

2.1. Data Collection

Whiteleg Shrimp production data was sourced from Marine Products Export Development Authority for four districts of Tamil Nadu for span of 2015 to 2023. Climate data of temperature and precipitation was sourced from India Meteorological Department for the same period. The time series of both dependent and independent variables were aligned temporally to ensure proper synchrony between climatic conditions and production output. All data was organized as a time series, with each observation representing a discrete time point (yearly). The time series structure facilitates the analysis of lag effects and temporal dependencies in the relationship between climate variables and shrimp production.

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 value. 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 general form of the Transfer Function Model is expressed as:

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

Y_t represents the dependent variable (log-transformed shrimp production) at time t

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

The determination of optimal lags for the exogenous variables is based on theoretical considerations, as well as model selection criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). The lags account for delayed effects of climate variables on shrimp production, which are critical for capturing the dynamics of shrimp processes.

2.2.2. Model Estimation

The ARIMA regression model with transfer function components is estimated using maximum likelihood estimation (MLE) or, alternatively, least squares estimation. This method estimates both the internal dynamics of shrimp production (via the ARIMA components) and the influence of exogenous climate variables. The estimation process is iterative, where the parameters are optimized to best fit the observed data. After the model is estimated, various diagnostic checks are performed to ensure that the model is appropriate for the data. The residuals should exhibit no autocorrelation, ensuring that all temporal dependencies are captured. The Ljung-Box test is applied to examine any remaining autocorrelation in the residuals.

2.2.3. Model Evaluation

The overall performance of the model is assessed using information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Lower AIC and BIC values indicate a better model fit with fewer parameters, providing a balance between model complexity and explanatory power. Each coefficient is tested for statistical significance, typically using t-tests. A p-value below 0.05 indicates that the corresponding variable has a statistically significant impact on shrimp production. Significant coefficients offer insights into the key climatic drivers affecting shrimp yield. The predictive accuracy of the model is evaluated by comparing the predicted shrimp production values with the actual values. Performance metrics such as the Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared provide quantifiable measures of forecasting accuracy. A close alignment between predicted and actual production values indicates the reliability of the model for future forecasting.

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 the 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 remarkably 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 (Akinawo, 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 ($\beta=21.185$, $p=0.000$), suggesting that moderate warmth during the growing season is favourable while winter maximum temperature has a marginally significant positive effect ($\beta=7.966$, $p=0.052$), 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 (Akinawo, 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 ($\beta=-0.992$, $p=0.000$), 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.

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.

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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 temperature	75.92	26.65	0.004	-39.27	9.64	0.000	-13.62	3.19	0.000	31.86	.	.
Winter minimum temperature	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

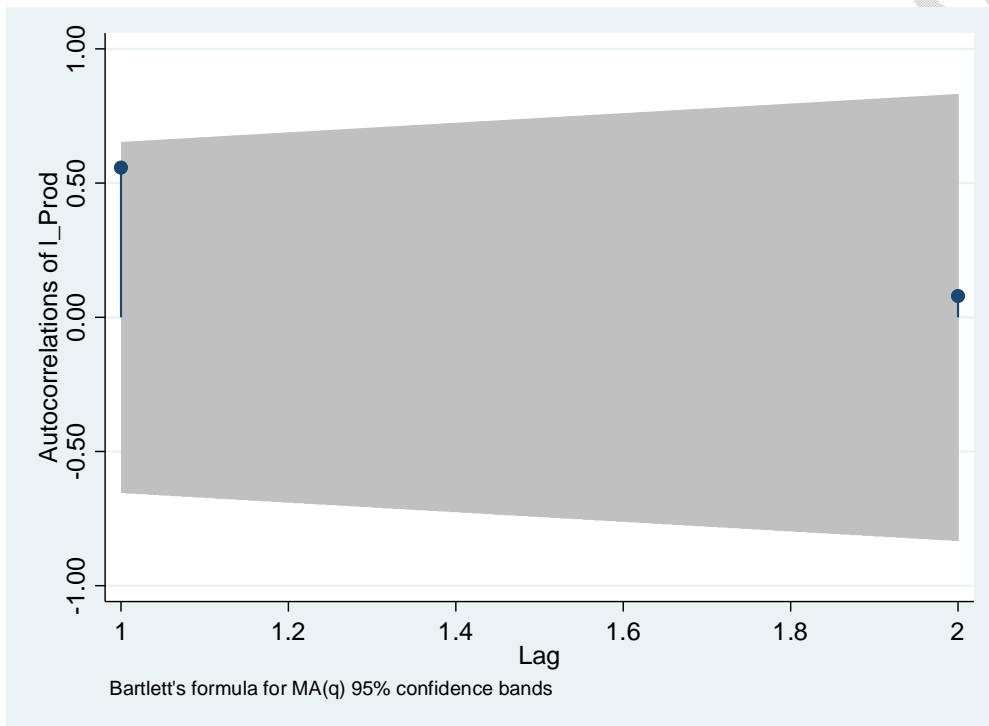


Figure 1. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Tiruvallur

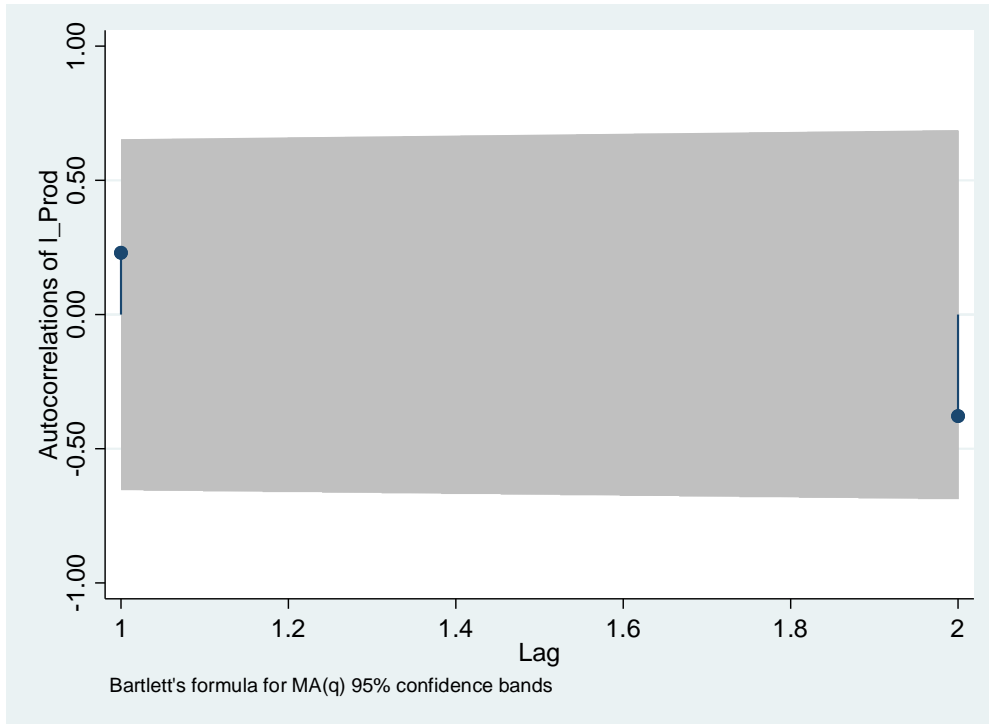


Figure 2. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Cuddalore

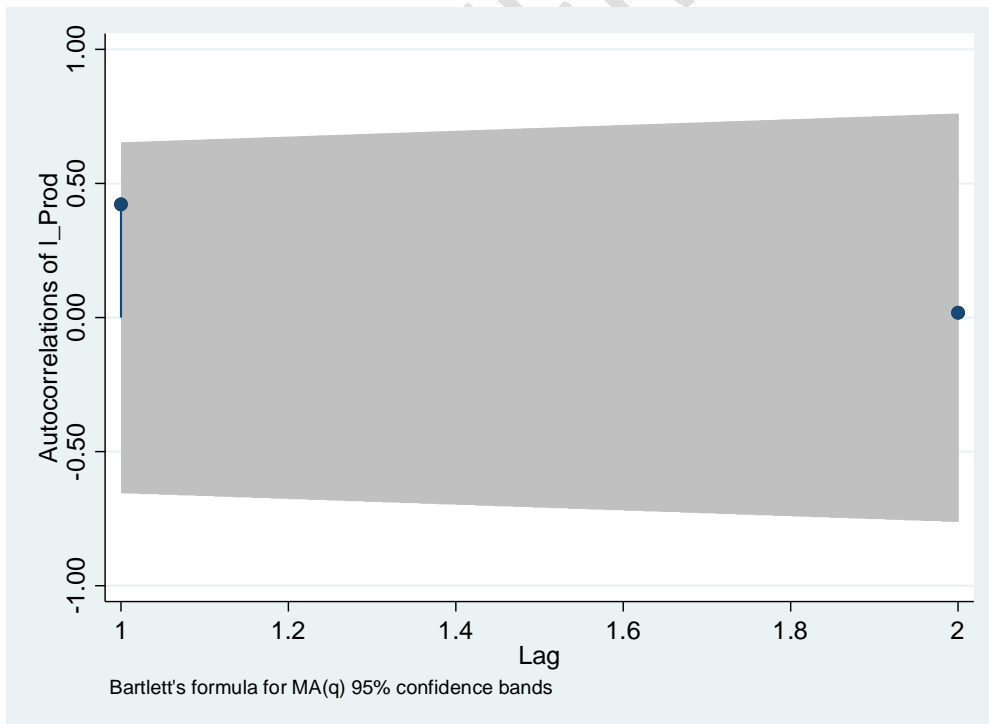


Figure 3. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Thanjavur

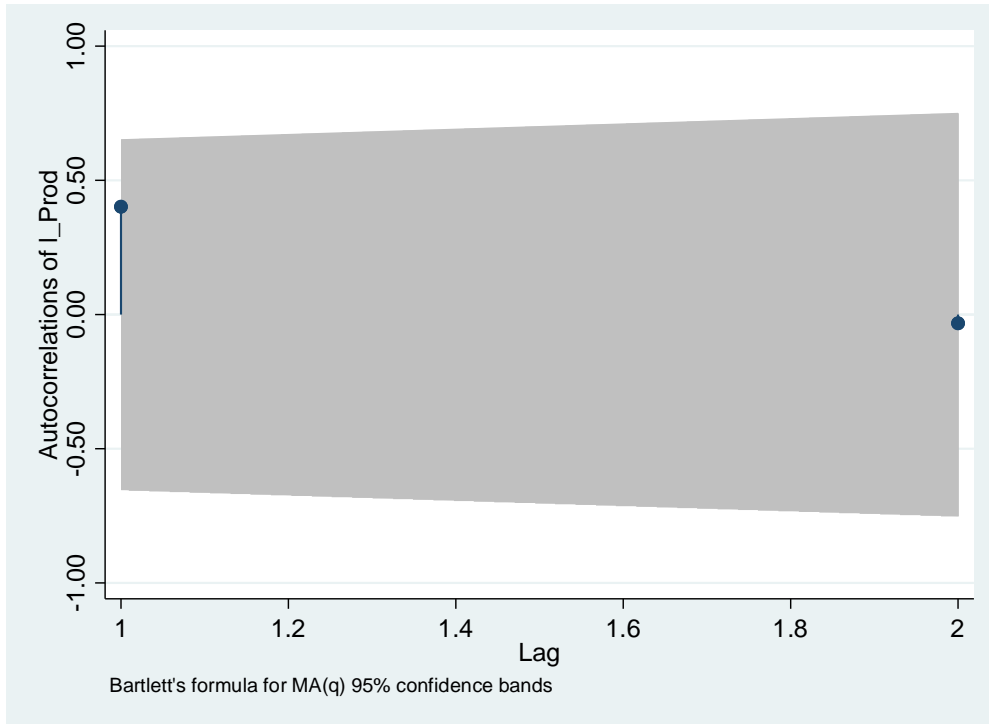


Figure 4. Autocorrelations of Log-Transformed Production with 95% Confidence Intervals Using Bartlett's Formula for Nagapattinam

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