FYP FSB

ECONOMIC IMPACT OF FLOODING ON AGRICULTURAL PRODUCTION IN MALAYSIA

by

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DECLARATION

I declare that this thesis entitled "Economic Impact of Flooding on Agricultural Production in Malaysia" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date : 29/2/2024

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Economic Impact of Flooding on Agricultural Production in Malaysia

ABSTRACT

The flood disaster in Malaysia can result in many losses especially in economy, destruction of natural resources, and destruction of the environment including in the agricultural sector. Plants die when flood water remains in agricultural areas for too long. Farmers will suffer economically if their crops are destroyed. In general, agricultural production will be negatively affected. Therefore, this research was conducted to examine the impact of flooding on agricultural production in Malaysia. This study uses secondary data from 2002 until 2021 from the Department of Irrigation and Drainage Malaysia (DID) and the World Bank. The method used in this study is Time Series Data Analysis by using autoregressive and distributed lag model (ARDL) test. This method used to establish a long-run cointegration relationship between the variables. Throughout the study period, there was no significant correlation between Malaysia's agricultural production and the flood. This suggests that, over an extended period of time, the flood has little effect on Malaysia's total agricultural productivity. Therefore, we recommend that Malaysian government should invest in modernizing and diversifying the agricultural sector, focus on developing and maintaining robust infrastructure, including water reservoirs, drainage systems, and flood barriers, and establish financial instruments and insurance mechanisms.

Kesan Ekonomi daripada Banjir Terhadap Pengeluaran Pertanian di Malaysia

ABSTRAK

Bencana banjir di Malaysia boleh mengakibatkan banyak kerugian terutamanya dalam ekonomi, kemusnahan sumber asli, dan kemusnahan alam sekitar termasuk dalam sektor pertanian. Tumbuhan mati apabila air banjir kekal di kawasan pertanian terlalu lama. Petani akan menderita dari segi ekonomi jika tanaman mereka musnah. Secara amnya, pengeluaran pertanian akan terjejas secara negatif. Oleh itu, kajian ini dijalankan untuk mengkaji kesan banjir terhadap pengeluaran pertanian di Malaysia. Kajian ini menggunakan data sekunder dari tahun 2002 hingga 2021 daripada Jabatan Pengairan dan Saliran Malaysia (JPS) dan Bank Dunia. Kaedah yang digunakan dalam kajian ini ialah Analisis Data Siri Masa dengan menggunakan ujian autoregressive dan distributed lag model (ARDL). Kaedah ini digunakan untuk mewujudkan hubungan kointegrasi jangka panjang antara pembolehubah. Sepanjang tempoh kajian, tidak terdapat korelasi yang signifikan antara pengeluaran pertanian Malaysia dengan banjir. Ini menunjukkan bahawa, dalam jangka masa yang panjang, banjir mempunyai sedikit kesan ke atas jumlah produktiviti pertanian Malaysia. Oleh itu, kami mengesyorkan agar kerajaan Malaysia melabur dalam memodenkan dan mempelbagaikan sektor pertanian, menumpukan pada pembangunan dan penyelenggaraan infrastruktur yang teguh, termasuk takungan air, sistem perparitan, dan halangan banjir, dan mewujudkan instrumen kewangan dan mekanisme insurans.

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LIST OF ABBREVIATIONS

AP	Agricultural Production
F	Annual Flood Frequency
LF	Labour Force
K	Capital
L	Land
R	Rain
CUSUM	Cumulative Sum
ADF	Augmented Dickey-Fuller Test
PP	Phillips-Peron
ECM	Error Correction Model

LIST OF SYMBOLS

%	Percentage
β	Beta
εt	Stochastic error term
Δ	Delta

CHAPTER 1

INTRODUCTION

1.0 Introduction

Floods are one of the most prevalent natural catastrophes that may harm one-third of the world's population because they are produced by water overflowing in a dry area (Aldardasawi & Eren, 2021). Short-rain floods, long-rain floods, snowmelt floods, and rain-on-snow floods are several types of flooding events (Hundecha et al., 2017). Flooding is caused by a multitude of reasons, including severe precipitation, release of water that exceeds drainage capacity, diminished water catchment areas as a result of residential development, individuals who clog rivers with waste, illegal logging, drainage overflow, and many more (Sholihah et al., 2020). In addition, the flood is very dangerous because it can cause terrible damages and harmful to environment and human.

Agriculture is a land use and economic framework that arises from the the combination of cultivation of crops and domestication, serving as a means to supply foodstuff and other commodities to the global human population (Harris & Fuller, 2014). Agricultural activities are crucial to a nation over time as the agricultural productivity has the ability to significantly positively impact national economic growth and the reduction of poverty (Dfid, 2014). Not only that, agricultural activities are important to provide the largest share of food supplies and support food security, ensure good health and wellbeing to people, and it is also essential to support the farmers' livelihoods (Viana et al., 2022).

Agricultural production cannot develop by itself. It is highly dependent on several factors, namely labor force, capital, land, and rain. The labour plays a role in agricultural productivity. Agriculture is typically seasonal, geographically distributed, and labour-intensive, with inconsistent and low labour productivity (Christiaensen et al., 2021). Regional agriculture requires appropriate regulatory frameworks and greater labour-saving techniques in order to address numerous social and economic problems (Otchia, 2014). Not only that, capital is a factor of production that describes the acquisition of products manufactured with money used in production, such an agricultural tractor, seeds, fertilizers, equipment, and other farming technologies and machinery. Land is a crucial factor in agricultural production and a country's economy. Half of the world's habitable land is used for agriculture (Ritchie, 2019). Sufficient rainfall is crucial for crop development because it supplies the moisture required for plant growth. On the other hand, too much rain can cause soil erosion, waterlogging, and a higher risk of plant diseases, all of which lower agricultural production (Nichepom, 2023).

Natural precipitation is an essential source of irrigation water for agriculture since it aids farmers in crop production. Excessive water resources, on the other hand, might lead to floods. Therefore, floods are one of the biggest hazards to agriculture because they may harm the agricultural ecology, which lowers agricultural productions (Guan et al., 2021).

1.1 Background of Study

According to the World Meteorological Organization (2022), Floods are the worst natural disasters, affecting numerous places throughout the world every year. Flood damage has increased extremely in recent decades. Not only that, floods endanger the lives, health and property of the population and economic activities of society. Floods not only harm assets, but they also interrupt economic activities, such as agricultural activity. The floods cause about two-thirds of all crop damage and loss (Food and Agriculture Organization of the United Nations, 2017). According to an analysis of UN food security monitoring documents, floods harmed the food security of 35 countries that are developing in 2020 (Food and Agriculture Organization of the United Nations, 2017).

Monsoon floods and flash floods are two forms of flooding that exist in Malaysia. Monsoon floods require many days to fully recover and may persist for a week or more, whereas flash floods can recover within a few hours. (D et al., 2014). According to Shah et al. (2017), Malaysia experiences temperatures between 26°C and 32°C with an average precipitation of 2000 to 4000 mm. Malaysia has seen many floods since 1920. One of the most tragic floods ever experienced in Malaysia, the latest monsoon flood between December 2014 and January 2015 has been reported have harmed more than 100,000 people. Table 1.1 provides an overview of Malaysia's experience and the losses caused by monsoon floods and flash floods from 1996 to 2016 (Buslima et al., 2018).

Table 1.1: Flooding History in Malaysia.

No.	Years	Occurrence of floods	The consequences of flooding
1	1996	Keningau, Sabah had floods as a result of Tropical Storm Greg.	• There were 241 fatalities. • Infrastructure and property losses are expected to total more than USD 97.8 million. • Numerous residences were destroyed.
2	2000	Kelantan, Terengganu, and the northern part of Peninsular Malaysia have been flooded by rainstorms.	• In Terengganu and Kelantan, 15 people dead. • Northern Peninsular Malaysia had more than 10,000 evacuees impacted by the flood.
3	2001	Tropical Storm Vamei resulted in flooding in eastern Malaysia.	• A storm in eastern Malaysia causes both flooding and a landslide. • There were five deaths. • The expected damage amounts to USD 3.6 million.
4	April & Oct 2002	Flash Flood	• Kuala Lumpur had a sudden and severe flood.
5	Oct 2003	Flooding in the northwest Malaysian Peninsula	• Kedah, Penang, and northern Perak states were all hit by this flood, which was widespread throughout northwest Peninsular Malaysia.
6	Dec 2006 & Jan 2007	Flooding in Johor	• 18 individuals died. • The damage is expected to be USD 489 million.
7	2008	Flooding in Johor	• There were 28 passing away. • The estimated damage is predicted to amount to USD 21.19 million.
8	2010	Flooding in Kedah and Perlis	• There were 4 fatalities. • The evacuation affected around 45,000 hectares of rice fields in Kedah.
9	2013	Cameron Highlands Flooding	• A flash flood is caused by the outflow of water from the Sultan Abu Bakar Dam. • Three people were dead. • 100 cars destroyed and 80 residences impacted.
10	Dec 2014 & Jan 2015	Peninsular Malaysia	• The states of Kelantan, Terengganu, Pahang, Perak,

		Flooding	Sabah, Negeri Sembilan, Johor, Perlis, Kedah, and Sarawak in Peninsular Malaysia were impacted. • More than 200,000 individuals were affected, resulting in the loss of 21 lives. • The estimated value of the damage exceeds RM1 billion.
11	May 2016	Flooding in Kuala Lumpur and Selangor	• Four major roadways in Kuala Lumpur were flooded as a result of a flash flood. • 15 automobiles were buried in Kuala Lumpur, while hundreds more were stranded. • There are more than 300 evacuees in Dengkil, Selangor.

(Source: (Hafizah Ismail et al., 2017))

The total loss and damage brought on by the flood in Malaysia in 2022, according to Hafizah Ismail et al., 2017, involving the destruction of residential quarters, cars, companies, and industrial sites, has been calculated. Losses for the living quarters amounted to RM157.4 million, cars to RM18.8 million, manufacturing to RM8.7 million, commercial premises to RM50.3 million, agricultural to RM154.5 million, and public assets to RM232.7 million. The figure below depicts the total damages caused by floods in Malaysia in 2022.

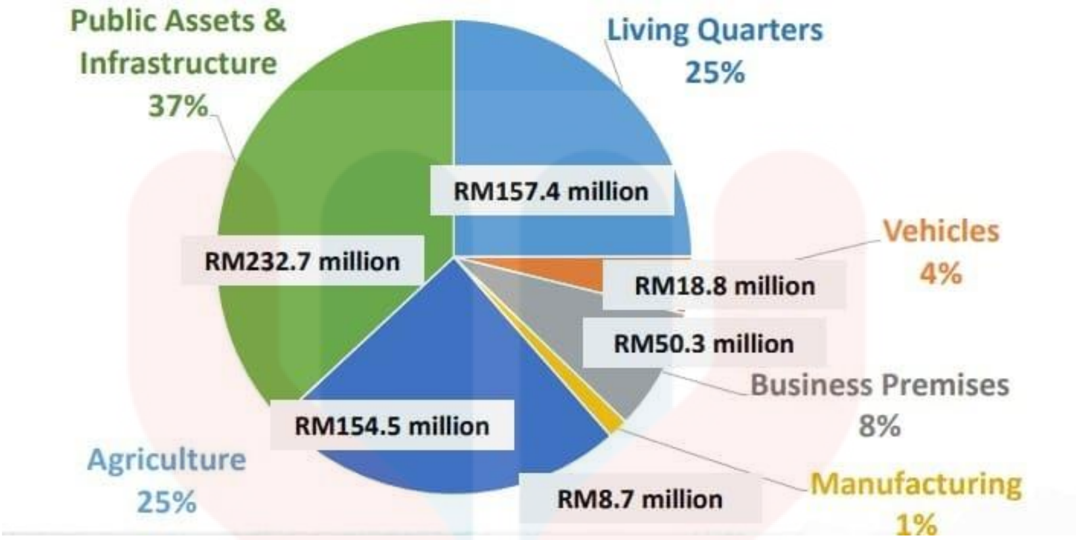


Figure 1.1: The total losses due to floods in Malaysia, 2022.

Source: (MINISTRY OF ECONOMY DEPARTMENT OF STATISTICS MALAYSIA Special Report on Impact of Floods in Malaysia 2022, n.d.)

Flooding is a big barrier for agriculture in this study. Floods can cause inundated fields, soil erosion, and soggy conditions, all of which can harm agricultural yield. Flooding affects the planting and harvesting seasons, resulting in crop losses and damage. Furthermore, the deposition of sediments and pollutants during floods can deteriorate soil quality further, threatening the long-term viability of agricultural land. The economic consequences go beyond immediate crop losses, encompassing reduced yields, increased production costs, and supply chain disruptions. This condition emphasizes the vital need to study and address the multiple implications of floods on agricultural sustainability in Malaysia.

1.2 Problem Statement

The occurrence of the flood disaster can result in many losses, destruction of natural resources, and destruction of the environment including in the agricultural sector. Floods will cause slow viability growth in agricultural sectors because the plants might die when flood water remains in agricultural areas for too long. The crops can be completely destroyed by the floods as the crops are exposed to a variety of abiotic stresses as a result of the submersion, including less light availability, decreased oxygen levels, and changed soil chemical properties (Wang et al., 2022). Not only that, irrigation and agricultural infrastructure may be also harmed by river damage brought on by river flooding along the banks. Therefore, crops such as rice fields placed along river channels or in vulnerable to flood lowlands have the potential to destroy since paddy is vulnerable to flooding.

Malaysia's most important economic activity is agriculture. The majority of Malaysians live in rural areas making agriculture their main source of income. The Department of Statistics Malaysia states that Selangor, Pahang, Melaka, Negeri Sembilan, Johor, and Kelantan are the states that are the most vulnerable to floods. The flood will cause the farmers in these states to suffer economically if their crops are destroyed because agriculture is an important economic source for them. Figure 1 illustrates Malaysia's flood-prone area (Department of Irrigation and Drainage Malaysia, 2023).

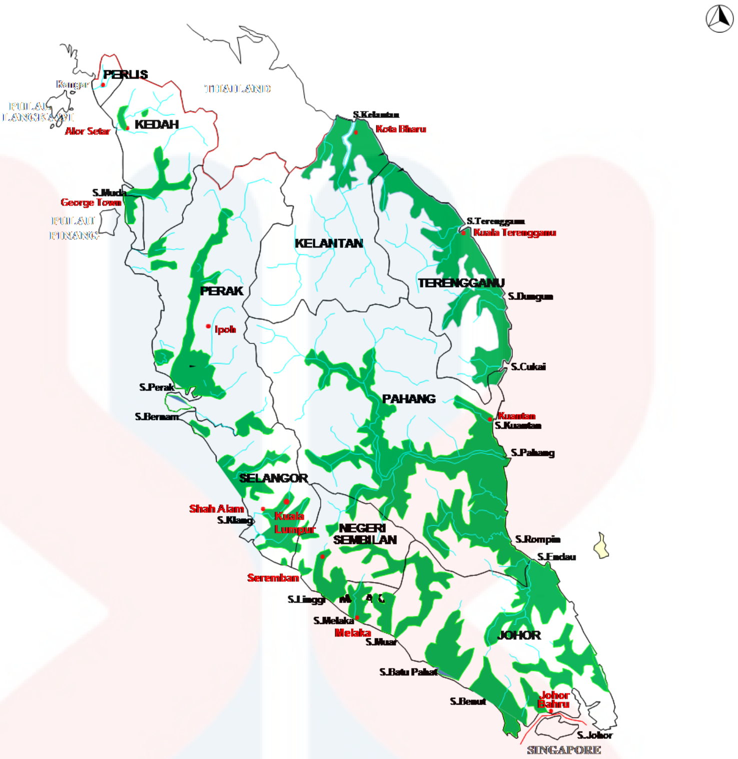


Figure 1.2: Malaysia's flood-prone area.

(Source: Department of Irrigation and Drainage, 2017)

1.3 Objectives

1. To investigate the relationship between the floods and agricultural production in Malaysia.
2. To examine the impact of flooding on agricultural production in Malaysia.

1.4 Scope of Study

This study primarily investigates the correlation between floods and agricultural productivity in Malaysia from 2002 to 2021. The study was built utilizing relevant details and data from earlier research. Next, this study was undertaken to look at how floods have affected Malaysian agricultural production. The floods in Malaysia and agricultural products in Malaysia are the primary variables that have been explored in this paper.

This study is to explore into the overall Economic Impact of Flooding on Agricultural Production in Malaysia, adopting an integrated approach to illuminate the complexity surrounding this topic. This study analyzes historical flood records and agricultural production statistics from secondary data sources to create a more comprehensive picture of economic implications. In this study, analysis employs time series data by using the ARDL model to quantify the intricate relationships between flood events and their ramifications on various facets of agricultural production. EViews software is harnessed as the analytical tool, offering a robust platform for conducting sophisticated time series analyses and facilitating accurate predictions. This study covers agricultural areas across Malaysia. Additionally, the research extends beyond immediate crop losses, encompassing an economic indicator such as the overall resilience of agriculture production.

Furthermore, the study explores potential adaptation strategies and policy implications, aiming to provide actionable insights for policymakers, agricultural practitioners, and stakeholders. By addressing the holistic impact of flooding on agricultural production, this research contributes valuable knowledge to the ongoing discourse on sustainable agricultural practices in Malaysia.

1.5 Significance of Study

The main purpose of this study is to determine how flooding in Malaysia affects agricultural productivity. The Malaysian government should use the findings of this study as a guide for taking action to protect the environment, improve it, and preserve ecosystem variety, wetlands, forests, aquaculture, and livestock in order to retain the viability of agriculture.

Not only that, the government will be more responsible and more sensitive to the threat of flooding from various aspects such as social, the environment and the economy. As a result, the government of Malaysia and policy makers will improve strategies and policies to create suitable solutions and protect agricultural land from the risk of flooding that could negatively affect the country's economy.

Collaboration and coordination between agencies such as the Ministry of Agriculture and Food Industries (MAFI), Department of Irrigation and Drainage (DID), Malaysian Meteorological Department (MetMalaysia), Natural Resources and Environment Ministry (NRE), and other local government authorities will be especially important. By incorporating these specialized businesses, the government can assure a thorough and well-coordinated effort to reducing flood risks and promoting sustainable agriculture practices.

1.6 Study Area

Malaysia is the main focus of the study. Southeast Asian nations include Malaysia among them. Malaysia has 3 federal territories in addition to 13 states. Malaysia's peninsula is divided into 11 states and 2 federal territories. There are 11 states in total: Johor, Kelantan, Terengganu, Pahang, Negeri Sembilan, Perlis, Kedah, Penang, Perak, Selangor, Negeri Sembilan, Malacca, and Negeri Sembilan. The two federal territories are Putrajaya, the federal government's headquarters, and Kuala Lumpur, the capital of Malaysia. Two states and one federal territory comprise East Malaysia. The two states consist of Sarawak and Sabah. In East Malaysia, Labuan is the only federal territory. The population of Malaysia is unevenly distributed between Peninsular and East Malaysia, with most people living in Peninsular Malaysia. The population is racially, linguistically, culturally, and religiously diverse. Malaysians may be broadly divided into four ethnic groups such as Malays, Chinese, South Asians, and 'Orang Asli' (Britannica, T., 2021). Figure 2 displays a map of Malaysia.

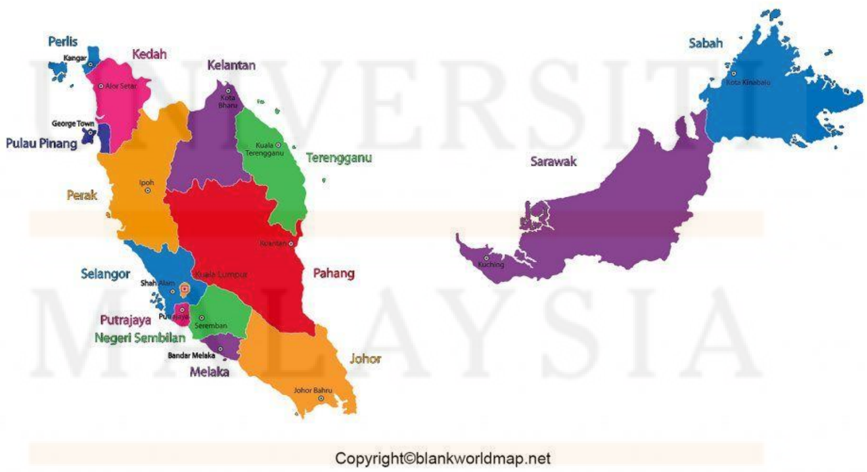


Figure 1.3: Map of Malaysia.

(Source: blankworldmap.net, 2023)

CHAPTER 2

LITERATURE REVIEW

2.1 Discussing Concept of Study

2.1.1 Flooding

Flooding happens when water's level increase to the point where it overflows its natural banks or man-made levees and drowns areas that are normally dry. Heavy rain frequently leads to flood occurrences. Short-term and strong rainfall may cause simple flooding in small mountain streams/creeks, while long-term and low-intensity rainfall can cause major floods, mostly in bigger plains basins (Luino, 2020).

Van Der Veen & Logtmeijer, (2005) expand the damage concept by including indirect economic effects on other of the regional and national economies using a table with bi-regional input and output. The concept of vulnerability is included in the damage estimation. Dependability, redundancy, and susceptibility all have an impact on vulnerability. Dependency refers to how closely a certain activity is connected to other national economic activities. While redundancy refers to an economic activity's capacity to respond to a catastrophic occurrence by postponement, replacement, or relocation. Next, the susceptibility refers to the likelihood and scale of floods.

Therefore, this concept concludes that the more important an economic activity is, the less opportunities for production transfer it has and the more susceptible it is to floods.

2.1.2 Agricultural Production

Agricultural productivity has particular significance for the poor's income and nutritional condition since in most developing nations, the poorest people have no option but to produce and feed themselves and their families with their own energy and available land. Increased farmer productivity not only boosts income and purchasing power, but it can also lower food prices for those who need it to feed their families (Norton et al., 2021).

Agricultural economics is described as an applied science that focuses mostly on economic issues related to farmers' struggles to support themselves. Agriculture is the primary sector of the economy and provides the majority of the raw materials that are converted into finished goods that are used as a fundamental necessities for the human race attests to the importance of agriculture in the economic development of any nation, rich or poor. In addition, Agriculture is required to produce a lot of the raw materials for industry to supply food. Not only that, Agriculture also has to produce export surpluses in order to acquire foreign currency to pay for the import of capital goods and specific types of industrial raw materials (Desai & Ed, 2010).

2.2.3 Impact of Flooding on Agricultural Production

The rise in precipitation has led to enhanced catastrophe of crops due to excessive rainfall, causing the loss of soil and nutrients beyond the boundaries of the farmland (Morton et al., 2015). Along with floods, Heavy precipitation episodes create soil waterlogging, which contributes significantly to productivity losses. (Kozdrój & van Elsas, 2000). According to Kaur et al. (2020), waterlogging stress can result in yield losses that vary from 1% to 100%, depending on factors such as the kind of crop, length of waterlogging, and development stage of the crop. Flooding can harm crop development and yields by depositing mud and crop residues on the plants, as well as causing sand deposition and soil crusting.

2.1.3 Theoretical Literature Review

2.2.1 Agricultural Vulnerability Theory

Vulnerability is the measure of a system's susceptibility or inability to cope with the adverse impacts of climate change, namely changes and extremes in climate (Agassiz, 2001). Vulnerability is the term used to describe the extent to which an agricultural system is susceptible to or lacks the ability to cope with the adverse effects of climate change, such as climate change itself and extreme weather events (Hinkel, 2011). The purpose of study by (Loi et al., 2022) is to assess Ha Tinh province's agriculture vulnerability to climate change. Based on the findings, climate change has had a significant impact on Ha Tinh's agriculture, with Huong Khe and Thach Ha districts being the most vulnerable. People and their behaviors can help reduce agriculture's vulnerability to climate change.

2.2.2 Adaptive Capacity

Adaptive capacity is an analytical framework and theory that allows for the integration of person, biophysical, and social components that relate to the topic of research (Brooks et al., n.d.). Adaptive capacity theory can inform cost-benefit analyses to evaluate the economic impacts of flooding. They analyze the direct costs of damage to crops, infrastructure, and equipment, as well as indirect costs, such as reduced productivity, increased production costs, and market disruptions. Therefore, it can determine the economic viability of various flood mitigation and adaptation strategies. According to Datta & Behera (2022), their research looked at the capacity of agricultural households to adapt in three climate-risky communities in West Bengal, India's Eastern Himalayan foothills. Farmers' adoption of suitable adaptation techniques is critical for mitigating the negative consequences, and farmers with higher adaptive ability are predicted to be better suited to adjust to rapidly changing climatic circumstances. Understanding the elements that are likely to impact farmers' adaptive ability is therefore crucial for directing adaptation and capacity-building activities efficiently.

2.2.3 Economic Efficiency of Agricultural

Bashev & Denchev's states that the number of agricultural efficiency studies has expanded in line with agriculture's economic importance, societal progress, and the quantity of resources committed to agricultural production development. In the last ten years, there has been notable advancement in establishing the approach to evaluating the efficiency of agricultural research. This has been done by using analytical approaches in agricultural economics and identifying the components that affect the increase of efficiency in research and innovation.

2.3 Empirical Literature Review on Relationship Between Flooding and Agricultural Production

A geospatial model is used in a case study to investigate the impact of severe floods on agricultural output in Vietnam's Quang Nam province. The water surface in this study was created by using the inverse distance weighting (IDW) method to interpolate 86 flood depth markers. The flood inundation map was generated using a digital elevation model (DEM). A different overlay method using the land use map and flood inundation map via geographic information system (GIS) modeling to anticipate the potential impact of floods on agricultural land. The floods of 1:10, 1:20, and 1:100 years flooded 27%, 31%, and 33% of agricultural land, respectively, according to maps. In each flood event, wet rice was the most badly damaged crop, accounting for more than 40% of the province's supply (Chau et al., 2013).

Norouzi & Taslimi, (2012) study the effects of flood damage on agricultural productivity using a Vector Auto Regressive (VAR) model. According to the findings, flood damage has a substantial and dangerous influence on agricultural production. The results of impulse response functions in agricultural productivity show that flood damage has a detrimental influence on agriculture in the near term, with the greatest impact coming in the medium term.

Following that a study seeks to provide a worldwide framework for quantifying the economic implications of coastal flooding on agriculture. The researchers integrated existing flood models with satellite crop data, soil salinity measurements, and crop sensitivity information to develop a unique and complete evaluation of the impact of salt on agricultural productivity over a period of time. Their case study specifically examined flood-prone lower agricultural zones in Lincolnshire, UK. The effects of agricultural flood damage differed across the research area. Implementing a new farming system that is more resistant to salt after the flood would reduce the financial losses caused by each flooding, which now range from £1,366/ha to £5,526/ha, by 35% to 85%. The damages incurred are much greater compared to the losses estimated using a flood risk assessment method that has been traditionally employed for evaluating freshwater flood risks over an extended period of time. The discrepancies can be linked to their longer-term salt damage projections, which have a long-term impact (Gould et al., 2020).

Food insecurity in Pakistan has been compounded by agricultural output declines in the most fertile plains of the Indus basin. Qamer et al. (2023) devised a way to calculate agricultural production losses after a catastrophe using satellite data from many sensors. This approach is used in the evaluation of loss and damage (L&D) caused by the disaster. A comprehensive assessment was conducted to determine the extent of crop losses for each individual crop. This assessment involved the use of many indicators derived from both pre- and post-harvest images captured by Sentinel-1 (for mapping the area affected by the crop), Sentinel-2 (for analysing the crop cover), and GPM (for measuring the intensity of precipitation). According to the statistics, over 2.5 million hectares, which accounts for 18% of Sindh's whole land area, experienced flooding. Out of this, almost 1.1 million hectares were agricultural land. Around 57 percent or 2.8 million hectares of Sindh's total agricultural land area, which is 4.9 million hectares, suffered damage.

Monteleone et al. (2023) conducted a case study to examine the difficulties involved in calculating agricultural losses due to flooding. The study utilised data obtained from surveys, on-site inspections, and model simulations. The objective of this study is to enhance comprehension of the disparities in agricultural loss estimations derived from two distinct techniques, namely crop models and expert-based models. Additionally, the study aims to assess the vulnerability of these estimations to variations in flood hazard inputs. The assessment of agricultural output losses resulting from the flood event of the Panaro River in Northern Italy on December 6, 2020 utilized two crop models (APSIM and WOFOST) as well as the expert-based model AGRIDE-c. Furthermore, in the aftermath of the incident, surveys were carried out among nearby farmers to assess flood characteristics such as the depth, extent, and duration of the water, as well as the extent of crop damage. The survey data, however, was insufficient to substantiate the damage estimates presented by the models, but it might be utilized to create a qualitative portrayal of the event.

2.3.1 Gap in Literature Review

Several publications have undergone evaluation based on an empirical literature review concerning the correlation between floods and agricultural productivity. From these articles, it can be concluded that there hasn't been a proper article on the investigation of the relationship between flooding and agricultural production that give impacts on economy. Hence, this study is proposed as a study on the investigation of the relationship between flooding and agricultural production in Malaysia.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter discusses the predictive approach and econometric model employed to examine the correlation between floods and agricultural productivity in Malaysia spanning the years 2002 to 2021. This chapter is divided into multiple sections. Section 3.1 is dedicated to the theoretical framework, while section 3.2 focuses on the model specification. Section 3.3 covered the estimating approach. Section 3.4 pertains to the variable description and data sources.

3.2 Theoretical Framework

3.2.1 Economic Efficiency and Competitiveness

An agricultural holding attains economic efficiency when the marginal value of the inputs aligns with their corresponding unit costs. If the marginal value exceeds the unit costs, the holding can enhance output without affecting the profit level, hence enhancing efficiency. If the marginal value declines, the farm should decrease its output in order to boost its income (Kelly et al., 1996).

Figure 3 illustrates the journey towards economic efficiency and was adapted from the White Paper of the G20 Meeting of Agricultural Chief Scientists (Fuglie et al., 2016). The y-axis indicates the output value, and the x-axis refers to the input expenditures. The points on this line indicate that the agricultural holding is producing at its maximum yield or output given the type and quality of inputs used, i.e., it is technically efficient. The black line depicts how inputs are transformed into output. For technically efficient holdings, every increase in production value (from VA to VB, for example) derives from consuming more input (from CA to CB), assuming input and output prices remain constant. The measure of value generated by each unit of input currency is determined by the ratio of output value to input value, or by the economic return per unit of currency invested. This metric is also known as profit margins or unit margins.

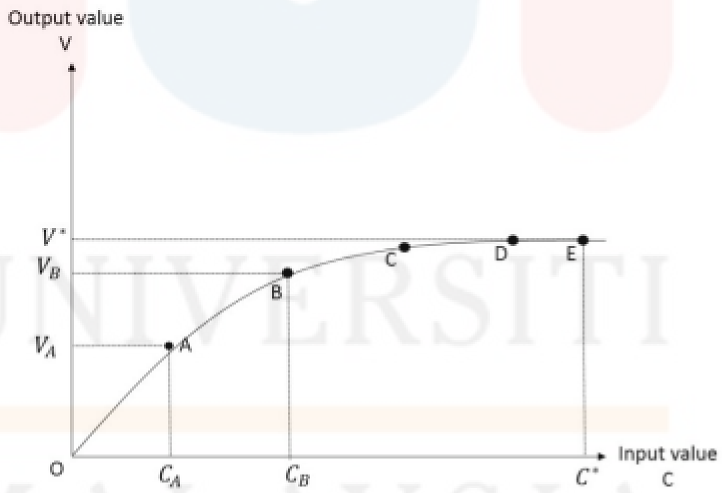


Figure 3.1: Illustration of Economic Efficiency

The figure illustrates a declining marginal return, where the added value gained by adding inputs decreases as the number of inputs grows. Specifically, the increase in value from moving from point A to point B is greater than the increase in value from moving from point B to point C, and so on until reaching point E. Any additional input used after E does not result in increased output, implying that the additional return is 0. Before E, when the farm is economically efficient, there is space to increase overall profitability by employing additional inputs. Further usage of input after E results in a decline in profits. This is due to the occurrence of declining returns to scale in agriculture, which is a well-known and documented phenomenon driven by physical yield and production constraints. When additional inputs are used, yields can increase to a point when more inputs have little influence on yields and merely result in higher costs (Food and Agriculture Organization of The United Nations, 2017).

3.3 Model Specification

The model employed in this study was adapted from the framework proposed by Ayinde et al. (2011), modifications based on the specific characteristics and objectives of this study. The adapted model is represented as follows:

$$\mathbf{AP = f\ (F_t, LF_t\ K_t, L_t, R_t)}$$

Where **AP** is agricultural productivity, **LF** is the number of agricultural labour, **K** is capital, **L** is total agricultural land area, **R** is total rainfall, and **F** is the frequency of annual flooding.

The model had been used in this study is as follows:

$$\mathbf{AP_t = \beta_0 + \beta_1 F_t + \beta_2 LF_t + \beta_3 K_t + \beta_4 L_t + \beta_5 R_t + \varepsilon_t}$$

Where $\beta_0 - \beta_5$ are parameters of the equation and ε_t is term for stochastic error. Lastly, t is the time span examined by the study.

The modification of the original equation was carried out to align the model with the specific context and objectives of our research. This adjustment allows us to better capture and analyze the complex relationships between agricultural productivity and the variables under consideration in this study. The decision to modify the equation was made in order to enhance the model's applicability and relevance to the particular conditions of the study, providing a more accurate representation of the factors impacting agricultural productivity in this study.

3.4 Estimation Method

This study employed the Autoregressive Distributed Lag (ARDL) model. The ARDL model is commonly used in a single-equation framework to examine dynamic relationships using time series data (Kripfganz & Schneider, 2018). A time series refers to a sequence of measurements of a certain variable taken at regular intervals over a period of time. The predominant frequency series are yearly, quarterly, monthly, weekly, and daily. Economic time series data often have distinct characteristics, including a noticeable trend, a significant degree of shock persistence, a tendency for volatility to increase with time, a wandering pattern, and correlations with other series (Enders et al., 2008).

In this study, the statistical tools used in econometrics and time series analysis are the descriptive statistics, correlation matrix, unit root tests, cointegration tests, ARDL long-run and short-run test, and diagnostic test. Descriptive analysis provides an initial overview of the data, summarizing key features and characteristics. Descriptive analysis used to calculate summary statistics, such as mean, median, standard deviation, and distribution of variables related to agricultural production and flooding. The correlation matrix used to examine the strength and direction of relationships between different variables. In this study, understanding the correlations between key factors such as agricultural productivity, rainfall, and flooding frequency is essential. This analysis provides insights into potential interdependencies and helps identify variables that may exhibit multicollinearity, which can impact the accuracy of regression models.

Next, unit root tests are employed to assess the stationarity of time series data. In the context of this study, it is imperative to determine whether the variables under consideration for example; agricultural productivity, rainfall, and flooding frequency are integrated of order one (I(1)) or stationary. A failure to address non-stationarity can lead to spurious regression results. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests assist in detecting and mitigating potential issues associated with non-stationarity. Moreover, cointegration analysis is crucial when dealing with multiple non-stationary time series variables. In this case, the economic impact of flooding on agricultural production involves examining the long-term relationships among variables. The cointegration test helps determine whether a stable, long-term relationship exists between these variables. In the ARDL framework, cointegration is essential for establishing the existence of a stable equilibrium among the key factors impacting agricultural production.

Next, the ARDL long-run and short-run test used to investigate the long-run and short-run dynamics between variables. This test estimates the Autoregressive Distributed Lag (ARDL) model to examine the relationship between agricultural production and flooding variables over time. It also evaluates the coefficients to understand both short-term and long-term effects. Diagnostic test used to assesses the validity and reliability of the estimated ARDL model. This test conducts diagnostic tests such as, Breusch-Godfrey Serial Correlation, Breusch-Pagan-Godfrey Heteroskedasticity, Model Specification Ramsey RESET, and Normality. These tests ensure the model's assumptions are met and results are robust.

As a result, the ARDL model will be utilized in this study to investigate the relationships between floods, agricultural productivity and examine the impact of flooding on agricultural production, as well as additional control parameters. The ARDL model should be used to analyze data series where specific variables are stable at initial differences and others are stationary at level (Pesaran, 1997).

The ARDL model can be analyzed by using EViews software. This software provides various suitable tools and features to analyze ARDL model. The ARDL model can be estimated manually using an equation object and the Least Squares estimation method, or using the built-in equation object specialized for ARDL model estimation.

3.5 Variable Description and Data Sources

Table 3.1: Description of Variables

Variables	**Description**	**Measurement**	**Sources of Variables Data**
F	Annual Flood Frequency	The volume of water flowing through a certain cross section per unit time is known as discharge, and it is generally measured in cubic feet per second or cubic meters per second.	Department of Irrigation and Drainage
AP	Agricultural Productivity	The agricultural total output to total input ratio.	World Bank's Database of World Development Indicators
LF	Labour Force	Number of workers employed.	
K	Capital	The difference in value between the sale of an operational farm and the selling of property in its natural form.	
L	Total agricultural Land Area	Measured in hectares and in percentage.	
R	Total Rainfall	The total rainfall depth during a given period, expressed in millimeters (mm)	

The data for this study was obtained from the World Bank's Database of World Development Indicators, as well as the Department of Irrigation and Drainage. This research encompasses the period from 2002 to 2021. This study will utilize time series data. Data covering the period from 2002 to 2021 has been utilized for the time series analysis. The study employed EViews software to analyze data, benefiting from its strong capabilities for time series and ARDL model.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter provides a detailed analysis and interpretation of the empirical findings obtained from the investigation. The conversation started with the first analysis and progressed to the ultimate phase of the process. The chapter is divided into several sections. The section on descriptive statistics is included in Section 4.2, the correlation matrix test is discussed in Section 4.3, the unit root test is covered in Section 4.4, and the bound test of cointegration is explained in Section 4.5. Additionally, the long run ARDL model and short run test are presented in Section 4.6. Section 4.7 concludes with the diagnostic tests performed on the model.

4.2 Descriptive Statistics

Table 4.1: Descriptive Statistics

Variable	Observation	Mean	Std Deviation	Min	Max	Jarque-Bera	Probability
AP	20	95.544	8.820	73.660	107.420	2.594	0.273
F	20	298.150	290.493	68.000	1057.000	9.756	0.007
L	20	2.620	0.158	2.443	2.944	3.143	0.207
K	20	6.077	1.798	3.598	8.596	1.987	0.370
LF	20	1341	2341	9908	1691	1.662	0.435
R	20	2875.400	1.429	2873.000	2879.000	2.290	0.318

Note: AP is agricultural production, F is annual flood frequency, L is total agricultural land area, K is capital, LF is labour force, R is total rainfall.

Table 4.1 displays the descriptive statistics of the analyzed variables from 2002 to 2021. The provided information displays the summary of typical statistics, including the observation, mean, standard deviation, minimum and maximum values, Jarque-Bera, and probability for each series prior to being transformed into logarithmic form.

Based on the result, we can see that the mean agricultural production is 95.544, with a relatively low standard deviation, which is 8.820, suggesting consistent production. The normality test (Jarque-Bera) of agricultural production does not reject normality as the p-value is 0.273. Next, the high standard deviation in annual flood frequency 290.493. It indicates variability, which can impact agriculture. The normality tests the annual flood frequency rejects normality at a 1% significance level as the p-value is 0.007. The mean of land area is 2.620, and the variability is low, which is the standard deviation is 0.158. The land area seems relatively stable, as indicated by a non-significant Jarque-Bera test as the p-value is 0.207. In addition, the mean of capital is 6.077, with moderate variability where the standard deviation is 1.798. The capital investment is relatively stable, as the Jarque-Bera test is not significant as the p-value is 0.370. For the labour force, the variability is high as the standard deviation is 2341, with a wide range from 1691 to 9908. The Jarque-Bera test is not significant because the p-value is 0.435, suggesting a potential non-normal distribution. Total rainfall shows little variability where standard deviation is 1.429, with a mean of 2875.400. The normality test is not significant as the p-value is 0.318.

The study indicates that while agricultural production shows stability, the annual flood frequency poses a potential risk, being highly variable and significantly non-normal. This suggests that flood events may impact agricultural production negatively. Other factors like land area, capital, labor force, and rainfall show relative stability, providing a foundation for agricultural resilience. Since the Jarque- Bera is higher than 0.05 or at 5% level of significance, the result showed it was not normally distributed. This estimation can be proceeded.

4.3 Correlation Matrix

Table 4.2: Correlation Matrix

	L	**F**	**K**	**LF**	**R**
L	1				
F	0.416	1			
K	0.713	0.552	1		
LF	0.710	0.747	0.747	1	
R	0.178	0.203	0.319	0.232	1

Note: L is total agricultural land area, F is annual flood frequency, K is capital, LF is labour force, R is average rainfall.

Based on the correlation analysis presented in table 4.2, we can see that the correlation between total agricultural land area and annual flood is 0.416 which indicates that they're moderate positively correlated. Next, the correlation between total agricultural land area and capital is 0.713. This reveals that they're moderately positive correlation. In addition, the correlation between total agricultural land area and labour force is 0.710 which also indicates they're moderately strong positive correlation. Besides, the correlation between total agricultural land area and annual rainfall is 0.178 which implies that they are weak positively correlated. A positive linear relationship exists annual flood frequency and capital which is 0.552. Not only that, the correlation between annual flood frequency and labour force is 0.747 shows that they are moderately positive correlation. The correlation between annual flood frequency and average rainfall is 0.203. This indicates a weak positive correlation between them. The correlation between capital and labour force is 0.747 which indicates that they are strongly positively correlated. Moreover, a weak positive correlation exists between capital and average rainfall, which is 0.319. Next, the correlation between labour force and average rainfall is 0.232 which implies that they are weak positively correlated. The correlation of all variables are less than 0.8. Therefore, there is no problem of Multicollinearity as they are not high in correlation. Therefore, the analysis can be proceeded

4.4 Unit Root Test

A time series model is employed to run a Unit Root test, which determines the stationarity of the variables and detects the presence of spurious regression. Both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are performed for each level and initial difference. The outcomes of both examinations are presented in Table 4.3.

Table 4.3: Unit Root Test Result

Variable	Level				First Difference			
	ADF		PP		ADF		PP	
	Constant	Constant & Trend	Constant	Constant & Trend	Constant	Constant & Trend	Constant	Constant & Trend
L	-2.171 (0.221)	-2.161 (-2.161)	-3.238** (0.033)	-1.797 (0.665)	-4.474*** (0.002)	-5.120*** (0.006)	-4.952*** (0.001)	-9.631*** (0.000)
F	2.427 (0.999)	0.779 (0.999)	1.364 (0.997)	-0.603 (0.966)	-6.435*** (0.001)	-8.104*** (0.000)	-6.063 (0.000)	-8.104*** (0.000)
K	-1.318 (0.598)	-0.020 (0.992)	-1.281 (0.615)	-0.693 (0.958)	-2.611 (0.108)	-2.860 (0.1964)	-2.605 (0.110)	-2.860 (0.196)
LF	-0.615 (0.8439)	-2.093 (0.508)	-0.161 (0.928)	-1.722 (0.700)	-2.395 (0.156)	-2.301 (0.412)	-2.461 (0.140)	-2.341 (0.393)
R	-4.932*** (0.001)	-4.817*** (0.005)	-4.934*** (0.001)	-4.817*** (0.005)	-7.878*** (0.000)	-7.623*** (0.000)	-21.822*** (0.000)	-20.748*** (0.000)

Note: ***significant at 1%, **significant at 5%, *significant at 10% levels. ADF is Augmented Dickey-Fuller, and PP stands for Phillips-Perron.

The table 4.3 presents the results of unit root tests which are Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) for different variables at both the level and first difference. The unit root tests are commonly used to assess whether a time series variable is stationary or exhibits a unit root, which implies a non-stationary process. Stationarity is crucial in time series analysis because many statistical methods assume that the underlying data is stationary. Based on the result, we can see the variables L and F become stationary after differencing, indicating that their first differences are stationary time series. Next, the variables K and LF do not require differencing for stationarity as their levels are already stationary. However, the variable R requires differencing to achieve stationarity. The significance levels of the tests are denoted by asterisks, and it is observed that many variables become significantly stationary after differencing at the 1% and 5% levels. The ARDL model is a cointegrating regression model suitable for situations where some variables are stationary and some are non-stationary but become stationary after differencing. Therefore, ARDL approach method utilized in this study is allowed. The ARDL bound test was performed to determine if agricultural production was associated with the explanatory variables over time.

4.5 Cointegration Test (Bound Test)

Table 4.4: Cointegration test result

Model	F-statistics	Lag	Level of Significance	ARDL Bound test critical values (Unrestricted intercept and no trend)	
				I(0)	I(1)
	6.353	3	1%	4.134	5.761
			5%	2.91	4.193
			10%	2.407	3.517
n = 20					

According to the bound test procedure, the F-statistics should exceed the critical value of the upper limit at a 5% significance level. Cointegration is assessed through the application of the ARDL bound test with a maximum lag of three. According to Table 4.4, the test yielded an estimated F-statistic of 6.353. This value surpasses the critical value of the upper bound, which is 4.193 at a significance level of 5 percent. Therefore, we reject the null hypothesis that there is long-term relationship in this model, as there is a consistent and enduring association between all variables within the period being examined. In simple terms, both agricultural production and other independent factors have a large combined effect.

4.6 ARDL Long-run and Short-run Results

Table 4.5: ARDL test result

Variable	Coefficient	T-statistic	P-value
Long-run			
LNF	0.056	1.192	0.271
LNK	0.738**	3.092	0.017
LNR	-0.089***	-3.754	0.007
LNLF	-0.888*	-2.200	0.063
LNL	1.173	1.903	0.098
Short-run			
ΔLNF	-0.003	-0.304	0.769
ΔLNAP (-1)	-0.593***	-5.969	0.000
ΔLNAP (-2)	-0.178*	-2.011	0.084
ΔLNLF	2.987***	10.587	0.000
ECT_{t-1}	-0.616***	-10.908	0.000

Note: ***significant at 1%, **significant at 5%, *significant at 10%, K is capital, F is annual flood frequency, R is average rainfall, LF is labour force, L is is total agricultural land area, and AP is agricultural production.

Table 4.5 shows the coefficient of the LNF (annual flood frequency) in the long-run equation is 0.056 but it is insignificant, which indicates that flood does not affect overall agricultural production in Malaysia in the long-run. This indicates that shifts in the annual flood variable have no long-term influence on agricultural productivity. This condition is probably because Malaysia's agricultural economy is diverse, which means the country is not solely depends on one specific crop or commodity. This helps this country to maintain food security even if floods damage specific crops. Malaysia also grows sugar cane, maize, soya beans, and groundnuts in addition to its primary crops. This diversification improves the country's agricultural system and assures that, even if some crops are flooded, overall production can continue (Courtenay, 1984). The p-value for the annually flood in the long-term equation is 0.271. The p-value of 0.271 indicates that the coefficient for yearly flood is not statistically significant at the 0.05 significance level. Hence, with a p-value of 0.271, the correlation between agricultural productivity and the annual flood coefficient may not be statistically significant at a significance level of 0.05.

Next, the long-run coefficient of LNK (capital) is 0.738. This implies that over time, a one-unit rise in capital is linked to a 0.738-unit rise in agricultural productivity. A positive sign suggests a positive relationship, implying that higher levels of capital are associated with higher levels of agricultural production in the long run. The p-value associated with the coefficient is 0.017. This p-value is less than the significance level of 0.05, indicating that the coefficient is statistically significant.

The table indicates that the long-run coefficient of LNR (average rainfall) is -0.089. This implies that a rise of one unit in the average rainfall is linked to a decline of 0.089 units in agricultural productivity. The presence of a negative sign indicates an inverse correlation, indicating that increased yearly rainfall is linked to decreased agricultural output. The coefficient has a p-value of 0.007. The p-value is below the significance threshold of 0.05, suggesting that the coefficient is statistically significant.

Furthermore, the long-run equation's LNLF (labour force) coefficients is -0.888, with a p-value of 0.063. This means that, in the long run, a one-unit increase in labour force is related with a 0.888-unit drop in agricultural productivity. The negative sign indicates a negative association, meaning that increased labour force participation is connected with poorer agricultural production. The coefficient is related with a p-value of 0.063. This p-value is somewhat higher than the significance level of 0.05, but it is near. It denotes a marginal relevance. The finding is marginally significant, indicating that the observed association between labour force participation and agricultural output may or might not be attributable to random chance. The evidence for statistical significance is lower than it would be with a p-value less than 0.05.

The LNL (total agricultural land area) coefficients is 1.173, with a p-value of 0.098. This means that a one-unit increase in total agricultural land area corresponds to a 1.173-unit increase in agricultural productivity. The positive sign indicates a positive association, meaning that more overall agricultural land area is related with greater agricultural productivity. The coefficient is related with a p-value of 0.098. This p-value is somewhat higher than the 0.05 level of significance. It implies that the coefficient is not statistically significant at the standard level of significance. However, it is close, and it may be considered marginally significant. The observed relationship between the total agricultural land area and agricultural productivity may or may not be due to random chance.

Based on the results above, the long-run coefficient variables of capital, labour force, and total agricultural land area are in accordance with economic efficiency and competitiveness theory. This finding substantiates the finding of Kelly et al. (1996), where if the marginal value is higher, the holding may be able to expand output while maintaining the same amount of profit, resulting in greater efficiency. If the marginal value is lower, the farm's output should be reduced to increase revenue.

Meanwhile, the coefficient of the annual flood frequency in the short-run equation is -0.003. While maintaining other factors constant, this coefficient indicates the expected change in agricultural productivity for a one-unit change in annual flood frequency. In this case, with a coefficient value of -0.003, a one-unit increase in annual flood is related with a 0.003 unit drop in agricultural productivity in the short-run. A negative sign of coefficient indicates an inverse relationship between annual floods and agricultural production in the short run. As the annual flood frequency increases, agricultural production tends to decrease. However, the p-value associated with the coefficient is 0.769. This p-value is relatively higher than the significant level, and typically, a high p-value suggests that the coefficient is not statistically significant. In this context, it implies that the observed relationship between the annual flood frequency and agricultural production in the short run may not be statistically reliable. The results are not likely to be significantly different from what might occur by random chance. The short-run coefficient of the agricultural production one year ago is -0.593 while the short-run coefficient of agricultural production 2 years ago is -0.178.

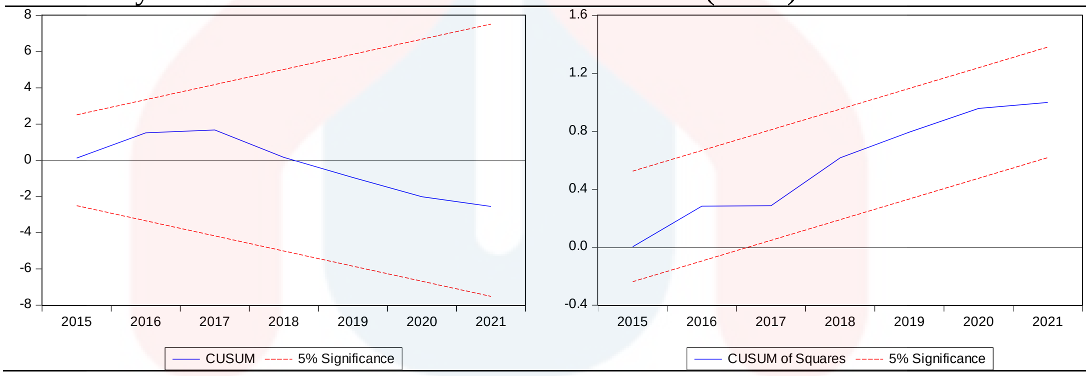
On other hand, the coefficient of the labor force in the short-run equation is 2.987 with the p-value is 0.000. This indicates that, in the short run, a one-unit increase in the labour force is associated with an increase of 2.987 units in agricultural production. The positive sign suggests a positive relationship, implying that higher levels of the labour force are associated with higher levels of agricultural production. The p-value associated with the coefficient is 0.000. This p-value is very low, indicating that the coefficient is highly statistically significant. A p-value of 0.000 typically means that the observed relationship between the labour force and the dependent variable is extremely unlikely to be due to random chance.

The Error Correction Model (ECM) coefficient is a crucial parameter in time series analysis, particularly when studying the long-run relationship between variables. Based on Table 4.5, the ECM coefficient value is -0.616. In the context of an ECM, this coefficient typically reflects the speed of adjustment or the short-run impact of deviations from the long-run equilibrium between the variables involved. The negative sign suggests that the system tends to correct deviations from equilibrium, with a magnitude of 0.616. The p-value associated with the ECM coefficient is 0.000. This very low p-value indicates high statistical significance. In practical terms, it suggests that the ECM coefficient is highly unlikely to be zero, and there is strong evidence to reject the null hypothesis that there is no error correction mechanism.

4.7 Diagnostic Test

Table 4.6: The Results of ARDL Diagnostic Test

Test Statistic	F-statistic
Breusch-Godfrey Serial Correlation	0.103 (0.903)
Breusch-Pagan-Godfrey Heteroskedasticity	1.748 (0.255)
Model Specification Ramsey RESET	22.101 (0.003)
Normality	0.678 (0.712)



Note: These are compared at 5% level of significance.

The serial correlation test conducted and displayed in Table 4.6 indicates that the p-value of 0.903 is higher than the 0.05 significance level, suggesting the absence of serial correlation. The test for heteroscedasticity reveals that the residuals are homoscedastic since the p-value of 0.255 is higher than the 0.05 level of significance. The Ramsey Reset Test result of 0.003 is lower than the 0.05 significance level, indicating a potential issue with the model specification. With the variables being normally distributed with a probability value of 0.678 greater than 0.05, it's important to clarify whether this is a test for normality. Typically, a p-value above 0.05 would suggest that we cannot reject the null hypothesis of normality, but it doesn't necessarily confirm a normal distribution. The CUSUM and CUSUM of Squares tests being within the 5 percent critical bound is generally positive, indicating stability in the model.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter summarizes the conclusion in Section 5.2, policy recommendations in Section 5.3, and Recommendations for future studies in Section 5.4.

5.2 Conclusion

The goal of this study is to assess the economic impact of floods on agricultural productivity in Malaysia. This study employed an ARDL testing methodology to evaluate the existence of a long-term relationship between the variables. This study is mainly focused on the period from 2002 to 2020. The dependent variable is agricultural production (AP), followed by the independent variables which are annual flood frequency (F), labour force (LF), capital (K), total agricultural land area (L), and average rainfall (R). From the result, the long-run model was estimated with ARDL, and the result reveals that the flood has insignificant relationship with the agricultural production in Malaysia within the study period. This indicates that the flood does not affect overall agricultural production in Malaysia in the long-run and short-run periods.

Each model underwent diagnostic tests, and the findings discovers that they were all well-fitted and had mostly conformed with the key standards of classical linear regression. Overall, it can be said that both long-run and short-run models indicates that there is an insignificant relationship between the flood and agricultural production in Malaysia.

Malaysian government should invest in modernizing and diversifying the agricultural sector, focus on developing and maintaining robust infrastructure, including water reservoirs, drainage systems, and flood barriers, and establish financial instruments and insurance mechanisms

5.3 Policy Recommendations

In order to maintain the economic resilience of Malaysians, who have a strong dependence on agriculture, some comprehensive policy recommendations are crucial. Firstly, the Malaysian government should invest in modernizing and diversifying the agricultural sector. This involves adopting advanced technologies, promoting sustainable farming practices, and providing training to farmers. By diversifying crops and introducing high-value agriculture, Malaysia can reduce its reliance on a narrow range of products, making the sector more robust in the face of climate-related risks, such as floods. Additionally, the implementation of precision farming techniques can enhance productivity while minimizing environmental impact.

Secondly, an effective flood management strategy is crucial for safeguarding agricultural assets and ensuring food security. The government should focus on developing and maintaining robust infrastructure, including water reservoirs, drainage systems, and flood barriers. Early warning systems, powered by advanced meteorological and satellite technologies, can be employed to provide timely alerts to farmers, allowing them to take preventive measures. Collaborative efforts between government agencies, research institutions, and local communities are vital to creating a comprehensive flood resilience plan that integrates climate science, engineering solutions, and community engagement.

Lastly, financial instruments and insurance mechanisms should be established to support farmers in the aftermath of floods. The government can design and implement risk-sharing programmes where farmers and the state contribute to a fund that provides compensation in the event of crop losses due to floods. This not only alleviates the financial burden on individual farmers but also incentivizes the adoption of risk-reducing practices. Furthermore, the government can collaborate with the private sector to create innovative insurance products tailored to the agricultural sector, providing a safety net for farmers and encouraging them to invest in resilient and sustainable agricultural practices. By adopting these policy recommendations, Malaysia can fortify its economic resilience in agriculture while effectively managing the impact of floods on its national economy.

5.4 Recommendations for Future Study

For the future study, the researchers should study the impact by focusing on crop specific studies. By focusing on specific crops, we can understand how different agricultural products respond to flood events. Some crops may have adaptive mechanisms or resilience to flooding, while others may experience more severe negative effects. This approach can provide insights into the diversification of crops and adaptive agricultural practices.

Not only that, the researchers should do a temporal and a spatial analysis. By conducting a more detailed temporal and spatial analysis, we can examine how the impact of floods on agricultural production varies across different regions and seasons. Certain crops or regions may be more susceptible to short-term disruptions, while others might demonstrate resilience or even benefit from flood events in the long run.

In addition, the socioeconomic factors should be examined. The researcher should examine the socioeconomic factors that influence the resilience of farmers and their ability to recover from flood-related disruptions. They also should investigate the role of government policies, support mechanisms, and the accessibility of financial resources in helping farmers adapt to and recover from flood events.

Last but not the least, the researchers should conduct farm-level studies. Through this kind of method, we can understand the specific management practices adopted by farmers in response to flood events. Not only that, we can also explore how farmers diversify their crops, implement water management strategies, or invest in resilient agricultural techniques to cope with and recover from floods.

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APPENDIX A

Preliminary Test

	ALP	F	K1	LF	R
Mean	2.620447	298.1500	6.0776891	13415876	2875.400
Median	2.544818	181.0000	6.1115467	13371612	2875.000
Maximum	2.944757	1057.000	8.5967451	16915825	2879.000
Minimum	2.443159	68.00000	3.5987621	9908787.	2873.000
Std. Dev.	0.158463	290.4935	1.7987654	2341692.	1.429022
Skewness	0.938605	1.600405	-0.000584	0.010525	0.706116
Kurtosis	2.502183	4.209326	1.455665	1.587691	3.868424
Jarque-Bera	3.143115	9.756379	1.987476	1.662549	2.290464
Probability	0.207721	0.007611	0.370190	0.435494	0.318150
Sum	52.40895	5963.000	1.213452	2.686782	57508.00
Sum Sq. Dev.	0.477102	1603343.	6.078965	1.045678	38.80000
Observations	20	20	20	20	20

	CPI
Mean	95.54450
Median	96.48500
Maximum	107.4200
Minimum	73.66000
Std. Dev.	8.820844
Skewness	-0.878043
Kurtosis	3.172808
Jarque-Bera	2.594752
Probability	0.273248
Sum	1910.890
Sum Sq. Dev.	1478.338
Observations	20

	ALP	F	K1	LF	R
ALP	1	-0.4160290440553416	-0.7131512859501672	-0.7103444734053368	0.1780547300211683
F	-0.4160290440553416	1	0.5528980397424214	0.747058434763573	-0.2031363784560504
K1	-0.7131512859501672	0.5528980397424214	1	0.747109506183721	-0.319077639540598
LF	-0.7103444734053368	0.747058434763573	0.747109506183721	1	-0.2323642076328658
R	0.1780547300211683	-0.2031363784560504	-0.319077639540598	-0.2323642076328658	1

Null Hypothesis: ALP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.171740	0.2218
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(ALP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.474993	0.0029
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: ALP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.161798	0.4820
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(ALP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.120036	0.0061
Test critical values:	1% level	-4.800080	
	5% level	-3.791172	
	10% level	-3.342253	

Null Hypothesis: ALP has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.238574	0.0334
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(ALP) has a unit root
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.952173	0.0011
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: ALP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.797578	0.6655
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(ALP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 17 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.631766	0.0000
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: F has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.427090	0.9999
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: D(F) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.435495	0.0001
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: F has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.779045	0.9992
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: D(F) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.104531	0.0000
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: F has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		1.364973	0.9979
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(F) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.063657	0.0001
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: F has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.603804	0.9663
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(F) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.104531	0.0000
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: K1 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.318828	0.5986
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(K1) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.611842	0.1089
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: K1 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.020511	0.9924
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(K1) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.860176	0.1964
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: K1 has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.281185	0.6159
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(K1) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.605393	0.1101
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: K1 has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.693635	0.9586
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(K1) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.860176	0.1964
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: LF has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.615536	0.8439
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: D(LF) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.395782	0.1565
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: LF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.093183	0.5082
Test critical values:	1% level	-4.728363	
	5% level	-3.759743	
	10% level	-3.324976	

Null Hypothesis: D(LF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.301099	0.4125
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: LF has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.161637	0.9284
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(LF) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.461725	0.1404
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: LF has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.722627	0.7008
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(LF) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.341931	0.3934
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.932210	0.0010
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.878386	0.0000
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.817994	0.0058
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.623738	0.0000
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

Null Hypothesis: R has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.934148	0.0010
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant
Bandwidth: 17 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-21.82207	0.0000
Test critical values:	1% level	-3.857386	
	5% level	-3.040391	
	10% level	-2.660551	

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.817994	0.0058
Test critical values:	1% level	-4.532598	
	5% level	-3.673616	
	10% level	-3.277364	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 17 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-20.74808	0.0001
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

APPENDIX B

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	6.353428	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
			Finite Sample: n=35	
Actual Sample Size	19			
		10%	2.331	3.417
		5%	2.804	4.013
		1%	3.9	5.419
			Finite Sample: n=30	
		10%	2.407	3.517
		5%	2.91	4.193
		1%	4.134	5.761

APPENDIX C

Levels Equation
Case 1: No Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNK1	0.738220	0.238723	3.092363	0.0175
LNF	0.056975	0.047779	1.192478	0.2719
LNR	-0.089256	0.023772	-3.754729	0.0071
LNLF	-0.888639	0.403772	-2.200845	0.0637
LNALP	1.173374	0.616415	1.903547	0.0987

EC = LNCPI - (0.7382*LNK1 + 0.0570*LNF -0.0893*LNR -0.8886*LNLF + 1.1734*LNALP)

ARDL Error Correction Regression
Dependent Variable: D(LNCPI)
Selected Model: ARDL(3, 0, 1, 0, 1, 0)
Case 1: No Constant and No Trend
Date: 12/17/23 Time: 14:30
Sample: 2002 2021
Included observations: 17

ECM Regression
Case 1: No Constant and No Trend

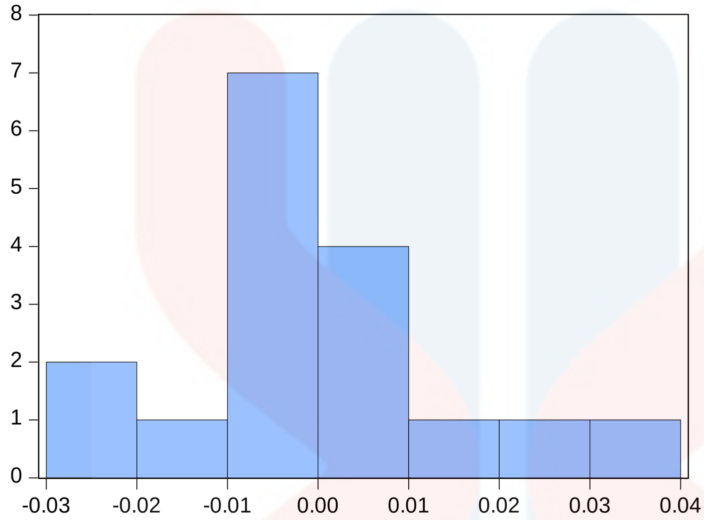
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNCPI(-1))	-0.593807	0.099475	-5.969398	0.0006
D(LNCPI(-2))	-0.178388	0.088676	-2.011687	0.0842
D(LNF)	-0.003471	0.011404	-0.304334	0.7697
D(LNLF)	2.987211	0.282134	10.58791	0.0000
CointEq(-1)*	-0.616113	0.056481	-10.90828	0.0000

R-squared	0.937418	Mean dependent var	0.007351
Adjusted R-squared	0.916558	S.D. dependent var	0.056643
S.E. of regression	0.016362	Akaike info criterion	-5.147758
Sum squared resid	0.003213	Schwarz criterion	-4.902696
Log likelihood	48.75595	Hannan-Quinn criter.	-5.123399
Durbin-Watson stat	1.714620		

* p-value incompatible with t-Bounds distribution.

APPENDIX D

Normality test



Series: Residuals
Sample 2005 2021
Observations 17

Mean	2.65e-05
Median	-0.003219
Maximum	0.031272
Minimum	-0.024726
Std. Dev.	0.014170
Skewness	0.487950
Kurtosis	3.077599
Jarque-Bera	0.678869
Probability	0.712173

Serial correlation test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.103514	Prob. F(2,5)	0.9035
Obs*R-squared	0.675911	Prob. Chi-Square(2)	0.7132

Hetroskedasticity

F-statistic	1.748861	Prob. F(10,6)	0.2550
Obs*R-squared	12.65747	Prob. Chi-Square(10)	0.2435
Scaled explained SS	2.233383	Prob. Chi-Square(10)	0.9942

Model Specification Test (Ramsey)

Ramsey RESET Test
Equation: UNTITLED
Specification: LNCPI LNCPI(-1) LNCPI(-2) LNCPI(-3) LNK1 LNF LNF(-1) LNR LNLF LNLF(-1) LNALP
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	4.701271	6	0.0033
F-statistic	22.10195	(1, 6)	0.0033

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.002527	1	0.002527
Restricted SSR	0.003213	7	0.000459
Unrestricted SSR	0.000686	6	0.000114