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Indonesian Food Production Challenges: Climate, Land and Industrialization

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Abstract

The increase in agricultural production has become a global issue related to food security. Indonesia faces challenges in fulfilling its food needs. Climate change, land conversion, and industrialization play a role in food crop production. This study aims to examine the short-term and long-term effects of climate change, land conversion, and industrialization on the food production index. The analysis method used is the Autoregressive Distributed Lag (ARDL). The ARDL analysis was chosen because it can explain the short-term and long-term effects as well as the effects at each lag time. The results showed that there is positive and significant long-term cointegration or influence between rainfall, per capita energy consumption, agricultural land area, and forest area on the food production index. There is also a significant negative long-term effect between air temperature, industrialization, and population density on the food production index. In the short term, the previous year's food production, land area and forest area, air temperature, energy consumption, rainfall in two and three years ago, current of industrial share, and one and two years ago industrial share, population density two years ago influence the current food production index. The conclusion and findings of this study are that there is long-term cointegration and short-term effects at different lag times for climate change, land conversion, and industrialization variables on the food production index.

Key words : Food, Production, Climate, Land Conversion, Industrialization, ARDL

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INTRODUCTION

The development of the agricultural sector is important for developing countries as it is related to fulfilling food needs and its significant contribution to GDP. The welfare of farmers also depends on the food produc-tion generated, especially if the agricultural sector is supported by the food crop sector.

Indonesia is one of the largest food produ-cers in the world. According to data from the Central Statistics Agency (BPS). In 2021, the production of food crops in Indonesia reached 153.06 million tons, an increase of 1.15% compared to the previous year. The main food commodities produced are rice, corn, soybeans, and cassava. Rice production in 2021 reached 63.4 million tons, an increase of 0.73% compared to the previous year. Meanwhile, corn production reached 29.88 million tons, an increase of 0.57%, soybean production reached 11.88 million tons, an increase of 3.97%, and cassava production reached 23.15 million tons, an increase of 1.88%.

Despite the increase in food crop production in Indonesia, a significant amount of food still needs to be imported to meet domestic demand. Therefore, increasing the production and productivity of the food crop sector is one of the government's priorities to strengthen food security and achieve food self-sufficiency. Some food commodities that are still imported include rice, corn, soybeans, wheat, and meat.

At the end of 2021, global food commodity imports reached more than USD 1.7 trillion, according to data from the Food and Agriculture Organization (FAO). Indonesia recorded food imports amounting to USD 1.50 billion, with the largest being soybean imports. The high food imports indicate that domestic production has not been able to meet demand. Imports also occur due to fluctuations in production caused by various factors.

One of the factors contributing to the volatility of food production is climate change (First, 2018; Fischer et al., 2012; Hatfield et al., 2011). Rising temperatures and irregular rainfall disrupt agricultural and plantation productivity, which in turn affects food availability. A study by Singh et al (2014) showed that a decrease in rainfall would lead to a decrease in crop yields.

On the other hand, land conversion in Indonesia is also a factor contributing to low food security (Harini & Hartono, 2012). According to the 2018 Performance Report of the Ministry of Environment and Forestry, the rate of land conversion in Indonesia reaches 0.48 million hectares per year. Agricultural and plantation land that should be managed sustainably often converts to housing, industrial, and infrastructure land. This causes land that should be used for food production to become increasingly narrow and limited. Land conversion leads to a decrease in production and productivity (Zhou et al., 2021, Umanailo et al., 2021; Francis et al., 2012; Quasem, 2011).

Indeed, serious actions are needed to address land use conversion in areas that should be used for food production. Some actions that can be taken include protecting and preserving agricultural or plantation land from conversion, providing incentives or assistance to farmers to maintain agricultural production sustainability, and promoting sustainable farming practices to maintain the quality and sustainability of the land. These efforts are crucial to ensure that food production can be sustained and improve food availability for communities in those areas.

The consequences of industrialization are also affects food security. Industrialization is a linear stage of development marked by a change in economic structure from agrarian to industrial. Its impact is the shift of surplus labor to the non-agricultural sector (Arthur, 1955), conversion of agricultural land to non-agricultural use, pollution, and changes in consumption patterns towards certain food sources.

Research by Khan et al. (2021) and Angelo (2017) explains that industrialization, combined with climate change, leads to disruptions in food production. The link between industrialization, climate change, and declining food production can occur due to several factors. Firstly, uncontrolled and unsustainable industrialization cause high emissions, which are the main cause of climate change. Climate change can lead to irregular temperature and rainfall patterns, which negatively impact crop productivity and food production.

As a country that is transforming towards industrialization, Indonesia is also facing conse-quences of the change in economic structure from agrarian to industrial. There has been a decrease in agricultural land area, environmental changes due to the pollutive effects of industrialization, migration of labor force, and changes in the urban-rural population profile as a result of the shift of surplus labor force from agrarian to industrial sector.

Unsustainable industrialization can lead to environmental degradation and soil damage, which can also affect food production. This happens because food production is highly dependent on good environmental conditions and fertile soil. Environmental degradation and soil damage can affect the availability of water and nutrients, which negatively impacts plant productivity and food production (Lal, 2015).

Climate change in the form of increasing average air temperature and changes in rainfall patterns certainly have an impact on the agriculture production. This is because the agricultural sector, especially food crops, is still highly dependent on natural factors that cannot be controlled by farmers. Climate change is certainly one of the consequences of the massive impact of industrialization, which changes the environmental profile and causes global warming. In addition, the agricultural sector, especially food crops, is also faced with the rate of land conversion, which is also a consequence of industrialization. The employment profile is also changing as a result of the industrial transformation.

Several studies have used the Autoregressive Distributed Lag (ARDL) approach to explain the impact of climate change, land use change, and industrialization on food crop production in the short and long term. This is because the effects of these variables are not expected to occur immediately, but rather over a period of time.

Based on the studies by Khan (2021), Chandio et al. (2021), and Rehman et al. (2022), industrialization and its emissions have negative impacts on agricultural exports and production in Pakistan in both the short and long term. Ceesay et al. (2022) conducted a study in Gambia and found that the decrease in food production can lead to a decrease in GDP in both the short and long term. However, there is currently no research on the effects of climate change, land use change, and industrialization on food production in Indonesia in the short and long term. As we know, the climate, land degradation and industrialization has been hit the food production. The impact of variables also need to explained in a short or long period towards production. It is important to estimate the impact of each variables by sequence. That is the novelty of this research. Therefore, this study aims to fill the literature gap using a locus approach and analytical methods.Based on the studies by Khan (2021), Chandio et al. (2021), and Rehman et al. (2022), industrialization and its emissions have negative impacts on agricultural exports and production in Pakistan in both the short and long term. Ceesay et al. (2022) conducted a study in Gambia and found that the decrease in food production can lead to a decrease in GDP in both the short and long term. However, there is currently no research on the effects of climate change, land use change, and industrialization on food production in Indonesia in the short and long term. As we know, the climate, land degradation and industrialization has been hit the food production. The impact of variables also need to explained in a short or long period towards production. It is important to estimate the impact of each variables by sequence. That is the novelty of this research. Therefore, this study aims to fill the literature gap using a locus approach and analytical methods.

METHOD

This study belongs to a quantitative study using an econometric approach. Quantitative research is used to analyze populations or samples using research instruments in the form of quantitative data to test predetermined hypotheses. The study aims to determine the effect of rainfall, temperature, energy consumption, industrialization, population density, area of agricultural land, and forest area on the food production index in Indonesia. The method used in this study is Autoregressive Distributed Lag (ARDL). The type of data used in this study is secondary data obtained through observation processes sourced from the World Bank and Statista. The data used in this study is time series data for Indonesia from 1980 to 2020. Therefore, the number of observations used in this study is 41 years.

The variables used in this study are the food production index as the dependent variable, and 7 independent variables including: precipitation, temperature, energy consumption, industrialization, population density, land area of food crops, and forest area. Specifically, Table 1 shows the operational definitions for the variables used in this study:

Table 1. Operational Definition of Variables

Variables	Code	Descriptions	Unit	Source
Food Production	FPI	Indonesia's food production index	Index	World Bank
Precipitation	PREC	Annual precipitation in Indonesia per year	Millimeter/year	Statista
Temperature	TEMP	Annual average temperature	Degree celcius	World Bank
Energy consumption	ECON	Annual percapita energy consumption	Kilogram oil/capita	World Bank
Industrialization	IDSTY	Industry (include construction) Value added (% of GDP)	Percent	World Bank
Population density	DENS	Population density/ square kilometers of land area	People	World Bank
Land area	LAND	Land area for food crop cultivation	Hectares	World Bank
Forest area	FOREST	Number Forest area	Square kilometers	World bank

Source: Data Processed, 2023

This study uses two analysis methods, descriptive and time series analysis. Descriptive analysis used to provide an overview or describe data but is not used to generalize or draw conclusions from the data. This study uses descriptive analysis to describe the development of each variable from January 2010 to June 2022. In addition, this descriptive analysis is also used to determine the period in which the variables used in this study experience their lowest point, highest point, and fluctuations.

Next, this research uses the Autoregressive Distributed Lag (ARDL) approaches for time series analysis. The ARDL method determines whether there is a long-term relationship between time series variables. Operationally, the ARDL method has the advantage of not requiring the variables used to be stationary at the same level (Enders, 2004). In this study, we carried out several estimation steps using the ARDL model following previous research (Nkoro & Uko, 2016). First, we estimated and analyzed the ARDL model, which included selecting the model and conducting diagnostic tests to check for assumptions violations before proceeding to the next steps. Second, we constructed the selected model base on the optimum lag and conducted tests to determine the long-run cointegration relationship (Johansen & Juse-lius, 1990). Third, we analyzed the output to determine short-run dynamics. The last step is to analyze the long-term coefficients of the ARDL model.

Analyzing time series data requires ensuring that the data is stationary. In testing the stationarity of data in this study, the Augmented Dickey-Fuller (ADF) test (Hassler & Wolters, 2006) was used, which aims to determine the presence of a unit root. The ADF test is an AR(1) process with the following equation.

$$\Delta y_t = \alpha + \beta y_{t-1} + e_t \quad (1)$$

Where yt is the time series, t is the time period, α is the constant, and e is error term. The test is conducted by checking the stationarity of each time series included in the model at that level. If a time series is not stationary at the level, a stationarity test is performed at the first difference. If all variables are stationary at the first difference, then further analysis can be conducted.

After conducting the stationarity test, the next step is to estimate the ARDL equation. Based on the Monte Carlo experiments by Gerrard & Godfrey (1998), the ARDL model is considered better in estimating the coefficients of long-run cointegrating relationships. According to Pesaran & Shin (1995), the ARDL model is generally represented by the following equation:

$$Y = \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \mu_t \quad (2)$$

While the ARDL model in this study is transformed into a logarithmic form and the lag is as follows:

$$LnFPI_t = \beta_1 PREC_{t-i} + \beta_2 TEMP_{t-i} + \beta_3 ECON_{t-i} + \beta_4 IDSTY_{t-i} + \beta_5 DENS_{t-i} + \beta_6 LAND_{t-i} + \beta_7 FOREST_{t-i} + \mu_t \quad (3)$$

Where FPI represents the Food Production Index, PREC is the Annual Precipitation per year, TEMP is the average annual temperature, ECON is the energy consumption, IDSTY is industrialization represented through the share of industry value added, DENS is population density, LAND is the area of arable land for food crops, FOREST is the area of forested land, Ln is the natural logarithm, α is a constant, β1, β2, β3, β4, β5 are the coefficients of the independent variables, t-i represents the time period i, and μt represents the residual/error.

The use of the ARDL model depends on the optimal lag length used in the model. Therefore, the selection of the optimal lag length plays a very important role in determining the suitability of the ARDL model. Several measures, such as Sequential Modified LR Test Statistics (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ), can be used to identify the ideal lag length. The number of asterisks (*) in the test results of each criterion can be used to conclude the ideal lag length. The more asterisks in a lag, the lag will be selected as the optimal lag for the formed ARDL model. After the optimal lag length is known, it is necessary to determine the appropriate ARDL model. The criteria for determining a suitable model are based on the AIC graph, one of the outputs of data processing. The graph shows that the best ARDL model is the ARDL model that has the smallest AIC value among other alternative ARDL models.

The next testing is the Bound Test, which is a test to determine whether there is cointegration or a long-term relationship between the variables used in the study (Hunter, 2019). In the Bound Test, testing is done using an F-test. It can be concluded that there is a cointegration relationship between variables if the F-test value generated is higher than the critical value at I(1).
On the other hand, we can claim that the variables are not cointegrated if the F-test value generated is less than the critical value at I(1).

The next step is to estimate the short-term model using ECM after the long-term relationship between variables has been determined. The short-term equation used is as follows:

$$\mathrm{EC_t} = \varepsilon_t = y_t - \sum_{i=1}^{k} \theta_i x_{it} - \psi' \mathrm{w}_t \qquad (4)$$

Short-term impact elasticity of independent variables on dependent variables can be observed in the ECM created. The cointEq1 coefficient (in Eviews 12 output) or the error correction term (ECT) coefficient of the ECM model will also be obtained. These terms describe the level of adjustment or speed of residuals in the previous period to correct the dependent variable towards equilibrium in the next period. According to the t-test findings, the model is valid if the ECT coefficient is negative and significant.

Therefore, accuracy and stability testing of the model is needed in the final stage of modeling using the ARDL and ECM methods. Testing is performed through classic assumption tests to see if there is autocorrelation in the residual model using the Breusch-Godfrey LM Test method, and stability testing using the CUSUM test method (Cho et al., 2015). According to Chinenye et al. (2001), in the Breusch-Godfrey LM Test method, a model is said to have no autocorrelation if the resulting p-value is larger than the threshold value. On the other hand, a model is considered stable if the CUSUM test graph shows that the cusum line (blue line) is between the significance lines (red line).

RESULTS AND DISCUSSION

Basically, there are many studies that discuss the relationship between climate change and food security, particularly in agrarian countries such as Indonesia, such as the studies by Schmidhuber & Tubiello (2007); Murniati & Mutolib (2020); and Raj et al., (2022). However, there are not many studies that address the role of exogenous factors in the emergence of climate change, such as population growth, industrialization, and land use change as a result of globalization and economic development of a country in the short and long term. As one of the agrarian countries in the world, as well as the fourth most populous country in the world, Indonesia is facing food security problems in some of its agricultural commodities. This study attempts to examine Indonesia's overall food security performance by using a food security index to determine the factors that influence it. The autoregressive distributed lag (ARDL) model in this study is used to analyze the impact of climate change, land conversion, and industrialization on Indonesia's food production.

The first step in analyzing the ARDL model is the stationarity test. This is intended to determine whether the data is stationary or not. To avoid spurious regression, this stationarity test is intended to ensure the order of integration and ensure that the input data is not stationary at order 1 or I(1). Because if there are variables that are stationary in first difference, the ARDL method is not suitable for use. The stationarity test in this study uses Augmentet Dickey-Fuller (ADF) Test, specifically the results of the stationarity test for the research variables are shown in table 2.

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Table 2 shows that all variables used in this study are stationary at first difference I(1) as indicated by the probability values $\alpha<0.05$, and not stationary at level I(0) as indicated by the probability values $\alpha>0.05$. The selection of optimum lag is very significant in the ARDL model. Therefore, it is necessary to select the optimum lag criteria, which are specifically shown in Table 3.

Table 2. Unit Root Test Results with ADF Test Method

No.	Level		1st difference	
	Variable	Prob.	Variable	Prob.
1.	LnFPI	0.9914	D(LnFPI)	0.0000
2.	LnPREC	0.9945	D(LnPREC)	0.0001
3.	LnTEMP	0.0589	D(LnTEMP)	0.0001
4.	LnECON	0.3321	D(LnECON)	0.0000
5.	IDSTY	0.3657	D(IDSTY)	0.0000
6.	LnDENS	0.2873	D(LnDENS)	0.0009
7.	LnLAND	0.1526	D(LnLAND)	0.0000
8.	LnFOREST	0.0646	D(LnFOREST)	0.0000

Source: Data Processed, 2023

Table 3. Test Results for Optimal Lag Determination

Lag	LogL	LR	FPE	AIC	SC	HQ
0	235.4885	NA	8.72e-16	-11.97308	-11.62833	-11.85042
1	479.9532	373.1303	7.03e-20	-21.47122	-18.36843*	-20.36727
2	571.6574	101.3572*	2.62e-20	-22.92934	-17.06850	-20.84410
3	676.3721	71.64691	1.46e-20*	-25.07222*	-16.45334	-22.00569*

Note: * indicates lag order selected by the criterion

Source: Data Processed, 2023

Based on table 3, it can be seen that the ideal lag to be used in this ARDL model is (-3). Lag (-3) is chosen as the ideal lag because there are many asterisks (*) in the lag (-3) criteria value, specifically at lag 3 which is the lag optimum for most criteria including Final Prediction Error (FPE), Akaike Information Criterion (AIC), and Hannan-Quinn (HQ). Therefore, lag (-4) will be used for additional analysis.

The next step is to determine the best ARDL model using the AIC criteria. The best ARDL model is determined by comparing the AIC values of the automatically generated ARDL models through the analysis software used in this study, which is Eviews 12 application, based on the number of lags used for each model. The results of determining the best ARDL model in this study are shown in figure 1.

In the Figure 1, the horizontal axis represents the ARDL models created, and the vertical axis represents the AIC value. The optimal ARDL model is the one with the highest AIC value, so according to the table above, the best model is ARDL(1,3,1,3,2,3,2,1) with an AIC value of 3.484.

The next step is to test whether the variables used in this study have a long-run equilibrium relationship (cointegration). In conducting the cointegration test of variables, this study uses the F-Bound Test. The results of the cointegration test using the F-Bound Test are shown in Table 4.

In the cointegration bound-testing, the F-statistic value of 8.1059467 is greater than the upper limit value of I(1) at the 5% level which is 3.21. Moreover, the F-statistic value is also greater than the critical upper limit value of I(1) at the 1% level which is 3.90. This indicates that all variables have a long-run equilibrium relationship or can be said that the three variables move together in the long run. The results of the model testing using the Akaike Information Criterion (AIC) method show that the Autoregressive Distributed Lag (ARDL) model with lags (1,3,1,3,2,3,2,1) (see figure 1) is the best model. Thus, the long-run model estimation is obtained as follows (see table 5).

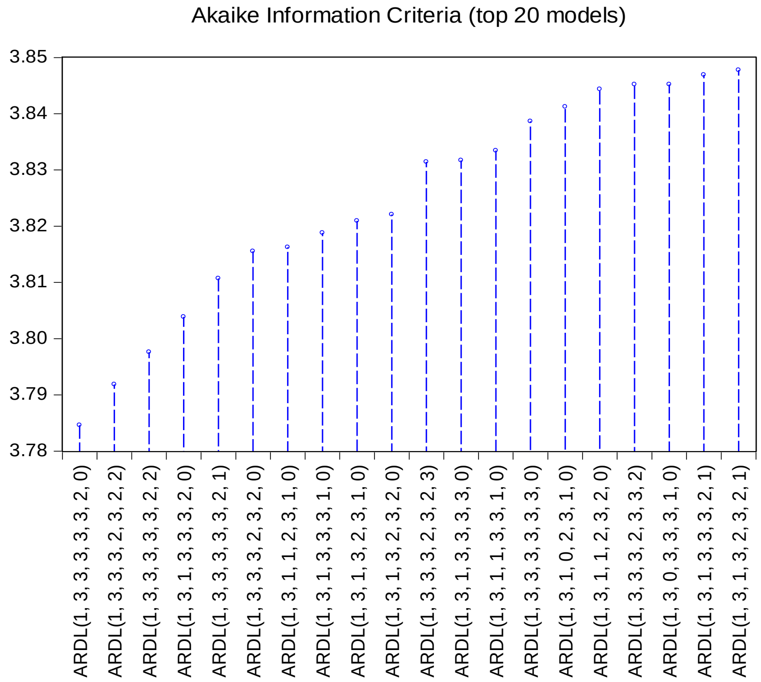

Figure 1. Results of Optimal Lag Length (Best Model) Determination Using AIC Criteria
Source: Data Processed, 2023

Table 4. Bound-Testing Cointegration Test (F-Bounds test)

Test Statistic	**Value**	**K**
F-statistic	8.1059467	7
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	1.92	2.89
5%	2.17	3.21
2.5%	2.43	3.51
1%	2.73	3.90

Source: Data Processed, 2022

Based on the short-run estimation results of the ARDL(1,3,1,3,2,3,2,1) model in table 5 above, it can be seen that all variables used in this study, including food production index, precipitation, temperature, energy consumption, industrialization, population density, food crop area, and forest area, explains 89.2% of the changes in Indonesia's food production index. Simultaneously, all variables also significantly affect Indonesia's food sproduction, as indicated by the F-statistic probability value that is less than the alpha level of 0.05.

Further examination of the partial estimation results reveals that if all variables are at 0, the food production index will increase by 4.89. The food production index in the previous year also significantly increases the food production index in the following year, with a 1% increase in the food production index leading to a 0.47 increase in the food security index in the next year. Furthermore, an increase in precipitation in the 2-3 years prior has been proven to be able to increase Indonesia's food production by 5.3 and 4.1 index units, respectively. An increase in the area of food crop cultivation has also been proven to significantly increase food production, every 1% increase in the area of food crop cultivation leading to a 1.27 increase in the food production index. In addition, every 1% increase in forest area will lead to an increase of 4.93 in the food production index in Indonesia.

Table 5. ARDL Short Run Estimation Results

Selected Model: ARDL(1,3,1,3,2,3,2,1)				
Dependent Variable: LnFPI				
Variable	**Coefficient**	**t-Statistic**	**Prob.***	**Explanation**
D(FPI(-1))	-0.474263	-2.671869	0.0217**	Significant
D(PREC)	-3.647405	-0.268022	0.7936	Not Significant
D(PREC(-1))	5.392724	0.266698	0.7946	Not Significant
D(PREC(-2))	4.413303	2.932313	0.0136**	Significant
D(PREC(-3))	4.888750	3.674987	0.0037***	Significant
D(TEMP)	-1.243564	-2.425166	0.0337**	Significant
D(TEMP(-1))	-5.125796	-1.353505	0.2031	Not Significant
D(TEMP(-2))	-1.509507	-0.326190	0.7504	Not Significant
D(TEMP(-3))	-4.569542	-1.222290	0.2471	Not Significant
D(ECON)	-5.881056	-2.178433	0.0520*	Significant
D(ECON (-1))	4.779706	0.181092	0.8596	Not Significant
D(ECON (-2))	-7.815587	-0.289266	0.7778	Not Significant
D(ECON (-3))	4.983276	1.897378	0.0843	Not Significant
D(IDSTY)	-0.680076	-2.887713	0.0148**	Significant
D(IDSTY(-1))	-0.736943	-2.927447	0.0138**	Significant
D(IDSTY(-2))	-0.501246	-2.644474	0.0228**	Significant
D(IDSTY (-3))	-0.152059	-0.987876	0.3444	Not Significant
D(DENS)	2.384734	1.553194	0.1487	Not Significant
D(DENS (-1))	-1.125970	-0.544371	0.5970	Not Significant
D(DENS (-2))	-3.647627	-2.210581	0.0492**	Significant
D(DENS (-3))	-2.295965	-1.446809	0.1758	Not Significant
D(LAND)	1.272122	4.606131	0.0008***	Significant
D(LAND(-1))	6.508190	1.827072	0.0949*	Not Significant
D(LAND(-2))	4.932334	1.332851	0.2095	Not Significant
D(FOREST)	4.932547	2.877473	0.0150**	Significant
C	4.895111	3.798987	0.0029***	Significant
R-Square				0.892167
Adjusted R-Squared				0.647092
F-Statistics				3.640384
Prob(F-Statistics)				0.014612

Note: ***Significance at α<1%; **Significance at α<5%; *Significance at α<10%;
Source: Data Processed, 2023

Based on the short-term estimation, several factors have been identified to cause a decline food security through its negative impact on the national food production index. Air temperature has a significant negative impact on food production, every 1-degree increase in air temperature resulting in a decrease of 1.24 in the food production index. A 1% increase in oil energy consumption also leads to a decrease of 5.88 in the food production index. Industrialization is a factor that has a significant negative impact on food production, 1% increase in industry value added leading to a decrease of 0.68 in the food production index. Likewise, an increase in industry value added in the previous 1-2 years will result in a decline in the food production index by 0.73 and 0.5 units. Finally, population density in the previous 2 years is also a factor that causes a decline in the food production index. For every 1% increase in population density, the food production index will decrease by 3.64.

The next step in this analysis is the stability test of the Autoregressive Distributed Lag (ARDL) model, which in this study uses the CUSUM test. This test is used to determine whether the model is stable or not. Figure 2 shows the CUSUM test which displays a blue line between the significance lines (red lines).

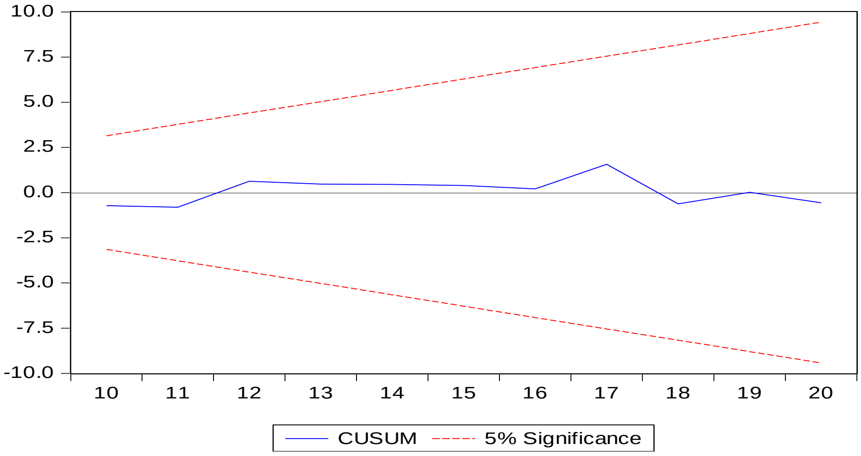

Figure 2. The Plot of Model Stability Test Results with the CUSUM Test Method
Source: Data Processed, 2023

Based on the CUSUM test results, it is evident that the blue line is still between the two red lines with a significance of 5%, indicating that the model in this study is stable and can be used to explain long-term cointegration. After it was determined that the model has long-term cointegration in the bound-test, the long-term model estimation can be obtained. Table 6 below shows the results of the ARDL long-term estimation model in this study:

Table 6. Long Run Estimation Model, Dynamic Cointegration and Speed of Adjustment

Cointegrating Form				
Variable	**Coefficient**	**t-Statistic**	**Prob.**	**Explanation**
CointEq(-1)	-0.416051	-2.343920	0.0389	Significant
Cointeq = D(FPI) - (6.42801*D(PREC) -1.60355*D(TEMP) + 7.16340*D(ECON) -1.4043*D(IDSTY) - 3.177742*D(DENS) + 1.638903*D(LAND) +3.34577*D(FOREST) + 3.3204)				
Long Run Coefficients				
Variable	**Coefficient**	**t-Statistic**	**Prob.**	**Explanation**
D(PREC)	6.428014	2.446632	0.0324**	Significant
D(TEMP)	-1.603546	-2.175861	0.0522*	Significant
D(ECON)	-7.163404	-2.334701	0.0395**	Significant
D(IDSTY)	-1.404311	-4.398688	0.0011***	Significant
D(DENS)	-3.177742	-2.286960	0.0430**	Significant
D(LAND)	1.638903	3.018183	0.0117**	Significant
D(FOREST)	3.345771	2.799124	0.0173**	Significant
C	3.320378	4.580122	0.0008***	Significant

Note: ***Significance at α<1%; **Significance at α<5%; *Significance at α<10%;
Source: Data Processed, 2023

Based on the long-term estimation results of the ARDL model in Table 6 above, it can be seen that the CointEq coefficient value will be used to explain the speed of adjustment or the speed of adjustment in response to changes. The CointEq value in the above estimation results is 0.416051 with a probability value of 0.0389, which can be said to be significant at $\alpha<5\%$. This means that the ARDL model has short term cointegration. In addition, the CointEq value of -0.416051 is a negative value indicating that the model will head towards equilibrium at a rate of 0.41% per year.

Based on the ARDL model estimation results above, it is known that in the long run, if all independent variables have a value of 0, the value of the food production index is 3.320378. In the long run, it is known that rainfall has a significant positive impact on the food production index, where every 1% increase in rainfall will increase the food production index by 6.42. The area of land used for food crops is also known to have a significant positive impact, where every 1% increase in the area of land used for food crops will increase the food production index by 1.63. Furthermore, the area of forest land is also proven to have a significant positive effect. Every 1% increase in forest land area will push the food production index up by 3.34.

On the other hand, the increase in air temperature will have a significant negative impact on food security, as a 1% increase in air temperature will decrease the food production index as a representation of food security by 1.60. Energy consumption in the form of crude oil is also proven to significantly decrease food security, as a 1% increase in energy consumption will result in a decrease in the food security index by 7.16. Industrialization also has a negative impact on food security, specifically, as a 1% increase in industry value added will decrease the food security index by 1.40. Increasing population density will also decrease the remaining land area. This study found a similar result that increasing population density will reduce the food production, as a 1% increase in population density will decrease the food production index by 3.17.

To ensure that the ARDL model used in this study is valid and best model, classical assumption tests were carried out, consisting of normality, autocorrelation, and heteroscedasticity tests. Table 7 shows the results of the classical assumption tests, and it is known that the ARDL model used in this study is free from all classical assumption problems.

Table 7. Classical Assumption Test

Classical Assumption	Type of Test	Result Score	Description
Normality	Jarque Bera Value	$0.46892 < \alpha\ 0.05$	Data normally distributed
Autocorrelation	Breusch-Godfrey Serial Correlation LM Test	$0.1092 > \alpha\ 0.05$	No Autocorrelation
Heterokedasticity	Harvey Test	$0.7105 > \alpha\ 0.05$	No Heterokedasticity

Source: Data Processed, 2023

The changes in temperature and precipitation related to sustained greenhouse gas emissions will bring changes in land suitability, crop yields, and ultimately endanger food security (Gregory et al., 2005). The findings of this study are consistent with the research conducted by Hou et al. (2022), which found that ecological restoration that includes air temperature, precipitation, and sunlight has a direct impact on agricultural productivity, as well as mediating increased food security. Although precipitation in this study has a significant positive impact on food security in both the short and long term, excessive precipitation can also be harmful to the environment by creating soil damage, reducing fertile land areas, and causing floods. Therefore, some literature has contradictory results on the impact of precipitation on food security. Ceesay & Ndiaye (2022) found that precipitation has a negative impact on food security using time-series data from the Gambia.

This study has proven the short-term and long-term effects of air temperature on food production, which is consistent with the findings of Mbowa et al. (2020) who found that an increase in air temperature in Uganda would reduce food productivity and have adverse effects on health, making it a crucial food security challenge for the government. According to Reza & Sabau (2022) in tropical countries like Indonesia, even small changes in climate change have significant impacts on their agricultural sector, including an increase in air temperature that would greatly affect the food crop sector and the potential for crop failures in the long term. Overall, climate change will have an impact on the four dimensions of food security, including production and productivity, food accessibility, supply stability, and food utilization (Ayinu et al., 2022).

This research used per capita oil consumption to represent energy consumption for human activities. The study confirms that in both short and long term, energy consumption has a significant adverse impact on food production in Indonesia. These findings are consistent with research by Seppelt et al. (2022), who found similar results in Africa. An important framework for understanding the impact of energy consumption on food security is that oil consumption is one of the main factors contributing to a country's carbon emissions through consumption and economic activities (Sola et al., 2016). Increased carbon emissions reduce agricultural yields. According to Pérez-Neira et al. (2023), this is possible given the natural resource wealth that has been bestowed upon Indonesia. This drives significant increases in natural resource exploration and hampers environmental performance with rising carbon emissions. Therefore, agricultural resources are expected to be affected, and as a result, agricultural production will also decline. Ultimately, increasing energy consumption is also one of the major factors that continue to exacerbate climate change issues around the world, including in Indonesia.

Rapid industrialization is also one of the issues that is particularly important for developing countries with high populations, such as Indonesia. According to Mohammed & Dain (2015), widespread industrialization has transformed most agricultural land, reduced the availability of water for agriculture, and increased the cost of transporting food due to the increased distance between production areas and urban markets. Industrialization is also closely related to land use change, rapid population migration, and increased technology-based economic activity, which ultimately leads to high energy and food consumption, but on the other hand, land availability continues to decline (Putra et al., 2020). This study proves that industrialization, represented by industry value added which is the increasing share of the industrial sector in the country's GDP, has a negative impact on food production. These findings are consistent with Khan et al. (2021), who used an ARDL approach and also found a negative relationship in both the short and long term between industrialization and food security in Pakistan.

This finding is consistent with the Dynamic Integrated Climate Economy (DICE Model), a theory developed by Dice-Nordhaus (Nordhaus, 2017). The Dice-Nordhaus theory is an economic model used to predict the impact of climate change on the global economy. The model combines aspects such as population growth, economic productivity, and carbon emissions to estimate how climate change will affect economic growth in the future. In terms of food production, climate change can affect key factors such as precipitation, air temperature, and water availability, which can impact crop production, animal growth, and overall food availability. This theory also explains the impact of climate change on economic growth through agricultural productivity, so if climate change continues to occur, future economic growth is predicted to decline.

Nowadays, population growth is also one of the issues that is quite important in the development process. The population is among one of the most crucial factors which increase the level of food insecurity (Kousar et al., 2021). Producing sufficient food for a growing population has always been a challenge because emergent population imposes pressures on the agricultural sector, and the rate of urbanization also increases and people start using the land for urban development instead of agriculture production, and thus the level of food insecurity increases (Efendi et al., 2021). This study has successfully proven that both in the short and long term, population density as a form of rapid population growth will harm food security in Indonesia. This is in line with the findings of Molotoks et al. (2021), who found a similar result, stating that an increase in population will result in decreasing agriculture production, consequently limiting a country's ability to provide food for its citizens and ultimately becoming an issue of food insecurity. These findings are also consistent with the Neo-Malthusian theory (1823), which explains that long-term population growth will increase resource consumption, increase pollution, and ultimately trigger environmental degradation. Furthermore, this theory also explains that excessive economic growth will result in a population boom that will cause many problems, mainly a decrease in environmental quality, climate change, and even famine.

Currently, 77% of global land is used by humans, and the resulting land use changes have important impacts on climate change that will ultimately lead to other issues such as environmental damage and food insecurity (Maisonet-Guzman, 2011). The massive land conversion over the past few decades has become one of the issues that governments need to consider in facing rapid urbanization and population growth. This study attempts to uncover the impact of land conversion on food security in Indonesia. The study successfully revealed that the area of food crop cultivation and forest area have positive and significant impacts in both the short and long term on food security in Indonesia.

This is consistent with the findings by Mora et al. (2020) which found that an increase in land conversion for industrial activities will worsen environmental quality and decrease agricultural sector production, which ultimately refers to climate change and food insecurity. Furthermore, Chen et al. (2019) found that arable land area is also a significantly contributing factor to increasing productivity in the agricultural sector in China. Therefore, the Chinese government continues to focus on the development and expansion of arable land for food crop agriculture in an effort to maintain national food security. Interestingly, Nurpita et al. (2017) found that land conversion from agricultural land has negative impacts on household farmer income in Indonesia. Furthermore, the decrease in household farmer income is partly due to the decrease in agricultural land. As a result, the loss of household farmer income exacerbates the vulnerability of households affected by food insecurity.

CONCLUSION

The previous year's food production index significantly increases the food production index in the following year. A 1% increase in the food production index will increase the next year's index by 0.47. Furthermore, an increase in rainfall in the previous 2-3 years has been proven to increase Indonesia's food production, means that the rain will impact the future production. Increasing the area of cultivated land for food commodities has also been shown to significantly increase food production. In addition, every increase in forest area will result in an increase the food production index in Indonesia.

In the opposite, air temperature, oil energy consumption has a significant negative impact on food production. Industrialization has a relatively significant negative impact on food production in Indonesia. Similarly, an increase in industry value added in the previous 1-2 years will result in a decrease food production index. Finally, population density in the previous 2 years is also a factor that causes a decrease in the food production, with every 1% increase in population density resulting in a decrease of 3.64 in the food production index.

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