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Agricultural Production Challenges: Climate, Land Area, and Industrialization in Batang Regency, Indonesia

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ABSTRACT: Climate change, land constraints, and industrialization pose major challenges to agricultural production in Indonesia, particularly in Batang Regency, Indonesia. This study examines the effects of temperature, precipitation, population density, agricultural land area, and industrialization on agricultural production using annual secondary data from Statistics Indonesia for the period 1979-2024. The Autoregressive Distributed Lag (ARDL) approach was employed to analyze both short run and long run relationship. The results indicate that the selected model is ARDL (1,1,0,0,0,0), with the Augmented Dickey Fuller (ADF) test confirming variable stationarity and The Bounds Test indicating a long run cointegration relationship. In the short run, lagged temperature and agricultural land area have significant negative effects on agricultural production, whereas population density and industrialization have significant positive effects. In the long run, temperature and agricultural land area are negatively associated with agricultural production, whereas population density and industrialization continue to exert positive effects. Precipitation did not significantly influence agricultural production during either period. These findings highlight the importance of strengthening climate adaptation, improving land productivity, and promoting industrial development that supports agricultural sustainability through technological advancement and stronger agricultural industrial linkages.

1. INTRODUCTION

Rapid industrial expansion has been one of the most visible structural changes in Batang Regency, Central Java, over the last decade. The establishment of the Batang Integrated Industrial Estate (KITB), covering more than 4,300 ha, accelerated investment, employment, and infrastructure development across the regency. Simultaneously, agriculture has continued to play an important role in the regional economy, contributing 18.35% of the Gross Domestic Regional Product (GDRP) in 2024 (Statistics Indonesia, 2024). The coexistence of these two sectors raises important questions regarding regional development. While industrialization is expected to stimulate economic growth, it also increases pressure on agricultural land, labor availability, and other productive resources that have traditionally supported farming activities (Bonye et al., 2021)

Changes in land use are not the only challenge faced by agriculture in the Batang Regency. Climatic conditions have shifted over the past few decades. The average temperature in Central Java has increased by approximately 0.60°C over the past 40 years, and Batang has experienced a similar warming trend (Indonesian Agency for Meteorological, 2024). Rainfall has become

more variable than in previous decades, with periods of intense precipitation alternating with prolonged, dry conditions. Such variability is particularly important because rice, maize, and several other major crops depend on adequate water availability during the sensitive stages of crop development. Previous studies have reported substantial yield losses when water shortages occur during these periods (Li et al., 2023). As industrial development and climate change occur simultaneously, changes in agricultural production are unlikely to be explained by either process alone.

Industrialization has not produced identical outcomes for agriculture across different regions. In several cases, improvements in transportation infrastructure, market accessibility, and logistics have strengthened agricultural activities by lowering the production and distribution costs (Vaka, 2024). In contrast, other studies have associated industrial expansion with declining agricultural performance because productive land is converted to nonagricultural uses and rural workers move into industrial employment (Ayenachew & Abebe, 2024). These contrasting findings suggest that industrial development may either support or constrain agriculture, depending on the region in which it occurs. Therefore, understanding this relationship requires evidence from locations undergoing rapid structural changes rather than relying solely on broader national patterns.

Industrial growth in Batang Regency has occurred during a period when agriculture has also faced other pressures. The population reached approximately 817,000 in 2022, while residential areas, industrial estates, and public facilities continued to expand (Statistics Indonesia, 2022). As land is increasingly required for nonagricultural purposes, farming must compete for the same resources. Farmers have also experienced greater variability in temperature and rainfall than in the previous decades. Because these changes occurred over the same period, it is difficult to consider any one of them in isolation when explaining changes in agricultural production.

Published evidence reflects this complexity in several ways. Studies conducted in different regions have reported different responses of agricultural production to industrial development, climate variability, and land resources (Chandio et al., 2023). In some cases, industrialization has supported agriculture by improving infrastructure and expanding market access (Ma & Huang, 2023; Yogi et al., 2025). In others, it coincided with farmland conversion and labor movement away from agriculture (Ayenachew & Abebe, 2024; Maharjan et al., 2020). These contrasting results suggest that regional context remains important when interpreting the relationship between structural change and agricultural production.

For Indonesia, much of the available evidence comes from analyses at the national and provincial levels. Less is known about districts where industrial expansion, climate variability, population growth, and changes in agricultural land occur simultaneously. Batang Regency represents one such setting. Examining these factors together may improve our understanding of how they shape agricultural production under conditions of rapid regional transformation.

This study examines the impact of temperature, rainfall, population density, agricultural land, and industrial GDP on agricultural production in Batang Regency from 1979 to 2024, employing the Autoregressive Distributed Lag (ARDL) approach. Estimating both short and long-term relationships reveals the association between environmental and structural changes and agricultural production over time, offering insights for regional development and agricultural policy.

2. MATERIALS AND METHODS

2.1 Study Area and Research Design

This study employs a quantitative approach within an econometric framework to examine the relationships among climate, land, industrialization, and agricultural output in Batang Regency, Indonesia. Quantitative methods were chosen to test hypotheses about how different factors affect agricultural production in both the long and short run using a statistical analysis. The econometric method employed is the Autoregressive Distributed Lag (ARDL) model, which is ideal for time series data with variables ordered at level $I(0)$ and first difference $I(1)$, but not at the second difference, $I(2)$. The dataset comprises annual time series data from 1979 to 2024, with 46 observations per country. All data were secondary and were sourced from Statistics Indonesia. The response variable in this study was agricultural production, and the independent variables were temperature, precipitation, population density, agricultural land area, and industrialization. The operational definitions of each variable are presented in Table 1.

Table 1. Details of The Selected Variables

Variables	Code	Description	Unit
Agricultural Production	PROD	Agricultural Gross Regional Domestic Product at constant prices	Rupiah
Temperature	TEMP	Annual average temperature per year	°C
Precipitation	PREC	Annual total precipitation per year	mm/year
Agricultural Land	AGRL	Land area used for agricultural activities	Hectares
Population Density	DENS	Number of people per square kilometer	People/km ²
Industrialization	INDU	Industrial Gross Regional Domestic Product at constant prices	% of GDP

2.2 Data Analysis

The ARDL bounds testing technique was used to analyze the relationships among economic growth, remittances, agriculture, and other factors. The ARDL model is ideal when some variables are stationary at the first difference and others at the level. It is also recommended for studies with small sample sizes (Pesaran et al., 2001). This study uses the ARDL model because some variables are stationary at the level and others at the first difference. The ARDL framework is beneficial because it estimates both long and short run dynamics simultaneously.

Various diagnostic tests and procedures were conducted to confirm the ARDL model. Initially, a unit root test was used to verify if the time series data were stationary. The Augmented Dickey Fuller (ADF) test was used for this. The ADF test accommodates higher-order autoregressive dynamics (Dickey & Fuller, 1981). The basic form of the ADF test equation is shown in Eq. (1).

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

where Y_t is the variable under investigation, t is the time trend, and α is a constant, γ is the coefficient of the lagged variable indicating the presence of a unit root, and ε_t is the error term.

If $\gamma=0$, the series has a unit root and is therefore nonstationary. The ADF test helps confirm that the variables are either stationary at level $I(0)$ or at first difference $I(1)$, which is a precondition for the ARDL bounds testing. Once the order of integration of the variables is identified, the ARDL bounds test for cointegration is implemented to examine the existence of long term relationships between the dependent and independent variables. The general ARDL model can be expressed in Eq. (2).

$$Y_t = \alpha_0 + \sum_{i=1}^p \lambda_i Y_{t-i} + \sum_{j=1}^k \sum_{i=0}^{q_j} \delta_{ji} X_{jt-i} + \mu_t \quad (2)$$

where Y_t is the dependent variable, X_{jt} denotes the independent variables, p is the lag length of the dependent variable, q_j is the lag length of the independent variable j , α_0 is a constant, and μ_t is the error term.

Specifically, the ARDL model was reformulated into natural logarithm. The lag, where agricultural production (PROD) is the dependent variable and temperature (TEMP), precipitation (PREC), population density (DENS), agricultural land area (AGRL), and industrialization (INDU) are the independent variables, can be expressed as in Eq. (3).

$$LPROD_t = \alpha_0 + \sum_{i=1}^p \lambda_i LPROD_{t-i} + \sum_{i=0}^{q_1} \beta_{1i} LTEMP_{t-i} + \sum_{i=0}^{q_2} \beta_{2i} LPREC_{t-i} + \sum_{i=0}^{q_3} \beta_{3i} LDENS_{t-i} + \sum_{i=0}^{q_4} \beta_{4i} LAGRL_{t-i} + \sum_{i=0}^{q_5} \beta_{5i} LINDU_{t-i} + \mu_t \quad (3)$$

where L denotes natural logarithm, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ represent coefficients of independent variables, $t - i$ refers to time period, and μ_t indicates the residual. The coefficient λ captures both the short and long run dynamic relationships.

This formulation captures the dynamic interrelationship between agricultural production and its determinants in the short and long run. Once cointegration is established, the short run dynamics are examined using the Error Correction Model (ECM) obtained from the ARDL specification. The short term equation is presented in Eq. (4).

$$EC_t = \varepsilon_t = y_t = \sum_{i=1}^k \theta_i x_{it} = \psi' W_t \quad (4)$$

The estimation process involved several steps. First, the best lag length was chosen applying criteria such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC). Second, the ARDL bounds test was used to check for cointegration. A long term relationship among the variables is confirmed if the F-statistic is above the upper critical value. Third, after confirming cointegration, both long term coefficients and short term dynamics were determined together using the ARDL-ECM framework. Fourth, to verify the model's validity, diagnostic tests such as the Breusch Godfrey LM test for serial correlation, White's test for heteroskedasticity, and the Jarque-Bera test for normality were conducted. Finally, stability tests, such as the Cumulative Sum of Recursive Residuals (CUSUM), assessed the stability of the estimated parameters over the study period.

3. RESULTS AND DISCUSSION

3.1 Unit Root Test

To begin analyzing the ARDL model, a unit root test was conducted to identify whether the data series was stationary. This step is crucial for avoiding false regressions that can lead to incorrect results. Stationarity testing helps determine the integration order of each variable, showing whether they are at level $I(0)$ or at first difference $I(1)$. This step is essential, as the ARDL model is only appropriate when the variables are a combination of $I(0)$ and $I(1)$, but not when any variable is integrated at the second order, $I(2)$. In this study, stationarity was examined using the Augmented Dickey-Fuller (ADF) test. The results for each research variable are shown in Table 2. As shown in Table 2, all variables were stationary at levels or in first differences, with no variable integrated of order 2. These findings confirm the suitability of applying the ARDL model in this research.

Table 2. Results of Unit Root Testing Using the ADF Test Method

No	Level		1 st difference		Outcome
	Variable	Prob	Variable	Prob	
1	LPROD	0.2021	D(LPROD)	0.0000*	I(1)
2	LTEMP	0.0000*	D(LTEMP)	0.0000*	I(0)/I(1)
3	LPREC	0.0000*	D(LPREC)	0.0000*	I(0)/I(1)
4	LDENS	0.8430	D(LDENS)	0.0002*	I(1)
5	LAGRL	0.0014*	D(LAGRL)	0.0000*	I(0)/I(1)
6	LINDU	0.0742	D(LINDU)	0.0000*	I(1)

1% significance level is denoted by * respectively.

Source: Author's calculation using Eviews

3.2 Optimal Lag Selection

The best lag length was found using the VAR Lag Order Selection Criteria, which include the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn (HQ). Table 3 shows that lag 2 had the most selection markers among the lag orders, making it the best choice. Therefore, the ARDL model in this study uses a lag length of two, yielding a more accurate view of the dynamic relationships among the variables.

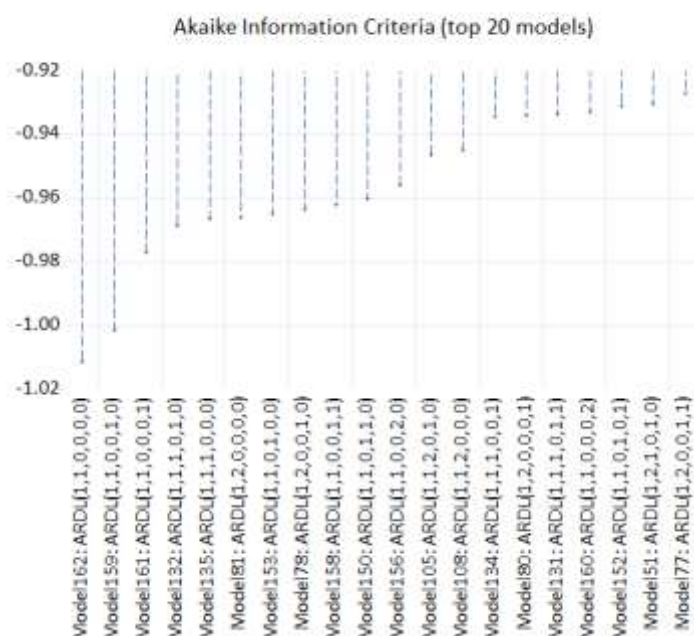
Table 3. Results of the optimal lag test conducted with VAR

Lag	LogL	LR	FPE	AIC	SC	HQ
0	109.021	NA	3.34e-10	-4.7916	-4.545	-4.701
1	274.213	276.601	8.36e-13	-10.800	-9.080*	-10.166
2	325.049	70.9342*	4.63e-13*	-11.490	-8.295	-10.312*
3	364.155	43.6528	5.28e-13	-11.635*	-6.965	-9.913

Source: Author's calculation using Eviews

After determining the optimal lag length, the following step is to identify the most appropriate ARDL specification using the Akaike Information Criterion (AIC). This procedure involves comparing the AIC values across various ARDL model combinations. As shown in Figure 1, the lowest AIC was obtained for the ARDL(1,1,0,0,0) model. Accordingly, this model was selected as the best-fitting ARDL model, as it yielded the most efficient estimates and demonstrated the greatest consistency with the characteristics of the research data.

Figure 1. Optimal Lag Selection Criteria And Best Model Using AIC Criteria



3.3 Cointegration Test using The F-Bound Test

After selecting the best ARDL model, the next step was to perform a cointegration test using the F-Bounds Test to assess long run relationships among the variables. As shown in Table 4, the calculated F-statistic of 24.157384 is much higher than the upper bound critical values (I(1)) at both the 5% significance level (3.38) and the 1% significance level (4.15). The results show a long-term connection among agricultural production, temperature, precipitation, population density, agricultural land area,

and industrial value added in Batang Regency. The ARDL (1,1,0,0,0,0) model meets the AIC selection criteria and confirms a valid long term relationship, making it suitable for further analysis.

Table 4. Bound Testing Cointegration Test using F Bounds Test

Test Statistic	Value	Significance	I(0)	I(1)
F-statistic	24.157384	10%	2.080	3
K	5	5%	2.39	3.38
		1%	3.06	4.15

Source: Author's calculation using Eviews

3.4 Short Run and Log Run Result

Table 5 reports the results of the short run ARDL estimation. This indicates that the coefficient for the previous period's agricultural production is 0.536593, with a 1% statistical significance. This means that a 1% increase in agricultural production in the previous period leads to a 0.53% increase in the current period, showing the ongoing influence of past agricultural productivity. This result is consistent with other studies, which suggest that a significant lagged dependent variable indicates short-run stability in the ARDL model (Cho et al., 2023; Derouez & Alqattan, 2025).

Table 5. Short Run ARDL Estimation Results

Variable	Coefficient	t-Statistic	Prob.*
D(LPROD(-1))	0.536593	4.836251	0.0000**
LTEMP	0.288541	1.100187	0.2786
LTEMP(-1)	-1.029082	-3.864104	0.0004**
LPREC	-0.038748	-0.389943	0.6989
D(LDENS)	2.230616	2.141927	0.0390*
LAGRL	-0.611902	-2.573055	0.0143*
D(LINDU)	0.581718	7.238380	0.0000**
C	9.242998	3.259166	0.0024
R-squared	0.746279		
Adjusted R-squared	0.696944		
F-statistic	15.12686		
Prob(F-statistic)	0.000000***		

1% and 5% significance levels are denoted by ** and * respectively.

Source: Author's calculation using Eviews

Table 5 presents a model with an R-squared of 0.7462, indicating that 74.62% of the variation in agricultural production is accounted for by these variables. Moreover, the F-statistic is significant at the 1% level, confirming the reliability of this estimation. These findings suggest that agricultural production in Batang Regency is mainly affected by internal factors in the short term.

Table 6. Long Run ARDL Estimation Results

Cointegrating Form			
Variable	Coefficient	t-Statistic	Prob.*
CointEq	-0.4634	-14.0458	0.0000***
Long Run Coefficients			
Variable	Coefficient	t-Statistic	Prob.*
LTEMP(-1)	-1.5980	-1.8362	0.0742*
LPREC	-0.0836	-0.3876	0.7005
D(LDENS)	4.8135	2.0211	0.0503*
LAGRL	-1.3204	-2.6532	0.0116**
D(LINDU)	1.2553	2.9637	0.0052***
C	19.9457	3.0954	0.0037***

1%, 5%, and 10% significance levels are denoted by ***, ** and * respectively.

Source: Author's calculation using Eviews

The long term estimation results in Table 6 indicate cointegration through the error correction term (CointEq), with a coefficient of -0.4634 and statistical significance at the 1% level. This means there is an adjustment mechanism toward long term equilibrium, correcting about 46.34% of any short-term imbalance in the next period. This result supports the validity and strength of the ARDL model applied in this study.

3.5 Diagnostic Test

To confirm the model used in this study, several classical assumption tests were performed. These tests assess whether the model meets the basic statistical standards, enabling an accurate and unbiased analysis of the estimation results. Table 7 presents the diagnostic checks, including tests for normality, heteroscedasticity, and autocorrelation.

Table 7. Classical Assumption Test

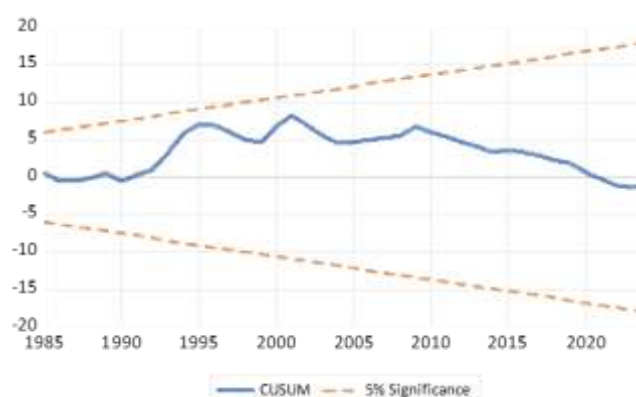
Classical Assumption	Prob	Conclusion	Description
Normality	0.4785	> 0.05	Data normally distributed
Autocorrelation	0.2156	> 0.05	No Autocorrelation
Heteroscedasticity	0.3438	> 0.05	No Heterokedasticity

Source: Author's calculation using Eviews

The classical assumption tests indicated that the regression model met the study's validity requirements. The normality test ($p = 0.4785$), autocorrelation test ($p = 0.2156$), and heteroskedasticity test ($p = 0.3438$) all had p -values greater than 0.05. This means the data were normally distributed and showed no autocorrelation or heteroskedasticity. Thus, the model was suitable for further analyses.

The last part of the analysis checks the stability of the Autoregressive Distributed Lag (ARDL) model using CUSUM tests. These tests were conducted to assess whether the model was stable over time. As shown in Figure 2, the blue line remains within the critical bounds (red lines), confirming the stability and reliability of the ARDL model. This result ensures that the estimation outcomes are reliable for analyzing both short term and long term relationships among the variables studied.

Figure 2. Plot of Model Stability Test Results with the CUSUM Test



3.6 Discussion

In the short run, agricultural production in the previous period ($D(LPROD(-1))$) has a positive and significant effect on the current agricultural production. The coefficient of 0.5366 indicates that changes in agricultural production in the previous period continued to influence current agricultural production. This finding suggests the presence of production persistence, in which agricultural production tends to persist from one period to the next because farming activities depend on previous input use, farmers' experience, and ongoing investments (Khalifa, 2025; Valliyangal & Mohammed Kasim, 2026). This also indicates that agricultural production adjusts gradually rather than immediately.

Temperature produced different results between the current and previous periods. However, this effect was not significant during the current period. One possible explanation is that farmers may employ adaptation strategies such as adjusting planting schedules or using heat tolerant varieties (M. Kumar et al., 2024; Saikanth et al., 2023; Suranny et al., 2022). In addition, the effects of temperature on crop growth often take time to manifest in production outcomes (Guerriero et al., 2024; Rustamova et al., 2026). In contrast, the lagged temperature variable ($LTEMP(-1)$) has a negative and significant effect, with a coefficient of -1.0291. This indicates that high temperatures in the previous period reduce agricultural production in the current period because the effects of heat stress accumulate over time. Prolonged exposure to high temperatures disrupts plant physiological processes, reduces photosynthesis and flower development, and triggers molecular changes that affect subsequent crop growth (Kwon & Choi, 2022; Liang et al., 2022; Sharma et al., 2024).

In the long run, temperature also has a negative and significant effect, with a larger coefficient of -1.5980, although it is significant only at the 10% level. Sustained high temperatures exceed plants' adaptive capacity, leading to reduced productivity (A. Kumar et al., 2025; Nadeem et al., 2018). Long term warming also alters precipitation patterns, soil moisture, and the spread of pests and diseases, further increasing plant stress and reducing crop yields (Mba et al., 2025; Raza et al., 2019). These findings highlight the importance of long term adaptation strategies to address the impact of climate change on agriculture.

Precipitation had no significant effect in either the short or long run. Although its coefficient is negative, the effect is not statistically significant. One possible explanation is that irrigation, water conservation practices, and adjustments in cropping patterns reduce farmers' reliance on seasonal precipitation, helping maintain agricultural production despite precipitation fluctuations (Ghosh et al., 2023; Suranny et al., 2022). Similarly, other studies have found that although precipitation can influence agricultural production, its effect may become neutral or insignificant over time as farming systems adapt through technological improvements and the adoption of crop varieties that are more tolerant to different precipitation conditions (Chandio et al., 2023).

Population density has a positive and significant effect on agricultural production in both the short and long run. In the short run, a 1% increase in population density increases agricultural production by 2.2306%, whereas in the long run, the effect increases to 4.8135%. This positive relationship suggests that a higher population density is associated with greater labor availability, improved market access, and stronger economic multipliers that support agricultural activities (Awasthi & Adhikari, 2024; Velázquez-Torres et al., 2025).

Agricultural land area has a negative and significant effect on agricultural production in both the short and long run. The long run coefficient (-1.3204) is larger than the short run coefficient (-0.6119), indicating that the negative effect becomes stronger over time. Although a larger land area is generally expected to increase agricultural output, the results suggest that land expansion alone does not necessarily improve productivity. This finding is consistent with other studies that reported a trade-off between land expansion and productivity intensification in OECD countries (Radmehr, 2026). The negative coefficient may suggest that proportional increases in productivity have not accompanied land expansion in Batang, Indonesia. However, because this study did not directly measure land-use efficiency, this interpretation warrants further investigation. Similarly, research in China found that both very small and very large farm sizes reduce production efficiency, with the relationship following an inverted U-shaped pattern in which productivity reaches its highest level at an optimal farm size ((Li et al., 2025). Evidence from Somalia also shows that agricultural land expansion is often accompanied by environmental degradation, which reduces crop productivity and yields, particularly in the short term (Nor & Yusof, 2025).

Industrialization has a positive and significant effect on agricultural production in both the short and long run. In the short run, a 1% increase in industrialization raises agricultural production by 0.5817%, whereas in the long run, the effect increases to 1.2553%. This indicates that the benefits of industrialization become stronger over time. Industrial growth is important for creating jobs, increasing income, and improving access to technology, all of which help to boost agricultural productivity (Ndiomaluke et al., 2025). Additionally, industrialization encourages technological progress and strengthens human skills, both of which are crucial for making agriculture more efficient (Adeyemo et al., 2024; Lakner et al., 2018). A recent example is the industrial development in Batang Regency, especially the creation of the Batang Integrated Industrial Estate (KITB), a Special Economic Zone (KEK). This estate includes infrastructure such as the Trans-Java Toll Road, logistics facilities, utilities, and port development, which help distribute agricultural inputs and outputs and expand market access for local products. These improvements are expected to benefit agriculture by lowering transaction costs, improving market integration, and accelerating the spread of technology. Evidence shows that industrialization does not necessarily harm agriculture; instead, it can boost agricultural production when strong connections between the industry and agriculture are formed.

4. CONCLUSION

The Autoregressive Distributed Lag (ARDL) method was used in this study to explore the factors affecting agricultural production in Batang Regency. The findings show that agricultural production varies over time, with past production having a strong impact on current production in the short term. Temperature negatively affects agricultural production, especially through its delayed short term impact and ongoing long term effects, emphasizing the growing challenges of climate change. In contrast, population density and industrialization positively contribute to agricultural production in the short and long run, suggesting that demographic dynamics, technological progress, infrastructure development, and stronger agricultural industrial linkages can support agricultural productivity. Agricultural land area had a significant negative effect in both periods, implying that expanding cultivated land alone is insufficient to increase production without improving land quality, management, and productivity. Meanwhile, precipitation did not significantly affect agricultural production in the short or long run. Overall, the findings show a long term balance between agricultural production and its factors. The findings suggest that sustainable agricultural development in Batang Regency may benefit from policy measures that enhance climate adaptation, improve land productivity, and foster industrial development that complements agriculture rather than displacing it. However, further research is required to evaluate the effectiveness of specific interventions.

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AUTHOR CONTRIBUTIONS

Levana Masitajasmin Putri: Conceptualization, Formal analysis, Methodology, Supervision, Writing original draft

Restie Novitaningrum: Investigation, Project administration, Visualization, Writing review & editing

Nur Indah Cahyaningtyas: Data Curation, Resources, Writing Review & editing

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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