Paddy Supply Response to Climate Change and Prices Dynamics in West Kalimantan, Indonesia

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Abstract. Climate change and land conversion adversely affected paddy productivity. On the other hand, paddy price has asymmetrically responded to changes in input costs. The price adjustment more slowly when input costs increase. The study investigated the impact of climate change and prices dynamics on the supply response of paddy in West Kalimantan. The study employed Auto-regressive Distributed Lag (ARDL) model approach to the cointegration with an error correction term and used monthly time series data from January 2018 – April 2023. The study found that climate change and energy prices index negatively effect paddy supply in the short and long run. The study further exhibited that paddy and fresh fruit bunches producer prices have a positively significant effect paddy supply in the short run. In the long run, increased paddy producer price show decreased productivity. The study recommends that supporting small farmers in increasing paddy supply requires policy interventions such as climate change adaptation, land expansion poli-cy, income diversification, input and output subsidies.

Keywords: Climate Change, Productivity, Paddy, Supply Response.

1 Introduction

Rice is the most important food in the world because more than half of the world's people eat it every day. Rice provides 20% of the world's energy through food. It is also the main basic food for the poorest and least-nourished people in Asia and Africa, who can't buy or don't have access to more healthy foods [1]. Consequently, rice is considered one of the most important goods in the world. It is linked not only to global food security, but also to economic growth, job creation, social safety, and peace in the area.

Rice (paddy) is recognized as a crucial agricultural commodity for the Indonesian economy [2]. In 2021, the paddy harvest area reached around 10.41 million hectares or decreased by 245.47 thousand hectares (2.30%) compared to 2020. Meanwhile, paddy production in 2021 was 54.42 million tons. If converted into rice, rice production in 2021 reached around 31.36 million tons, or a decrease of 140.73 thousand tons (0.45%) compared to rice production in 2020 [3]. On the other hand, there was an increase in rice consumption from 2019 reaching 77.5 to 114.6 kg per capita per year in 2021 [4]. In 2022 Indonesia is the fourth largest rice consumption country in the world reaching

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35.3 million tons [5]. A disparity in consumption and production suggests insufficient national rice. However, the rice production is still lower than the needs of Indonesia's 266.91 million population. In order to meet national rice needs, in the 2015–2019 period, on average, Indonesia imported 1.03 million tons of rice per year. Furthermore, rice production has a positive and significant effect on food security, this means an increase in paddy production [6]. Hence, national rice production should be maintained and even increased, such that that food security in Indonesia can be maintained [7].

Land use competition continues to grow as the regional economy develops [8]. The decrease of paddy fields as a result of functions being shifted for non-agricultural and the tendency for irrigated rice output to slope downward, particularly on the island of Java, which is the the center of rice crops in Indonesia. Conversion of paddy fields occurred at 96 thousand ha per year [9]. BPS shows that within 10 years, Indonesia lost 1 million ha of paddy fields. Existing paddy fields are decreasing due to conversion and levelling off, especially in intensive rice fields [10].

Seeing the conditions that occur in Java, the increase in production is directed at expanding production areas outside Java by utilizing neglegted land, transmigration area land and upstream watershed agricultural land. Beyond Java Province, there is potential land for the expansion of agricultural areas in wetlands in amounting to 7.3 million ha [10]. The cultivation of rice plants is targeted towards suboptimal regions, mostly located beyond the island of Java. West Kalimantan Province show that the potential land area for the development of wetland food crops reaches 1,090,514 ha [11]. However, the use of existing paddy fields in 2022 is only 241,479 ha [12]. This shows that there are still large opportunities for rice field expansion in West Kalimantan. The available land that can be developed for rice field development is identified as covering an area of 411,960 ha and more than half of them are in Sambas and Ketapang regencies [13].

However, at this time there is also increasing land use competition, especially between subsistence crops (rice) and commercial destination commodities in West Kalimantan Province. Land conversion from rice to oil palm is often associated with a decrease rice area, mainly in oil palm development centers [7]. Land use competition between oil palm and rice commodities like this has occurred in several oil palm development areas [14][15]. Farmers choose to cultivate oil palm because this plant is more economically profitable. This change in land use from rice to oil palm is feared to threaten the sustainability of food crops, especially rice. Hence, land use management should be carried out properly to prevent the decline in rice agricultural land as a result of the conversion to oil palm plantations [7]. This pressure has resulted in efforts to increase rice productivity or even its sustainability has been disrupted [8]. It is proven that West Kalimantan's rice productivity is still very low, only reaching 30.28 kw/ha from the national productivity which reached 52.38 kw/ha [12].

In some research trend yield explained more than 80 percent of the yield changes over time, suggesting a minor role for other factors such as prices. However, farmers' supply response is mostly dominated by non-price factors over price factors. Non-price factors include the area of production, rainfall, import, exchange rate, etc. Because of the imperfect condition of such factors, farmers may become reluctant to grow more rice in the next production period [16].

Climate change is clearly the dominant factor explaining the main part of yield deviations from the trend. Climate change has a variety of impacts on crop yields and is known to have potential effects on (regional) crop yield evolution [17]. El Ni˜no Southern Oscillation (ENSO) is one of the most important drivers of climate variability globally, affecting significantly the frequency of heavy rains,flooding, drought, and heat waves. Understanding the risks posed to agricultural production by the occurrence of El Ni˜no and La Ni˜na events (the warm and cool phases of ENSO, respectively) is crucial for guiding adequate responses that mitigate negative climate variability impacts [18]. The El Nino-Southern Oscillation affects Indonesian rainfall. ENSO is an atmospheric-sea interaction in the tropical Pacific Ocean that alternates between cold (La Nina) and warm events. (El Nino). Recent rainfall anomalies have reduced crop acreage, size, and yields, affecting grain output [19]. El Nino and La Nina dominated West Kalimantan from June to August [20]. In the resent years annual precipitation levels typically do not have a substantial influence on the production of paddy fields in the majority of the West Kalimantan area [21].

To better understand how economic decision making affects paddy yields, open the production technology-box and relate it to inferred agronomic activities and yields [22]. The measurement of supply elasticity, which quantifies the quantity response to changes in pricing, is a crucial tool for informing judgments on policy changes. The concept of supply elasticity has significant relevance in the field of production economics and is now used by agricultural economists as a means to assess the efficacy of pricing strategies in the allocation of resources among farmers. Estimations of supply responsiveness serve as valuable indicators for the development of economic policy formulations [23].

The current search problem arises because changing agricultural policies have caused significant structural changes in supply response; variations in costs, prices, production technologies, and climate conditions over time are considered the main factors that affect the supply response of any crop; and decisions about which crops to produce are optional. The discovery and evaluation of such correlations could improve future cultivated area projections, allowing farmers to make short- and long-term choices [24].

The issue of agricultural supply responsiveness has always been a crucial concern in the pursuit of sustainable economic growth. However, the desired outcome may not be realized by rice farmers even if the aforementioned structural issues, namely non-price constraints, persist. The primary focus of this study is to analyze the response of paddy supply to both climate change and price dynamics. Additionally, the explain the concept of responsiveness in both the short and long term? The assessment of supply response characteristics has significant potential in enabling informed decision-making among rice farmers and other stakeholders involved in the production and marketing processes. Moreover, the evaluation of agricultural supply response serves as a legitimate approach to analyzing the influence of climate change and price dynamics. The study used the Error Correction version of the Autoregressive Distributed Lag (ARDL) technique to cointegration. This approach allows for the inclusion of mixed regressors and enables separate estimation of both long-run and short-run elasticities.

2 Research and Methods

The study used secondary data, including paddy yield, the ENSO index, producer prices for paddy and fresh fruit, and the energy price index. The data used in this research were obtained from many sources, which included the Central Statistics Agency (BPS) of West Kalimantan Province, the International Monetary Fund, and the National Oceanic and Atmospheric Administration. The dataset included a time frame spanning from January 2018 to April 2023, with all values being converted into logarithmic representation. In order to assess the impact of climatic change and price dynamics on paddy supply in West Kalimantan, this study used the Autoregressive Distributed Lag (ARDL) technique developed by Pesaran[25].

2.1 Theoretical Framework of Supply Response Approach

The present study proposes a framework for analyzing the supply response of paddy using the Nelovian partial adjustment model. The Nerlove model established the concept of partial adjustment, which posits that due to the time required for equilibrium to be reached, only a partial adjustment occurs during a given time period. The delay seen in achieving equilibrium may be attributed to several factors, one of which being the time required for consumer preferences to evolve and adapt, as well as the time needed for production processes to adjust accordingly [26]. The supply model is characterized by its ability to determine the output based on a collection of exogenous variables, which include delayed output, input prices, and other factors that influence supply. Response models for supply are often calculated using either a direct process or a duality technique. One significant benefit of this method is its simplicity in terms of data needs and the potential for a reduced number of specification mistakes. The Nerlovian model is considered to be more realistic in comparison to other supply response models due to its assumption of a progressive and continual adjustment of short-run supply to long-run value, as well as the recursive creation of price expectations. The conventional structural format of the Nerlove model is as follows:

$$A_t^* = \alpha_0 + \alpha_1 P_t^* + \alpha_2 Z_t + U_t \quad (1)$$

Equation 1 delineates the relationship between desired productivity and expected price, with the former being influenced by the latter as well as an exogenous variable and a disturbance term. The Nerlove model included the addition of a significant non-market variable, denoted as Z, in order to mitigate challenges related to parameter identification. The symbols denoting the variables are presented in the following manner.:

A_t^* =desired productivity at time t

P_t^* = expected future price at time t

Z_t = any oyher relevant variable at time t

U_t = random residual

$\alpha_0, \alpha_1, and\ \alpha_2$ = parameters

2.2 Model Specification of Supply Response Approach

The assessment of the paddy supply response may be quantified by considering many factors such as the overall cultivated land area, the resulting output or yield, and the total production per unit of land area. The determination of aggregation levels is contingent upon the research purpose and the accessibility of data. The chosen approach for capturing the supply response models included using natural logarithmic transformation for both the dependent and independent variables. The incorporation of exogenous variables, such as the price of fresh fruit bunches serving as a proxy for the price of alternative crops, was expected in order to enhance the existing models. The ENSO index serves as a proxy for assessing climatic change, while the energy price index functions as a proxy for evaluating pricing inputs.

This study used the autoregressive distributed lag (ARDL) approach to assess the effects of climatic change and price dynamics on paddy output in the region of West Kalimantan [25]. The ARDL approach was chosen because to its ability to estimate both long and short-term cointegration connections among the variables under examination. In this study, the autoregressive distributed lag (ARDL) methodology is utilized to address the issue of cointegration. This approach ensures that the estimates of supply response remain consistent even in the presence of endogeneity in the regressors. Additionally, it allows for the estimation of separate long-run and short-run elasticities when exogenous variables do not possess the same level of integration [23]. This method can also be used to find out if variables are cointegrated at integration order I (0), I (1), or a mix of both.

The ARDL model encompasses many techniques as a starting point. To ascertain the integration order of the variables, the research used the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests prior to implementing the time series econometric model. It is important to guarantee that the study variables demonstrate stationarity and do not feature integration beyond the second level. When a variable exhibits integration beyond the second order, it has the potential to provide imprecise results. In order to evaluate the presence of cointegration among the variables, the boundaries cointegration test was used. This research examines the influence of climate change and price dynamics on paddy yields. The variables included are the ENSO index, energy price index, fresh fruit bunches, and paddy producer pricing.

Hence, the below expression represents the typical structure of the paddy yield function.:

$$Yield_t = f(ENSO_t, PPP_t, PFFB_t, ENERGY_t) \quad (2)$$

Yield for paddy productivity, Climate Change for ENSO Index, PPP for Paddy Producer Price, PFFB for Fresh Fruit Bunches Prices and ENERGY for Energy Price Index.

The linear model may be developed by using the natural logarithm:

$$LnYield_t = \alpha_0 + \alpha_1 LnENSO_t + \alpha_2 LnPPP_t + \alpha_3 LnFFB_t + \alpha_4 LnENERGY_t + \varepsilon_t \quad (3)$$

Where $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the coefficients to be estimated α_0 is the intercept and ε_t is the error term. In order to investigate the short-term and long-term paddy yield, The equation may be expressed equation 3 as the long-run cointegration of the ARDL equation as follows:

$$DLnYield_t = \beta_0 + \sum_{i=1}^{n} \beta_1 DLnENSO_t + \sum_{i=1}^{n} \beta_2\, DLnPPP_t + \sum_{i=1}^{n} \beta_3\, DLnFFB_t + \sum_{i=1}^{n} \beta_4\, DLnENERGY_t + \gamma_1 LnENSO_t + \gamma_2 LnPPP_t + \gamma_3 LnFFB_t + \gamma_4 LnENERGY_t + ECM_t + \varepsilon_t \tag{4}$$

Where $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficient of short-run dynamics and $\gamma 1$ is the coefficient of long-run for paddy yield

$D\ and \varepsilon_t$ represent the first difference operator and the error term, respectively. An Ordinary Least Square (OLS) regression was conducted using equation 3 in order to ascertain the presence of long-term cointegration among the variables. This research used the ARDL limits F-statistic to ascertain the presence of cointegration over time between climatic change, price dynamic variables, and paddy output in West Kalimantan. The null hypothesis of no association and the hypothesis of long-term solid cointegration were examined in our study. Consequently, the next assumptions were formulated:

$H0: \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4$ this null hypothesis demonstrates that in the long run paddy yield and climate change and prices are not cointegrated.

$H1: \gamma_1 \neq \gamma_2 \neq \gamma_3 \neq \gamma_4$ this alternative hypothesis indicates that in the long run paddy yield is cointegrated with climate change and prices.

The Johansen cointegration approach will validate long-term cointegration with climate change and pricing next. After establishing the long-term link between the variables of interest, analyze their short-term correlation. Equation (4) was employed. We can investigate short-term dynamics and error correction term using the ARDL model.

After identifying long-term relationships on study variables, we use diagnostic tests to check our results' dependability. Serial correlation was examined using the Breusch-Godfrey LM test. We also tested heteroscedasticity using the Breusch-Pagan-Godfrey test and model stability with the Ramsey Reset, CUSUM, and CUSUM Square tests.

3 Result and Discussions

Descriptive statistics for research variables are needed to start data analysis. Results of descriptive statistics are in Table 2. We find positive skewness in all variables and almost similar means and medians. All variables have kurtosis values below 3, which fulfills the cutoff value of 3.

Table 1. The summary of descriptive statistics.

	YIELD	ENSO	PPP	PFFB	ENERGY
Mean	1.109	(0.306)	8.605	7.510	5.072
Median	1.096	(0.450)	8.593	7.495	5.010
Maximum	1.311	0.900	8.780	8.252	5.931
Minimum	0.962	(1.300)	8.492	6.964	4.023
Std. Dev.	0.088	0.655	0.065	0.320	0.419
Skewness	0.433	0.324	0.532	0.321	0.011
Kurtosis	2.294	1.656	2.861	2.247	2.742
Jarque-Bera	3.333	5.933	3.074	2.608	0.179
Probability	0.189	0.051	0.215	0.271	0.914
Sum	70.947	(19.600)	550.721	480.672	324.596
Sum Sq. Dev.	0.487	26.998	0.270	6.465	11.076
Observations	64	64	64	64	64

To examine the enduring association between the variables being examined, this research used two kinds of unit root tests, namely the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Table 2 presents the results of the conducted tests, indicating that none of the variables exhibit stationarity at their respective levels. Nevertheless, when applying the first difference, it is seen that all variables exhibit stationarity and integration, so indicating the possibility of a legitimate long-term association between the underlying variables. Therefore, the Autoregressive Distributed Lag (ARDL) technique is considered appropriate for further investigation of this connection.

Table 2. Unit root test results.

Variable	ADF				PP			
	At Level	PROB	First Differences	PROB	At Level	PROB	First Differences	PROB
YIELD	-1.502857	0.5256	-5.235442	0.0000	-3.944978	0.0031	-14.70891	0.0000
ENSO	-2.311221	0.1717	-2.925819	0.0481	-1.659298	0.4468	-3.020938	0.0384
PPP	-1.872944	0.3428	-6.318104	0.0000	-2.150863	0.2261	-6.240754	0.0000
PFFB	-1.351271	0.6004	-7.397556	0.0000	-1.40933	0.5723	-7.387161	0.0000
ENERGY	-1.502857	0.5256	-5.235442	0.0000	-0.986265	0.7532	-5.071082	0.0000

Table 3 shows anticipated long-term cointegration ARDL bounds test results. Based on the ADF and PP unit root tests, we used the ARDL limits test to find long-term cointegration variables. Critical upper and lowest limits define test statistics. The null hypothesis is rejected if empirical F statistics exceed the upper limit, demonstrating cointegration between variables. ARDL bound test findings show that the estimated F-statistic value exceeds upper limit values at 1% significance.

Table 3. ARDL bound test.

F-Bounds Test		Null Hypothesis: No long-run relationships exist		
Test Statistic	Value	Significance	I0 Bound	I1 Bound
F-statistic	7.390776			
		10%	2.45	3.52
		5%	2.86	4.01
		2.50%	3.25	4.49
		1%	3.74	5.06

Table 3 shows anticipated long-term cointegration ARDL bounds test results. Based on the ADF and PP unit root tests, we used the ARDL limits test to find long-term cointegration variables. Critical upper and lowest limits define test statistics. The null hypothesis is rejected if empirical F statistics exceed the upper limit, demonstrating cointegration between variables. ARDL bound test findings show that the estimated F-statistic value exceeds upper limit values at 1% significance. Thus, ENSO index, energy price index, fresh fruit bunches, and paddy producer prices cointegrate with paddy yields throughout time. Johansen cointegration (Table 4) validated and confirmed the long-term cointegration between paddy yield and other parameters. The findings verified long-term cointegration, revealing varying correlations

Table 4. Johansent cointegration test results.

Dependent Variable Paddy Productivity				
Hypothesized	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
$r \leq 0$	0.554039	102.3709	69.81889	0.0000
$r \leq 1$	0.291984	53.11194	47.85613	0.0148
$r \leq 2$	0.250806	32.04938	29.79707	0.0271
$r \leq 3$	0.146271	14.43518	15.49471	0.0717
$r \leq 4$	0.075499	4.788547	3.841466	0.0286

Table 5 shows the long- and short-run ARDL calculation results. The negative ENSO index coefficient suggests that rising climate change anomalies affect paddy production in the short and long term. Our analysis shows that a 1% increase in average anomalous climate change reduces paddy production by 0.14 and 0.2%. Paddy productivity is affected by climate change. Climate change is anticipated to reduce agricultural yield in several nations [17][27]. Extreme weather and climate events lower agricultural productivity and cause food shocks via global supply systems, worsening food security and nutrition in vulnerable places [28]. Climate change impacts agriculture and making growing crops tricky. Climate change's direct and indirect consequences on agriculture include changed precipitation patterns, droughts, floods, and pest and disease spread [29]. Rice production processes vary according to numerous reasons, including natural resource degradation, biotic and abiotic causes, labor shortages, new technology, etc. Agriculture requires 70% of the world's freshwater, 40% of which is used for rice. Rice cultivation uses a lot of water and creates a lot of greenhouse gases (GHG), especially methane, which is more powerful than carbon dioxide [30].

Furthermore, the research demonstrates that the producer price of paddy has had an adverse effect on paddy production over a longer period of time. According to the findings, a 1% rise in the producer price of paddy is associated with a decrease in paddy production by 0.2%. The outcome aligns with other research findings, which suggest that the supply response of paddy exhibits a limited degree of sensitivity to fluctuations in price [2,31,32]. However, there is a positive short-term impact shown in lags 4 and 5 when the paddy productivity is raised by 1%, resulting in a corresponding rise of 1.1% in the paddy producer price. The price of rice is characterized by its inherent volatility and susceptibility to seasonal variations. In the majority of instances, farmers get a somewhat reduced price during the period of harvest. The potential for decreased market prices and unfavorable circumstances across several components may result in a reduction in rice production by farmers in subsequent years on their farmed area. Prices have a pivotal role in shaping the impact of economic policies on the supply of production and the generation of earnings. However, the augmentation of output necessitates a confluence of supplementary incentives, including the provision of productive technology and the establishment of sufficient private and public infrastructure[16].

In contrast, the producer price of fresh fruit bunches has a positive impact on paddy productivity in both the short and long term. Our study reveals that a 1% increase in the price change results in a respective 0.15 increase in paddy productivity. The rapid expansion of oil palm land area has not compromised the sustainability of rice, particularly in terms of land area development and productivity. The growth rate of oil palm land area surpasses that of rice plantations. From 1991 to 2017, rice fields in South Sumatra experienced a growth rate of approximately 4.6%. The rice development centers, namely Banyuasin, Ogan Ilir, and East OKU Regencies, continue to serve as significant rice production areas in South Sumatra. It is also crucial to enhance the income of rice farmers through various fertilizer supply programs, improve distribution patterns, and support agricultural infrastructure to ensure the continued interest of farmers in maintaining rice farming land [7].

The study concludes that the energy price index reduces paddy output in the short and long term. Paddy yield drops when energy prices rise. It may cause long-term damage. The consequences on agricultural productivity are minimal, but rising energy prices will reduce farmers' welfare by 0.6% to 1.4% [33].

Supply-side theory suggests that higher crude oil prices raise production costs and move the supply curve to the left, raising food prices. The energy price index and food price indexes (grains, other food, and oils) have bidirectional causation at different frequencies [34].Energy plays a crucial role in all stages of the crop production process [35]. The anticipated price surges are expected to have a significant influence on the whole of the food industry, resulting in escalated expenses along the value chain spanning from agricultural production to the final consumer. Various factors might potentially impact on-farm production costs, commodity transport costs, milling, processing, and value addition activities [36]. The impact of rising energy costs varies throughout various stages of production, both in terms of intensity and timing. This implies that the influence of heightened energy costs on the pricing of food items seen in supermarkets is minimal, whereas the impact on crop prices in agricultural fields is more substantial. The energy demand associated with various agricultural activities, such as land preparation, planting, crop upkeep (including fertilizer and weed control), threshing, and harvesting, is of significant importance. The energy input for fertilizer application in rice production had the highest values, accounting for 73.80%, 75.11%, and 76.90% of the total energy input in small, medium, and big farms, respectively [37]. Oil price increases may directly affect agricultural and food output. Mainly because oil and derivatives are utilized in primary (tractors, fertilizers, etc.) and secondary (drying, cooling, storage, transport, and distribution) agricultural product production. Thus, rising oil prices raise production costs. This implies increasing oil and gasoline costs for oil importers risk their energy and food security [38]. Only the following season's harvest is fully affected by rising energy costs [34]. To mitigate energy price impacts and reduce carbon emission in agriculture, several policy implications have been proposed, including strengthening energy market supervision, building an energy saving price-setting mechanism, launching policy instruments to improve energy efficiencies and facilitate cleaner farming, and formulating regional energy saving and emission reduction measurements [33].

Table 5. Short Run and Long Run ARDL model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Dependent Variable Paddy Productivity (YIELD)				
Short Run Dynamics				
D(YIELD(-1))	4.199284	0.815096	5.151888	0.0001
D(YIELD(-2))	3.83005	0.780644	4.906269	0.0001
D(YIELD(-3))	3.394149	0.730915	4.643701	0.0002
D(YIELD(-4))	2.157777	0.55613	3.879989	0.0011
D(YIELD(-5))	1.617138	0.390685	4.139235	0.0006
D(YIELD(-6))	1.276954	0.296115	4.312361	0.0004
D(YIELD(-7))	0.33921	0.208467	1.627165	0.1211
D(ENSO)	-0.141186	0.090432	-1.561231	0.1359
D(ENSO(-1))	0.117207	0.157193	0.745624	0.4655
D(ENSO(-2))	-0.158977	0.139943	-1.136011	0.2709
D(ENSO(-3))	0.188442	0.149253	1.262568	0.2229
D(ENSO(-4))	-0.082976	0.148108	-0.560243	0.5822
D(ENSO(-5))	0.117094	0.164882	0.710165	0.4867
D(ENSO(-6))	-0.156211	0.158832	-0.983498	0.3384
D(ENSO(-7))	0.103269	0.076101	1.356987	0.1916
D(PPP)	-0.36517	0.355908	-1.026023	0.3185
D(PPP(-1))	0.135455	0.436597	0.310252	0.7599
D(PPP(-2))	-0.459336	0.447359	-1.026772	0.3181
D(PPP(-3))	-0.604624	0.501735	-1.205068	0.2438
D(PPP(-4))	1.125181	0.54602	2.060695	0.0541
D(PPP(-5))	1.260492	0.554102	2.274837	0.0354
D(PFFB)	0.154754	0.080408	1.924599	0.0702
D(PFFB(-1))	0.101823	0.097776	1.04139	0.3115
D(PFFB(-2))	-0.277962	0.092696	-2.998643	0.0077
D(PFFB(-3))	-0.11503	0.103516	-1.111224	0.2811
D(PFFB(-4))	-0.090367	0.097889	-0.923165	0.3681
D(PFFB(-5))	-0.071092	0.073515	-0.967043	0.3463
D(ENERGY)	-0.256651	0.106693	-2.405516	0.0271
D(ENERGY(-1))	0.111979	0.177337	0.631445	0.5357
D(ENERGY(-2))	0.172388	0.177079	0.973506	0.3432
D(ENERGY(-3))	-0.299041	0.147224	-2.031192	0.0573
D(ENERGY(-4))	0.184777	0.097029	1.904361	0.073
CointEq(-1)	-5.340206	0.949405	-5.624792	0.0000
Long Run Coefficients				
ENSO	-0.020906	0.006083	-3.436695	0.0029
PPP	-0.226917	0.052609	-4.313268	0.0004
PFFB	0.150175	0.015469	9.708115	0.0000
ENERGY	-0.074126	0.006784	-10.926352	0.0000
C	2.30647	0.498711	4.624865	0.0002
R-squared	0.917665			
Adjusted R-squared	0.748419			
S.E. of regression	0.043207			
Sum squared resid	0.033603			
Log likelihood	128.257			
Diagnostic Test	F-satistics	Prob		
F-statistic	5.422104	0.000175		
Heteroskedasticity Test	1.760366	0.1001		
Correlation LM Test	2.156096	0.1268		
Jarque Bera Normality Test	0.227505	0.892479		

Table 5 illustrates long- and short-term ARDL calculations and diagnostic tests that demonstrate model stability. The study's climatic change and price dynamic components explain 91% of paddy production fluctuation, according to R2 = 0.91. As illustrated in Fig. 1, CUSUM and CUSUM squared tests assessed model stability. Both tests validate our findings that model residuals are structurally stable.

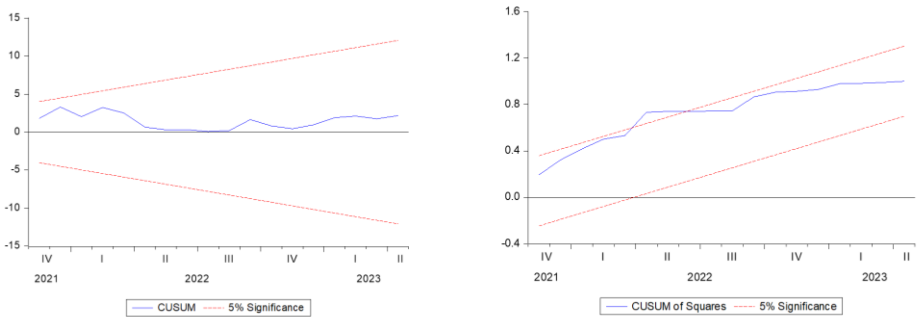

Figure 1. CUSUM and CUSUM squared tests

4 Conclusion

The research used monthly time series data from January 2018 to April 2023 to analyze how climate change and pricing dynamics affected West Kalimantan paddy production. The long-term link between variables was validated using ARDL bound testing and Johansen cointegration. Our research found that climate change, energy price index, and increasing impact paddy production in the short and long run. However, fresh fruit bunches boost paddy output in both timeframes. The research also shows that paddy producer price reduces output over time. In West Kalimantan, agricultural sustainability, climatic resilience, and resource management impact paddy yield. The policy suggests improving these factors. Extension personnel should train farmers to use new technologies and boost output.

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