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THE IMPACT OF LAND DEGRADATION AND CLIMATE ANOMALIES ON FOOD CROP PRODUCTIVITY IN ARID REGIONS OF INDONESIA: AN ARDL APPROACH

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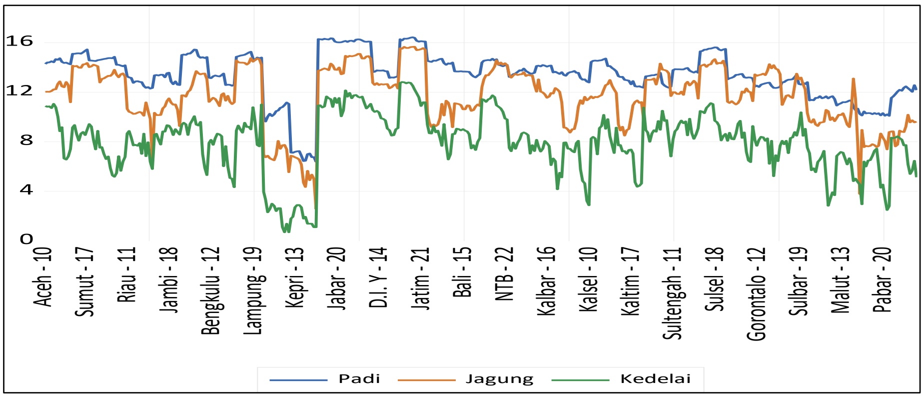
Abstract

In recent decades, Indonesia's agricultural sector has been faced with land degradation and climate change. These phenomena impact national food security in the long term. This study empirically analyzes the effects of land degradation and climate anomalies on the productivity of rice, corn, and soybean crops in the short and long terms in two dry regions in Indonesia, namely West Nusa Tenggara and East Nusa Tenggara. The analysis results show that the area of degraded land negatively impacts the productivity of rice, corn, and soybeans in both the short and long term. Annual air temperature has a positive impact on corn and soybean productivity in the short term. In the long term, an increase in annual temperature has a negative impact on corn productivity and a positive impact on future soybean productivity. Annual rainfall has a positive impact on corn and soybean productivity and also has a negative impact on soybean productivity in the short term. In the long term, rainfall has a negative impact on future corn and soybean productivity. Annual air humidity has a positive impact on corn and soybean productivity in the short term. In the long term, an increase in air humidity has a negative impact on corn productivity and a positive impact on future soybean productivity. These findings have implications for adaptation strategies and national agricultural development policies in response to climate change and land degradation. They also require further exploration of variables related to productivity, such as cultivation technology, capital, and labor, to obtain a comprehensive picture of the future of national food crop productivity. These include strengthening farmer capacity through extension programs, encouraging the adoption of climate-adaptive agricultural technologies, land conservation and restoration programs, and synergistic agricultural development policies for the sustainability of national food security.

Keywords: Climate Anomaly, Land Degradation, and Food Crop Productivity, Dry Regions

INTRODUCTION

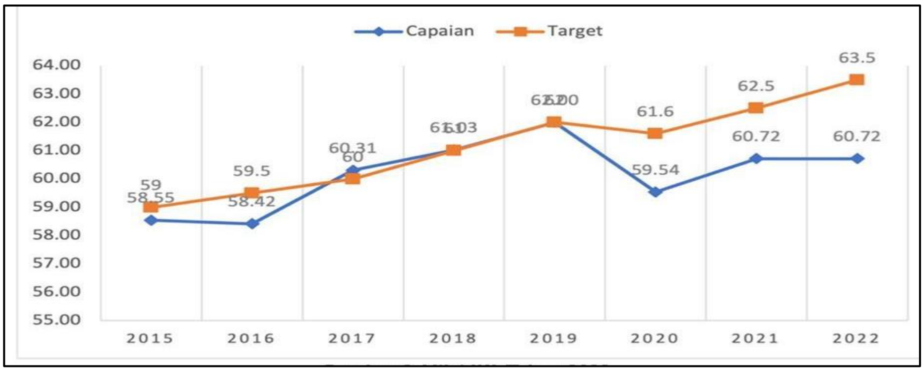
Economic and population growth as well as climate change are potential and threats to the existence of natural resources and the global environment today.(Almeida et al., 2017; Cole et al., 1997). The phenomenon of damage to natural resources and the environment has an impact on food insecurity and the global food supply chain, to the point that environmental issues are included in the priorities of the Sustainable Development Goals (SDGs).(Hapsari & Rudiarto, 2017a).Along with the rate of population growth and economic growth, national per capita consumption of rice, corn and soybeans continues to increase,On the other hand, the growth in production of major food commodities tends to slow down(BKP, 2023).Isoybean crop production index downvery significantby -181.75 percent or 61.14 points, followed byproduction indexThe rice crop index decreased by -45.21 percent, or 37.06 points, except for the corn crop production index, which increased by 22.57 percent, or 29.04 points (Food Security Statistics, 2020). This downward trend in production isthe impact of agricultural land damage and extreme climate change(Hapsari & Rudiarto, 2017b).



Source: BPS, Processed Data (2023)

Figure 1. Rice, Corn, and Soybean Production Trends per Province 2018-2022

On the other hand, the area lNational agricultural land that was degraded (critical, damaged and barren) reached 18 million hectares in 1993 and increased to 23.2 million hectares in 2003 (Research and Development Center for Agriculture 2004).According to the agency*Low Carbon Development Indonesia*Bappenas, (2010)The amount of critical land by 2045 is estimated to reach 25 million hectares, a significant increase of 58.7 percent from the 2000 projection of 14.7 million hectares.This increase in the number of critical landshas implications for the achievement of the quality of national land resources which is below the set target (Bappenas, 2010).This condition is exacerbated byanthropogenic activities such as the use of Nitrogen, Phosphate and Potash fertilizers continues to be massive(Adhitya et al., 2013),accompanied by kagricultural land conversionin various sectors and regions(Lisdiyono, 2011).



Source: (Low Carbon Development Institute (LCDI), Bappenas, 2010

Figure 2. Graph of Land Quality Index Trends in Indonesia 2018-2022

On the other hand, Indonesia's geographical location and climatic differences contribute to fluctuations and differences in national food production potential. The island clusters along the equatorcauseIndonesia is included in the wet tropical climate regionand subtropical,tropical monsoon, semi-arid climate. Besides that, Indonesia is also influenced by the circulation of the western monsoon winds from the Indian Ocean and the eastern monsoon winds from the Pacific Ocean.causes rainy and dry seasons(Taghizadeh-Hesary et al., 2019)and also vulnerablehit byheat wave (*El Niño*)and cold current waves (*La Nina*). According toStone (1997),*El Niño* hascausing drought and tropical forest fires in Southeast Asian countries with estimated economic losses exceeding $20 billion USDas well as hydrological damage, terrestrial agricultural land to the occurrence of long-term climate anomalies.

This study aims to empirically analyze the influence of land degradation and climate anomalies on the productivity of rice, corn, and soybean crops in the short and long term in dry climate areas, using the Auto Regressive model.*Distributed Lag*(ARDL) panel data for the 2010-2023 period. Data on degraded land area is sourced from environmental statistics from the Central Bureau of Statistics, rice, corn, and soybean productivity data from the National Food Security Agency (BKPN) and the Central Bureau of Statistics (BPS), while climate data such as air temperature, rainfall, and humidity are sourced from the National Meteorology, Climatology, and Geophysics Agency (BMKG).

RESEARCH METHODS

This research is based on the theory*Stochastic Production Frontier*which takes into account the shocks of exogenous variables to agricultural output,interaction of climatic and non-climatic factors(Aigner et al., 2023),Whichformulatedas follows :

$$\text{Produktivitas} = f\left((\text{Non\_Iklim}), (\text{Iklim})\right) \quad .....(3.1)$$

Proxy non-climate variables in this studyrepresented by the area of degraded agricultural land (LLD) and the climate variable proxy is represented by the variables Air Temperature (SHU), Rainfall (CHJ) and Humidity (KLB). According to(Josheski et al., 2012)The agricultural production function equation can be written in the form of a Cobb-Douglas function as follows:

$$\text{Protv} = f\left(A(\text{LLD})^{\beta_1}(\text{SHU})^{\beta_2}(\text{CHJ})^{\beta_3}(\text{KLB})^{\beta_4}\right)^{e} \quad ....(3.2)$$

Equality(3.2) transformed into the logarithm form of Maximum Likelihood to:

$$\text{Ln Protv}_{\text{it}} = \quad ....\text{Ln A} + \beta_1 \text{Ln LLD}_{\text{it}} + \beta_2 \text{Ln SHU}_{\text{it}} + \beta_3 \text{Ln CHJ}_{\text{it}} + \beta_4 \text{ Ln KLB}_{\text{it}} + e_i (3.5)$$

Since LnA =, the MLE regression equation becomes: β_0

$$\text{Ln Protv}_{\text{it}} = \beta_0 + \beta_1 \text{Ln LLD}_{\text{it}} + \beta_2 \text{ Ln SHU}_{\text{it}} + \beta_3 \text{Ln CHJ}_{\text{it}} + \beta_4 \text{ Ln KLB}_{\text{it}} + e_i \quad ......(3.6)$$

Analysis Model

To analyze short-term and long-term effects, the Auto-Regressive Distributed Lag (ARDL) model is used. which was introducedPesanan and Shin(1999) withthe following formulation:

$$\text{Ptotv}_{\text{it}} = \alpha_0 + \alpha_{1\,t} \sum_{i=1}^{\rho} \varphi_1 \text{Protv}_{i\,t-1} + \alpha_{2i} \sum_{k=0}^{n} \Delta\text{LLD}_{i\,t-1} + \alpha_{3i} \sum_{k=0}^{n} \Delta\text{SHU}_{i\,t-1} + \alpha_{4i} \sum_{k=0}^{n} \Delta\text{CHJ}_{i\,t-1} + \alpha_{5i} \sum_{k=0}^{n} \Delta\text{KLB}_{i\,t-1} + \beta_1 \text{LLD}_i + \beta_2 \text{SHU}_i + \beta_3 \text{CHJ}_i + \beta_4 \text{KLB}_i + \mu_t \quad ....(3.9)$$

Short Term ARDL model analysis:

$$\Delta\text{Protv}_{\text{ii}} = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta\text{LLD}_{\text{it}} + \sum_{k=0}^{\rho} \alpha_{2i} \Delta\text{SHU}_{\text{it}} + \sum_{k=0}^{\rho} \alpha_{3i} \Delta\text{CHJ}_{\text{it}} + \sum_{k=0}^{\rho} \alpha_{3i} \Delta\text{CHJ}_{\text{it}} + \sum_{k=0}^{\rho} \alpha_{4i} \Delta\text{KLB}_{\text{it}} + e_i$$

ARDL Error Correction Model (ECM) Analysis

$$\Delta\text{Protv}_{\text{it}} = \gamma_0 + \sum_{i=1}^{n} \gamma_1 \Delta\text{LLD}_{\text{it}} + \sum_{k=0}^{\rho} \gamma_2 \Delta\text{SHU}_{\text{it}} + \sum_{k=0}^{\rho} \gamma_3 \Delta\text{CH}_{\text{it}} + \sum_{k=0}^{\rho} \gamma_4 \Delta\text{K}_{\text{it}}$$

Model analysisARDLLong-term

$$\text{PTV}_{\textbf{it}} = \alpha_0 \sum_{i=1}^{n} \alpha_{1i} \Delta\text{LLD}_{\text{it}} + \sum_{k=0}^{\rho} \alpha_{2i} \Delta\text{SHU}_{\text{it}} + \Delta\text{CHJ}_{\text{it}} + \sum_{k=0}^{\rho} \alpha_{4i} \Delta\text{KLB}_{\text{it}}$$

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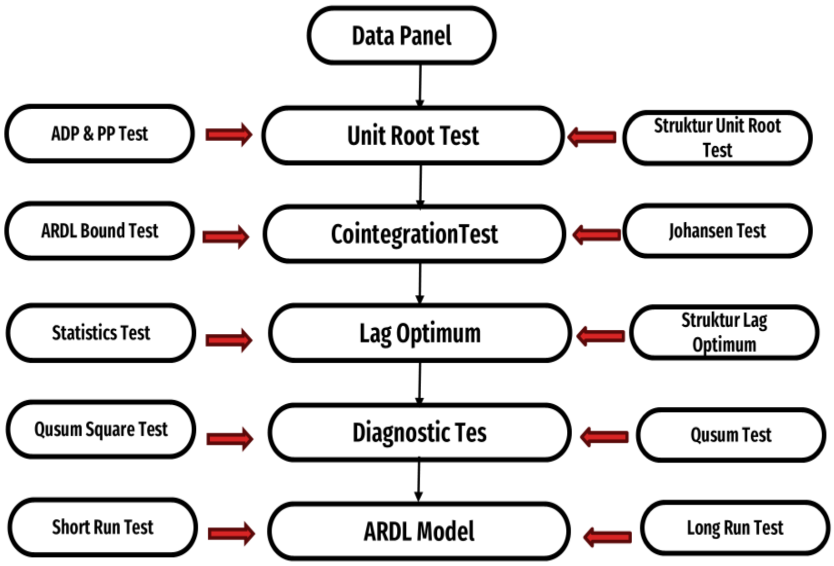
Analysis Stages



Empirical Results and Discussion

Descriptive Statistical Analysis of Variables

The descriptive statistical data analyzed empirically in this study included data centralization (mean, median, and most frequently occurring values), data range (standard deviation, maximum and minimum values), data distribution (skewness and skewness), and data normality. The analysis yielded the following data:

Table 1. Descriptive Statistics and Research Variables

Variables	ProtvP	ProtvJ	ProtvK	LLd	SHU	CHJ	Extraordinary Congress
Mean	40.61	34.18	12.34	500854.40	27.79	1831.74	76.93
Maximum	53.79	75.52	16.41	1477313.00	29.90	2834.00	83.80
Minimum	26.18	7.93	9.50	48210.00	25.80	1149.00	69.28
Std Dev	8.41	18.06	1.59	414604.50	0.96	441.00	3.60
Skewness	-0.24		0.70	0.26	0.27	0.19	-0.01
Jarque Bera	4.22	7.37	4.04	4.34	1.32	1.69	1.53
Prob	0.12	0.02	0.13	0.11	0.52	0.43	0.47

Source: Eviews Data Processing Results, (2024) The results of the data normality test based on the Jaque-Bera Probability value at significanceα= 0.05 obtained data on rice productivity, soybeans, degraded land area, temperature, rainfall, and humidity are normally distributed. Data variation is relatively moderate and small, the data distribution is relatively symmetrical, slightly skewed to the left and right. Meanwhile, corn productivity data is not normally distributed. Data variation is quite large (Std-dev = 18.06), the data distribution is relatively symmetrical, slightly skewed to the right (skewness = 0.93).

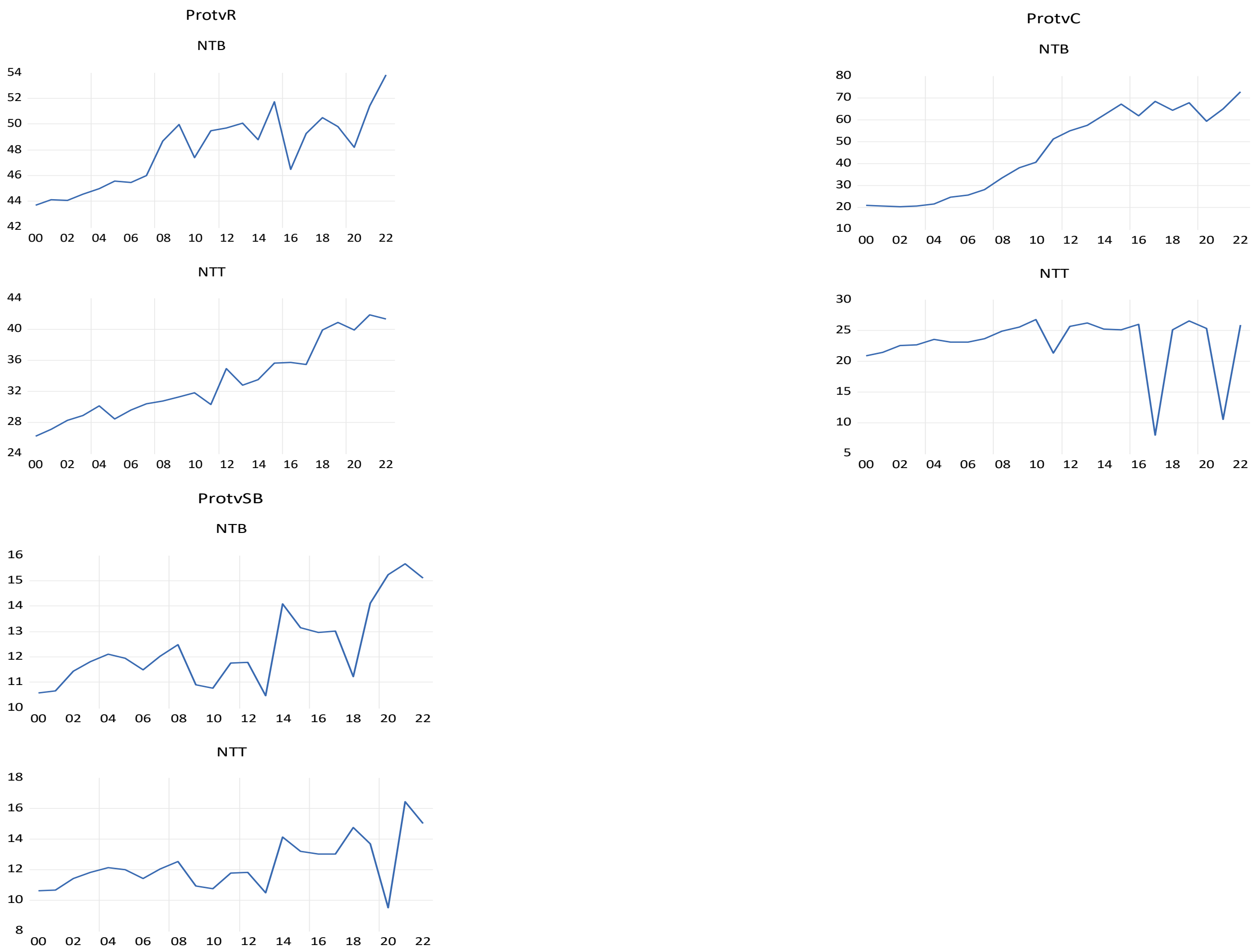


Figure 3. Graph of Rice, Corn and Soybean Productivity in the Research Area

Panel Data Stationary Test

Stationary data test was conducted using Levin, Lin & Chu, Augmented Dicky Fuller (ADF) & Philip Peron (PP) test criteria on significance.α= 0.05. The results of the stationary data test obtained the probability values and t-statistics of the variables as follows:

Table 2. Stationary Values of Variables

Variable Name	Symbol	Probability	t-Statistic	Summary Unit Root Test
Rice Productivity	ProtvR	0.0000	-5.6879	First diff
Corn Productivity	ProtvC	0.0000	-3.9608	First diff
Soybean Productivity	ProdtvS	0.0000	-6.6235	First diff
Degraded Land Area	LLD	0.0000	-4.8896	First diff
Air temperature	SHU	0.0000	-5,0590	First diff
Rainfall	CHJ	0.0000	-3.9768	First diff
Humidity	Extraordinary Congress	0.0000	-4,1809	First diff

Source: Processed Data, 2024

The results of the data stationary test show that all variables are stationary at the first difference level I(1) with a probability value smaller than 5% significance or (p-value < 0.05). Thus, all research variables can be used in the ARDL model analysis according to the nature of data integration.

Cointegration Bound Test

This Bound Tast cointegration test is needed to see whether or not there is a short-term and long-term relationship between variables in the model, by comparing the critical F value to the lower bound I(0) and upper bound I(1) values. The results of the cointegration test for the rice productivity model are as follows:

Table 3. Cointegration of ARDL Model of Rice Productivity

Variables	Coefficient	t-Statistic	Prob*	F-statistic Value	Sig	lower I(0)	Upper I(1)
Short-term							
D(DL,2)	-0.13916	-11,9170	0.0000				
D(DL(-1),2)	-0.02950	-2.4630	0.0264	7,0153	1%	3.29	4.37
CointEq(-1)	-1.29359	-7,4915	0.0000				
Long-term							
D(DL)	-0.14038	-5,13873	0.0001				
D (S)	-0.16445	-0.5768	0.5726	7,0153	1%	3.29	4.37
D (CH)	-0.01995	-0.4500	0.6591				
D (K)	-0.18169	-0.6566	0.5214				
C	0.00400	0.8159	0.4273				

Data Source: Processed Results, (2024)

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It is known that the F-Statistic value is greater than the lower limit I(0) and upper limit I(1) of the forecast line, so it is concluded that all exogenous variables have short-term and long-term relationships with current and future rice productivity variables. One lag and difference of the degraded land area variable have a short-term relationship with the current rice productivity variable, and the degraded land area variable has a long-term relationship with the future rice productivity variable. Meanwhile, the temperature, rainfall and humidity variables do not have a long-term relationship with the future rice productivity variable.

The results of the Bond Test Cointegration Test of the corn productivity model obtained the following data:

Table 4. Cointegration of ARDL Model of Corn Productivity

Variables	**Coefficient**	**t-Statistic**	**Prob***	**F-stat Value**	**Sig**	**lower I(0)**	**Upper I(1)**
Short-term							
D(ProdtvJ(-2),2)	-0.9896	14,4567	0.0048	13.93	1%	3.29	4.37
D(LLD,2)	-0.1967	-23,2943	0.0018				
D(LLD(-1),2)	0.2786	8,0963	0.0149				
D(LLD(-2),2)	-0.0999	-5.6771	0.0297				
D(S(-1),2)	10,8843	17,3796	0.0033				
D(S(-2),2)	5,8183	15,2862	0.0043				
D(CH,2)	0.1832	6.6155	0.0221				
D(CH(-1),2)	0.9077	16,4100	0.0037				
D(CH(-2),2)	0.4723	13,6077	0.0054				
D(K(-1),2)	1,8061	10,2906	0.0093				
D(K(-2),2)	3,8976	16,6780	0.0036				
CointEq(-1)							
Long-term							
D(DL)	-0.5014	-8,2681	0.0143	13.93	1%	3.29	4.37
C	-0.0078	-0.6106	0.6036				

Data Source: Processed Results, (2024)

Based on the criteria of F-statistic value, the lower limit value I(0) and the upper limit I(1) of the forecast line, it can be concluded that all exogenous variables have short-term and long-term relationships with the current and future corn productivity variables, with the composition of one lag of corn productivity variable, three lags of degraded land area variables, two lags of temperature variables, three lags of rainfall variables and two lags of humidity variables having a short-term relationship with the current rice productivity variable. The variable of degraded land area has a long-term relationship with future rice productivity, while the variables of temperature, rainfall and humidity do not have a long-term relationship with future rice productivity.

The results of the Bond Test Cointegration test on the soybean productivity model obtained the following data:

Table 5. Cointegration of ARDL Model of Soybean Productivity

Variables	Coefficient	t-Statistic	Prob*	F-stat Value	Sig	lower I(0)	Upper I(1)
Short-term							
D(DL,2)	-0.0382	-2,3017	0.0696	59,8781	1%	3.29	4.37
D(DL(-1),2)	-0.0775	-3.2834	0.0230				
D(S,2)	11,6979	15,8591	0.0000				
D(S(-1),2)	2,6936	3,4853	0.0176				
D(S(-2),2)	6,7878	10,1452	0.0002				
D(CH,2)	1,1937	16,1068	0.0000				
D(CH(-1),2)	-0.8939	-14,6467	0.0000				
D(CH(-2),2	0.1658	2.4487	0.0580				
D(K,2)	10,6252	0.5420	0.0000				
CointEq(-1)	-1.9060	-26,8055	0.0000				
Long-term							
D(DL)	0.0775	1,9850	0.1039	59,8781	1%	3.29	4.37
D(S)	7,8447	3,2190	0.0235				
D(CH)	1,0780	6,5453	0.0012				
D(K))	3.4415	5,3413	0.0031				
C	-0.0022	-0.1387	0.8951				

Data Source: Processed Results, (2024)

Based on the criteria of F-statistic value, the lower limit value I(0) and the upper limit I(1) of the forecast line, it can be concluded that all exogenous variables have short-term and long-term relationships with current and future corn productivity with the composition of one lag variable of degraded land area, three lag variables of temperature, two lag variables of rainfall and one lag variable of humidity having a short-term relationship with current soybean productivity in the first order difference, while the temperature variable, one variable of rainfall and the variable of humidity in the first order difference have a long-term relationship with future soybean productivity.

Lag-Optimum Test

The results of the optimal lag test based on the AIC/SIC criteria on the rice, corn and soybean productivity models obtained the optimal lag structure as follows:

Table 6. Optimal Lag Structure of ARDL Model for Rice, Corn and Soybeans

Data Source: Processed Results, (2024)

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The optimal lag test results for the rice productivity model obtained an optimal lag structure (1,2,0,0,0). This composition indicates that the rice productivity variable is influenced by one lag of itself, two lags of the land degradation variable, the temperature (S), rainfall (CH), and humidity (K) variables. Furthermore, the optimum lag structure for the corn productivity model was obtained (3,3,3,3,3). This composition indicates that corn productivity is influenced by three lags of itself, three lags of land degradation, three lags of temperature, three lags of rainfall, and three lags of the humidity variable.n.Furthermore, the optimum lag structure of soybean productivity was obtained (1,2,3,3,1). This composition shows that soybean productivity is influenced by one lag of itself, two lags of the variable area of degraded land., and three lags of the temperature variable, three lags of Rainfall and one lag of the humidity variable.

ARDL Model Stability Test

The results of the stability test on the ARDL model of rice productivity, in the short term, the blue forecast line (graph a) moves relatively stable not exceeding the lower limit I (0) and the upper limit I (1) of the error correction line, in the long term the forecast line (graph b) moves relatively stable not exceeding the lower limit I (0) and the upper limit I (1) of the error correction line. The Error Correction Term (ECT) value at a significance level of 1% is obtained at -1.2936, which means that the model has the ability to adjust itself in one period of 129.36% towards long-term equilibrium if a deviation or deviation occurs. This adjustment ability is included in the classification of "middle correction" or ordinary correction because the ECT value is less than 1.

ARDL Model of Rice Productivity

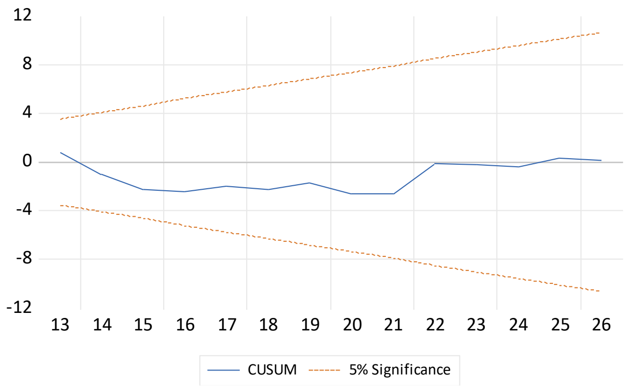

Figure (a) 5% Qusum Graph

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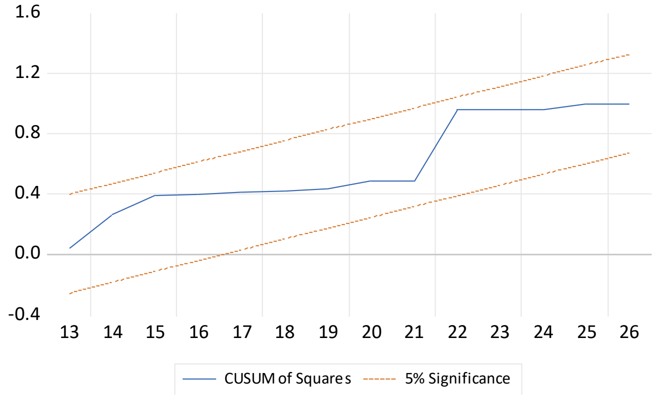

Figure (b) 5% Quasi-sum of Square Graph

The results of the ARDL corn productivity model stability test in the short term in graph (a), the forecast line (blue color) moves relatively stable not exceeding the lower limit I (0) and the upper limit I (1) of the error correction line, in the long term in graph (b) the forecast line (blue color) moves relatively stable still within the lower limit I (0) and the upper limit I (1) of the error correction. The Error Correction Term (ECT) value at 1% significance is obtained at -1.29359 which means that the model has the ability to adjust itself in one period of 129.36% towards long-term equilibrium if a deviation or deviation occurs. This adjustment ability includesinto the "middle correction" or normal correction classification because the ECT value is less than 1.

ARDL Model of Corn Productivity

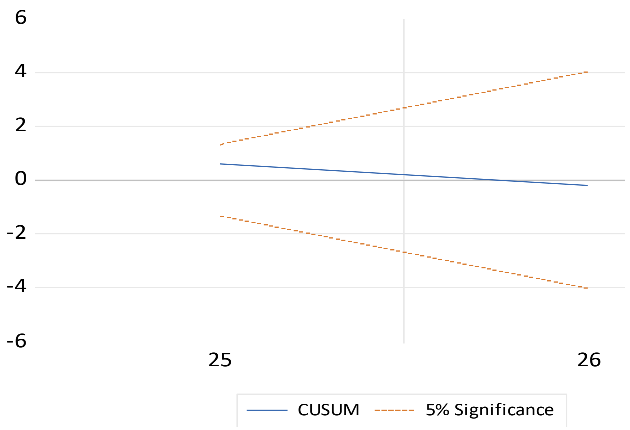

Figure (a) 5% Qusum Graph

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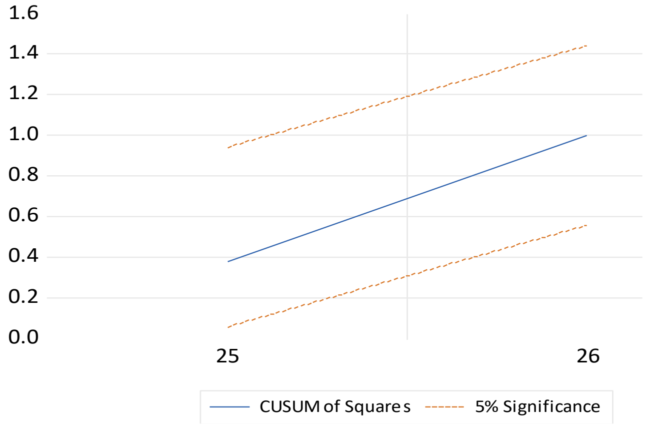
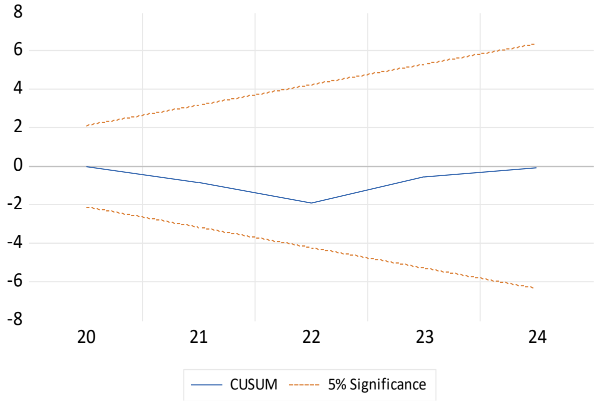


Figure (b) 5% Quasi-sum of Square Graph

The results of the stability test of the ARDL soybean productivity model in the short term (graph (a)), the forecast line (blue color) moves relatively stable, does not cross the lower limit I (0) and the upper limit I (1) of the error correction line, in the long term in graph (b) the forecast line moves relatively stable, does not exceed the lower limit I (0) and the upper limit I (1) of the error correction. The Error Correction Term (ECT) value at 1% significance is obtained at -1.9060, which means that the model has the ability to adjust itself in one period of 190.60% towards long-term equilibrium if a deviation or deviation occurs. This adjustment ability is included in the classification of "middle correction" or ordinary correction because the ECT value is less than 1.

Soybean Productivity Model



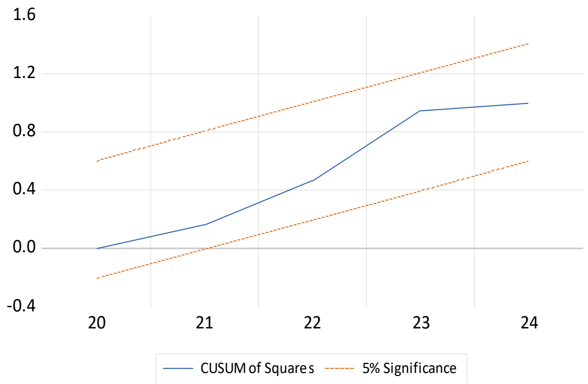


Figure (a) 5% Qusum Graph (b) 5% Quasi-Square Graph

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ARDL Model Estimation of Rice, Corn, and Soybean Productivity

After the diagnostic test stage has been carried out and the model is declared stable for use in estimating short-term and long-term relationships and influences, the next stage is to estimate the parameter values of the model to explain the strength of the relationship and influence of each exogenous variable on the endogenous variable.

The results of empirical analysis of the model, the short-term and long-term relationships are explained in the following model equation:

Table 6. Parameter Coefficients of Rice, Corn, and Soybean Productivity Models

ARDL Model	Function equation
Short-Term Rice Productivity	$\Delta \text{Ln ProdtvP}_t = -0{,}14\ \Delta^2\text{Ln DL}_{(-1)} - 0{,}03\ \Delta^2\text{Ln DL}_{(-2)}$ (0.0264)* (0.0000)*
Long-Term Rice Productivity	$\text{Ln ProdtvP}_t = 0{,}004 - 0{,}140\ \Delta\text{Ln(DL)} - 0{,}165\ \Delta\text{Ln (S)} - 0{,}020\ \Delta\text{Ln (CH)}$ (0.0001)* (0.5726) (0.6591) $- 0{,}182\ \Delta\text{Ln (K)}$ (0.5214)
Short-Term Corn Productivity	$\Delta\text{Ln ProdtvJ}_t = -0{,}0373\ \Delta^2\text{Ln ProdtvJ}_{(-1)} - 0{,}9896\ \Delta^2\text{Ln ProdtvJ}_{(-2))}$ (0.6468) (0.0048)* $- 0{,}1967\ \Delta^2\text{Ln DL} + 0{,}2786\ \Delta^2\text{Ln DL}_{(-1)} - 0{,}0999\ \Delta^2\text{Ln DL}_{(-2)}$ (0.0018)* (0.0149)* (0.0297)* $- 1{,}0619\ \Delta^2\text{Ln S} + 10{,}8843\ \Delta^2\text{Ln S}_{(-1)} + 5{,}8133\ \Delta^2\text{Ln S}_{(-2)}$ (0.0572) (00033)* (0.0043)* $+ 0{,}1832\ \Delta^2\text{Ln CH} + 0{,}9077\ \Delta^2\text{Ln CH}_{(-1)} + 0{,}4723\ \Delta^2\text{Ln CH}_{(-2)}$ (0.0021) (0.0037)* (0.0054) $+ 0{,}2786\ \Delta^2\text{LnK} + 1{,}8061\ \Delta^2\text{Ln K}_{(-1)} + 3{,}8976\ \Delta^2\text{Ln K}_{(-2)}$ (0.2375) (0.0093)* (0.0036)*
Long-Term Corn Productivity	$\Delta\text{Ln ProdtvJ}_t = -0{,}0078 - 0{,}5014\ \Delta\text{Ln (DL)} - 15{,}9524\ \Delta\text{Ln (S)}$ (0.0143)* (00691) $)-0{,}8048\ \Delta\text{Ln (CH)} - 6{,}2098\ \Delta\text{Ln(K}$ (0.0528) (00755)
Short-Term Soybean Productivity	$\Delta\text{Ln ProdtvK}_t = -0{,}0382\ \Delta^2\text{Ln DL} - 0{,}0775\ \Delta^2\text{Ln DL}_{(-1)} + 11{,}6980\ \Delta^2\text{Ln S}$ (0.0696) (00230)* (0.0000)** $+ 11{,}6980\ \Delta^2\text{Ln S} + 2{,}6936\ \Delta^2\text{Ln S}_{(-1)} + 6{,}7878\ \Delta^2\text{Ln S}_{(-2)}$ (0.0000)** (0.0176)* (0.0002)** $+ 1{,}1937\ \Delta^2\text{Ln CH} - 0{,}8939\ \Delta^2\text{Ln CH}_{(-1)} + 0{,}1658\ \Delta^2\text{Ln CH}_{(-2)}$ (0.0000)** (0.0000)** (0.0580) $+ 10{,}6252\ \Delta^2\text{LnK}$ (0.0000)**
Long-Term Soybean Productivity	$\Delta\text{Ln ProdtvK}_t = -0{,}0022 + 0{,}0774\ \Delta\text{Ln (DL)} + 7{,}8447\ \Delta\text{Ln (S)}$ (0.1039) (0.0235) $-1{,}0780\ \Delta\text{Ln (CH)} + 3{,}4115\ \Delta\text{Ln(K)}$ (0.0012)** (0.0031)

Data Source: Eviews Processed Results (2024) Note: Probability (*) (**) = Significant

Interpretation of the ARDL Model of Rice Productivity

In the short-term model, the variable area of degraded land isperiodone and two years previously had a negative effect on current rice productivity with coefficients of -0.14 and -0.03 respectively, which means that every increase in land areadegradation in the periodone year earlier by 1 hectare will reduce current rice productivity by 0.14 quintals per hectare per year and every increase in the area of degraded land in the previous two years by 1 hectare will reduce current rice productivity by 0.03 quintals per hectare per year. In the long-term rice productivity model, the area of degraded land has a negative effect on future rice productivity with a coefficient of -0.140, which means that every increase in the area of degraded land causes a decrease in rice productivity by 0.140 quintals per hectare per year. Temperature, rainfall, and humidity factors in the long term do not have a significant effect on future rice productivity. The intercept value of 0.004 is interpreted if all variables are assumed to be zero or ignored, then the average rice productivity is obtained at 0.004 quintals per hectare per year.

Interpretation of the ARDL Model of Corn Productivity

In the short-term corn productivity model, corn productivity in the previous one-year period has a negative effect on current corn productivity with a coefficient of which means that every increase in corn productivity in the previous one-year period by 1 quintal will reduce current corn productivity by 0.99 quintals per hectare per year. Furthermore, the increase in degraded land area, and the area of degraded land in the previous one and two years period has a negative effect on current corn productivity with a coefficient of which means that every increase in land degradation by 1 hectare will cause a decrease in current corn productivity by 0.20, 0.28 and 0.10 hectares per year. The temperature in the previous one-year period also has a positive effect on current corn productivity with a coefficient of which every increase in temperature in the previous one-year period by 10 C will increase current corn crop productivity by 0.28 quintals per hectare per year.$-0{,}99\ -0{,}20, -0{,}28\ \text{dan} - 0{,}10\ \ 0{,}28 + 0{,}2786$

Interpretation of the ARDL Model of Corn Productivity

Short-term soybean productivity is influenced by soybean productivity and rainfall in the previous year. Soybean productivity in the previous year has a negative effect on current soybean productivity with a coefficient of -0.12, meaning that every increase in soybean productivity in the previous year will reduce current soybean productivity by 0.12 quintals per hectare per year, while rainfall in the previous year has a positive effect on current soybean productivity with a coefficient of 0.059, meaning that every increase in rainfall in the previous year will increase current soybean productivity by 0.059 quintals per hectare per year.

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Conclusion

The findings of this study confirm that the productivity dynamics of major food crops—namely rice, corn, and soybeans—in dryland agricultural systems such as those found in West Nusa Tenggara and East Nusa Tenggara are significantly influenced by both environmental degradation and climatic variability. In particular, the empirical estimation using the ARDL framework demonstrates that changes in the extent of degraded land, along with annual variations in temperature, rainfall, and humidity, exert measurable impacts on agricultural productivity across both short-term and long-term time horizons. These interactions illustrate that food crop performance in arid and semi-arid agroecological zones is not solely determined by conventional production inputs but is increasingly shaped by environmental stressors associated with climate anomalies and declining land quality.

From a long-term perspective, the expansion of degraded agricultural land consistently contributes to declining productivity levels of staple crops. The results indicate that an increase in degraded land area per year leads to a reduction in rice productivity per hectare annually, while corn productivity experiences a decrease of approximately 0.50 quintals per hectare per year under similar conditions. This trend reflects the cumulative and persistent effects of soil fertility loss, erosion processes, and structural degradation of agricultural land resources, which ultimately constrain the productive capacity of cropping systems in dry climate regions. Furthermore, increased annual rainfall variability in these regions is associated with a decline in soybean productivity in the long run, suggesting that precipitation fluctuations beyond optimal thresholds may adversely affect crop growth cycles and soil moisture balance in marginal environments.

In the short term, however, the relationship between climate variables and crop productivity appears to be more complex and partially adaptive. In the dry climate corn productivity model, increases in land degradation, temperature, rainfall, and humidity are found to temporarily contribute to increases in current corn productivity, potentially reflecting short-run agronomic adjustments or physiological responses of crops to moderate climatic changes. Conversely, increases in past corn productivity and lagged land degradation tend to reduce present productivity levels, indicating the presence of delayed feedback mechanisms and productivity saturation effects. Similarly, in the soybean productivity model, short-term increases in rainfall positively influence current productivity, while increases in lagged soybean productivity are associated with declining present output.

Over the long term, however, these adaptive gains are outweighed by structural environmental constraints. Continued increases in degraded land area contribute to declining future national corn productivity, while rising humidity levels are associated with reductions in future soybean productivity. These results underscore the importance of maintaining land quality and ecological stability as a prerequisite for sustaining food crop productivity in dryland regions of Indonesia. Overall, the study highlights that without effective land conservation and climate adaptation strategies, the combined pressures of land degradation and climatic anomalies will continue to pose significant risks to long-term agricultural productivity and food security in vulnerable agroecosystems.

Implications

In the dry climate corn productivity model, in the short term, increases in land degradation, temperature, rainfall, and humidity lead to increases in current corn productivity, while increases in past corn productivity and increases in land degradation lead to decreases in current corn productivity. In the long term, any increase in land degradation leads to decreases in future national corn productivity. In the dry climate soybean productivity model, in the short term, increases in rainfall lead to increases in current soybean productivity, while increases in past soybean productivity lead to decreases in current soybean productivity. In the long term, increases in humidity lead to decreases in future national soybean productivity.

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