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Supply Response of Sugarcane (*Saccharum Officinarum*) in the Philippines

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Abstract:- This study has attempted to provide quantitative estimates of the supply response of sugarcane farmers to variations in its own price in the Philippines. It likewise examined the trends in area harvested for sugarcane, average rainfall, average temperature, and price of fertilizer. The study revealed that Philippine sugarcane industry is characterized with relatively erratic production from 1982 to 2020. Sugarcane production had annual average growth of -0.0037%. In 2020, the total land area harvested to sugarcane was 3.99 million hectares. The Philippines, in general, had relatively low productivity or yield per hectare at 60.73 metric tons per hectare throughout the 39-year period. These concerns are pivotal since it impacts food security since sugar is an essential component for processing of food and beverages products. Furthermore, vector autoregressive (VAR) model was used in estimating the quantity response of sugarcane to its own price, price of fertilizer, area harvested, average temperature, and average rainfall in the country. The short-run quantity sugarcane price elasticity is 0.51, for area harvested is 1.19, for average temperature 0.66, for average rainfall 1.58, and for price of fertilizer 1.25. Variables own price and average temperature are found inelastic, while variables area harvested, average rainfall, price of fertilizer, and average temperature are found elastic in the short-run.

Keywords:- *Farmers, Short-Run, Sugarcane, Philippines, Vector Autoregression.*

I. INTRODUCTION

➢ *Background of the Study*

Agriculture serves as one of the backbones of the Philippine economy, accounting for 9.2% of the country's GDP in 2020 (World Bank, 2021). However, the sector's growth has been hindered by several factors, including inadequate infrastructure, limited access to credit, and low productivity (Mandaluyong, 2021). One of the significant crops which is an input for industrial uses is sugarcane.

Sugarcane is a significant cash crop and a key contributor to the agricultural sector's growth in the Philippines. According to the Philippine Statistics Authority (PSA), sugarcane production in Mindanao contributes approximately 16% of the total production in the country, making it a crucial commodity in the region (PSA, 2021). Moreover, the sugarcane industry provides employment opportunities for thousands of people in Mindanao, where the unemployment rate is high (PSA, 2021). Additionally, sugarcane is a crucial input in several industries, such as the food and beverage industry, which contributes significantly to the Philippine economy's growth (DTI, 2020).

However, the limited and inconsistent supply of sugarcane in Philippines has had significant economic implications, including the partial closure of several businesses that rely on sugarcane as a primary input. For instance, the closure of several sugar mills in 2022 has led to a decrease in sugar production in the country, resulting in higher sugar prices and reduced availability of sugar for both domestic consumption and export markets (Philippine Star, 2022). This event highlights the critical importance of understanding the supply response of sugarcane in Philippines and developing strategies to enhance its production sustainably. A study on the supply response of sugarcane can inform policymakers and stakeholders about the strategies that can be employed to revive the sugarcane industry in Philippine and create more job opportunities in the counntry.

The supply response of sugarcane is influenced by various factors, such as production inputs, technology adoption, price, and government policies. Several studies have investigated the supply response of sugarcane in different regions worldwide, including India (Khan et al., 2020), Brazil (Silva et al., 2021), and Thailand (Phimmasan & Thalang, 2019). The industry is facing increasing competition from cheap imports, idle capacity, and periodic fluctuations in the in the quantity and quality of raw material. Therefore, this study aims to fill this gap in the literature and provide insights into the supply response of sugarcane in the Philippines.

Understanding the supply response of sugarcane is crucial to support policy formulation and decision-making in the agricultural sector. For instance, insights from this study can aid in the development of policies that support sustainable sugarcane production, such as providing incentives for technology adoption or improving access to credit and market information. Additionally, understanding the supply response of sugarcane can help identify the factors that limit its production and provide strategies to overcome these limitations, such as improving irrigation infrastructure or reducing post-harvest losses. Besides, the demand for sugarcane is expected to rise because of the growing population and per capita consumption. Given the foregoing, there is a need to increase sugarcane production.

Economic theory strongly suggests that prices of commodities are important factors that influence the decision of producers. A better knowledge of the supply and price relationship will make a more precise, reliable and

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confident forecast in making short-run and long-run decisions. This study attempts to provide updated quantitative estimates of the supply response of sugarcane farmers to changes in prices and other factors in the Philippines. It seeks to investigate the trends in sugarcane production, area harvested to sugarcane, productivity, and prices.

➢ *Significance of the Study*

The study of supply response for sugarcane in the Philippines holds significant importance for the country's economy, agricultural sector, and the well-being of its population. The sugarcane industry in the Philippines is a vital source of income for farmers and their families, and it plays a significant role in the country's export earnings (Manalili, 2017). Additionally, sugarcane production and processing provide employment opportunities in rural areas and contribute to the development of local communities (Galang & Geronimo, 2017).

Furthermore, understanding the supply response of sugarcane in the Philippines is crucial for policymakers to design and implement effective agricultural policies that can ensure food security, increase productivity, and improve the livelihoods of farmers. According to the Philippine Statistics Authority (2020), the country's agricultural sector has been experiencing fluctuations in production due to various factors such as extreme weather conditions, disease outbreaks, and changing market demands. Therefore, analyzing the supply response of sugarcane can help policymakers to anticipate the impact of such factors on production and plan accordingly.

➢ *Objectives of the Study*

This study aims to estimate the supply response of sugarcane in the Philippines. Specifically, this hopes to achieve the following objectives:

- *To examine the sugarcane industry in terms of volume produced, area harvested, own price, price of fertilizer, precipitation, and temperature; and,*
- *To estimate the elasticities for own price, price of fertilizer temperature, precipitation and area harvested of sugarcane.*

➢ *Scope and Limitations*

This study uses a set of time series data for the period of 39 years, from 1982 to 2022, focusing mainly on examining the relationship of inputs to sugarcane production using Granger-causality test. Particularly, the inputs considered in this study are the following: area harvested, own price of sugar, price of fertilizer, mean precipitation and temperature in the country. The reliability of the results depended on the accuracy of the data published by these agencies. The length of the series is adequate to overcome the problem of the degrees of freedom. Regional supply response was not possible because the data would not allow their estimation. No crop was chosen as a competing crop for sugarcane.

➢ *Organization of the Study*

The remaining sections of the study are organized as follows: Chapter 2 cites the review of related literatures; while Chapter 3 presents the methodology consisting of the theoretical, statistical method and conceptual framework, the variables and data sources. The result of the study is discussed in Chapter 4. The summary, conclusions, and recommendations are presented in Chapter 5.

II. METHODOLOGY

➢ *Research Design*

A descriptive-causal research approach, also called explanatory research, is adopted in this study to analyze the time series data of sugarcane production from 1982 to 2020. Descriptive-causal research is useful to identify, explain, and assess the range as well as the nature of the relationships between the independent and the dependent variables. Many studies that adopt this approach tend to focus on analyzing the causal relationships between variables in order to explain a specific phenomenon (Creswell & Creswell, 2018).

This method is widely used in the literature to study the supply response of agricultural commodities and have been shown to be effective in analyzing the dynamic relationships between multiple time series variables (Babula & Stosic, 2018; Serra et al., 2015). The use of these techniques allows us to estimate the coefficients of the independent variables and to analyze their impact on sugarcane production in the Philippines.

In the present study, the use of the descriptive-causal approach allows us to analyze the impact of various independent variables, such as own price of sugarcane, area in hectarage, price of fertilizer, mean temperature, and mean rainfall, on sugarcane production in the Philippines over the period 1982 to 2020. The use of time series data enables us to analyze the dynamics of these relationships over time and to model the short-term and long-term responses of sugarcane production to changes in the independent variables.

➢ *Research Locale*

This study covers the entire country Philippine located in the southeast Asia. The Island is comprised of three major islands considered home to a variety of physiographic developments. In addition, it has diverse and multifaceted cultures, religions, and traditions.

Philippines is composed of 17 regions. These regions comprise of different provinces, municipalities, or cities down to the barangay level. The use of country wide level data is explored since no regional panel time series data is available.

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Fig 1 The Map of the Philippines, by Region.
Source: Google.com

➢ *Theoretical Framework*

In a free market system, the allocation of output is determined in a decentralized manner, where prices serve as the fundamental coordinating mechanism. Prices, representing the unit selling price of a product, reflect the society's willingness to pay. The costs of production are influenced by input prices such as labor, land, and capital. Firms act as suppliers of output products, and the structure and quantity of firms within the agricultural industry significantly impact the supply. The size structure refers to the distribution and quantity of fixed factors, like land, throughout the agricultural sector, which affects the marginal cost curve of each firm based on its allocation of fixed factors.

The relationship between the quantity supplied to a market and the price of a product is not merely the summation of the marginal cost curves of the supplying firms. Producers determine the quantity to produce based on price signals, as they utilize production inputs to manufacture goods. Prices of commodities play a crucial role in influencing producers' decision-making. Economists gauge the responsiveness of producers to price changes by examining the price elasticity of supply, which measures the percentage change in the quantity supplied divided by the percentage change in the price of the product.

Understanding the dynamics of supply in a free market system relies heavily on the concept of price elasticity of supply. It is a significant measure of how producers react to fluctuations in product prices. The size structure of the agricultural industry and the number of firms supplying the market are influential factors impacting supply. Although the marginal cost curves of firms provide a general understanding of the relationship between quantity supplied and product price, this connection is considerably intricate. The prices of commodities play a pivotal role in shaping producers' decisions regarding production levels, and the price elasticity of supply serves as a valuable tool for evaluating the extent of producers' responsiveness to price signals.

According to Ritson (1997), the various types of elasticities are depicted in Figure 1. A perfectly inelastic supply curve, or zero elasticity, is represented by a vertical line, where quantity supplied remains constant despite changes in price. Conversely, an infinite elasticity or perfectly elastic supply curve is denoted by a horizontal line, indicating that a small increase in price causes an infinite increase in quantity supplied. Additionally, a supply curve that passes through the origin on a straight line indicates unit elasticity, where a given proportionate change in price is associated with an equal proportionate change in quantity supplied.

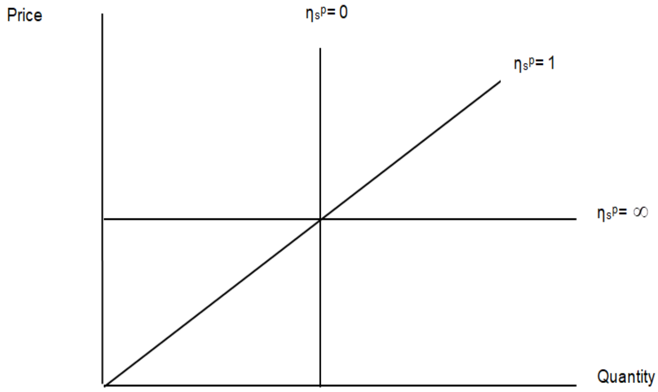

Fig 2 Price Supply Elasticities
Source: Case and Fair, 2003

➢ *Conceptual Framework*

Though the method used in this study can also test for the interrelationship among the variables, this study focuses on the effects of farm gate price of sugar, area devoted to sugarcane, price of fertilizer, mean temperature and mean precipitation to volume of produced sugarcane. This relationship is illustrated in Figure 1.

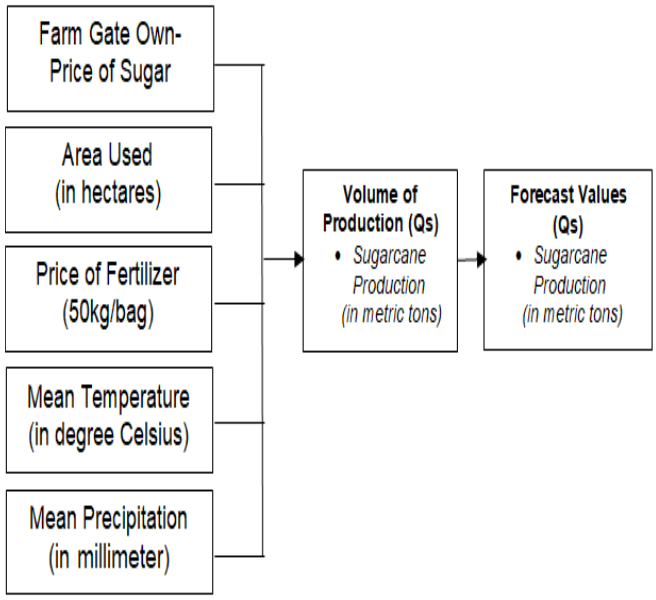

Fig 3 Conceptual Framework of the Study

III. STATISTICAL METHOD

➢ *Descriptive Analysis*

Descriptive statistics and graphical presentations of data are presented using Microsoft Excel.

➢ *Time Series Analysis*

Time series analysis is primarily concerned with the past behavior of a variance in order to predict its future behavior. It involves methods that aim at understanding the underlying theory on the sequence of observations ordered in time, or to make forecasts on the identified pattern based on past events. There are two main goals of time series analysis: (a) identifying the nature of the phenomenon represented by the sequence of observations, and (b) forecasting (predicting future values of the time series

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variable). Both of these goals require that the pattern of observed time series data is identified and more or less formally described. Once the pattern is established, it can be easily interpreted and integrated with other data. Regardless of the depth of the understanding and the validity of the interpretation (theory) of the phenomenon, the identified pattern can be extrapolated to predict future events (www.statsoft.com).

- *Test for Stationarity*

Stationarity is a critical assumption of time series analysis. The need to initially test the time series variables for stationarity before employed in any regression analysis is a necessary condition since violations of some assumptions could be fatal (Gujarati, 1995).

A stochastic time series (y_t) is said to be weakly stationary or covariance stationary or simply stationary if, and only if, it satisfies the following requirements:

E(y_t) = μ (y_t has constant mean); (1)

Var(y_t) = σ^2 = y_0 (y_t has constant variance); (2)

Cov(y_t,y_{t-k}) = y_k for all (the covariance between any two of the terms of the series is a function only of the distance betweenthem). (3)

The first and second requirements simply imply that the means and variances are constant over time. The third requirement implies that the covariance between observations in the series is a function of how far apart they are in time and not the time at which they occur (Greene, 2000). In other words, stationarity occurs in a time series when the mean, variance and autocorrelation structure do not change over time (www.statsoft.com). If the series does not satisfy one or more of the conditions, it would mean that the series is not stationary, and to proceed with regression analysis would lead to false results, where it is possible to obtain very high value for R^2 but insignificant estimates.

A time series is also said to be stationary if the trends revert to a constant long run narrow value, and if the effects of shocks are only temporary. On the other hand, the series is non-stationary if the effects of shocks are permanent, or if the time series evolves along a trend. Most economic time series do not satisfy the stationarity conditions, and they should be re-expressed so that they become stationary with respect to the variance and the mean.

Phillips and Perron (PP) propose an alternative (non parametric) method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented Dickey-Fuller test equation. It modifies the t-ratio of the α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic (*www.EViews.com*). In this study, the Phillips-Perron was considered three different regression equations that can be used to test the presence of a unit root.

$\Delta y_t = \gamma y_{t-1} + \varepsilon_t$ random walk (4)

$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \varepsilon_t$ random walk w/ drift (5)

$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_{2t} + \varepsilon_t$ mixed process (6)

Random walk is a special case of the unit root process. It does not include an intercept or a drift term. Random walk with a drift has an intercept or drift term, and mixed process includes linear time trend and a drift term. To determine whether the series contains a unit root, the parameter γ is tested over the null hypothesis that $\gamma = 0$. When the test fails to reject the null hypothesis, then the series contains a unit root and therefore is non-stationary. However, a series tested as non-stationary may be transformed to a stationary series. An easy and commonly used method for transforming a non-stationary series is by differencing, and the resulting series is referred to as integrated. If the series does not pass the test, the next higher level of differencing is chosen and the process of transforming is repeated (Boken, 1998). Hence, if the series is differenced *p* times, we have a series integrated of order *p* or I (*p*).

- *Unit Root Test*

In the estimation process, it is important to conduct a standard unit root test on each variable if it exhibits a trending behavior or non-stationarity in the mean. If this exists, then some form of trend removal is required (Danao, 2002). Moreover, if the variance of y_t is not constant; hence, a random walk is not stationary. Stationarity refers to a condition wherein the series have constant variance. Augmented Dickey-Fuller (ADF) test is used in testing for the presence of unit root and is applied to the data series. The specification is:

$$\Delta y_t = \beta_0 + \beta_1 + \delta y_{t-1} + \alpha_i \sum \Delta\, y_{t-1} + \varepsilon_t \qquad (7)$$

Where ε_t is a white noise error term. The error term is assumed to be independent and identically distributed. If the ADF test fails to reject the null hypothesis, it indicates the presence of a unit root. In case of non-stationarity, achieving a stationary condition can be attained through differencing process. Differencing process is frequently employed to detrend the data and control autocorrelation by subtracting each datum in a series from its predecessor (www.stat.ucla.edu). If the results of the ADF test will reveal that the series are stationary in level, then the time series analysis could not proceed to cointegration process, and could proceed to Vector Autoregression (VAR) modeling.

- *Vector Autoregressive (VAR) Model*

In understanding VAR model, specification of correct lag order in VAR modeling is one of the important things to be considered and must be done first, since selection of inappropriate lag *p* will decrease the accuracy of the estimated coefficients in VAR(p) model. The vector autoregressive (VAR) model of Sims (1980) is one of the most successful, flexible, and easy-to-use models for the analysis of multivariate time series. It is an econometric model used to capture the evolution and the

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interdependencies between multiple time series generalizing the univariate Autoregressive (AR) models (www.wikipedia.com). The model describes the evolution of a set of k variables over the same sample period (t = 1, 2 …T) as a linear function of only their past evolution (Watson, 1994). Basically, Var (p) is an AR model with at least two time series having (p) as the number of lags and is expressed by Aktar (2009) as:

$$y_t = A_0 + A_1 y_{t-1} + \ldots + A_P y_{t-P} + \varepsilon_t \qquad (8)$$

Where,

- ✓ y_t = is a (nx1) vector containing each of the variables in VAR
- ✓ A_0 = is a (nx1) vector of intercept items
- ✓ A_1 = is a (nx1) matrix (for every i=1….p), and
- ✓ ε_t = is a (nx1) vector of error terms satisfying the foregoing equation

- *With the following Assumptions:*

- ✓ E(ε_t) = 0 ; the error has a mean 0,
- ✓ E($\varepsilon_t \ \varepsilon_{t-k}$) = Ω ; the contemporaneous covariance matrix of error terms is Ω (a nxn positive definite matrix), and
- ✓ E($\varepsilon_t \varepsilon_{t-k}$) = 0 ; for any non-zero k, there is no correlation across time; in particular there is no serial correlation in individual error terms.

The multivariate VAR model for the variables degree of inputs to production (sugprice, area, precip, temp, fertprice) and sugarcane production is illustrated in matrix form:

$$\begin{pmatrix} VolSug_t \\ SugPrice_t \\ Area_t \\ Precip_t \\ Temp_t \\ FertPrice_t \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{pmatrix} + \begin{pmatrix} A^1_{1,1} & A^1_{1,2} & A^1_{1,3} & A^1_{1,4} & A^1_{1,5} & A^1_{1,6} \\ A^1_{2,1} & A^1_{2,2} & A^1_{2,3} & A^1_{2,4} & A^1_{2,5} & A^1_{2,6} \\ A^1_{3,1} & A^1_{3,2} & A^1_{3,3} & A^1_{3,4} & A^1_{3,5} & A^1_{3,6} \\ A^1_{4,1} & A^1_{4,2} & A^1_{4,3} & A^1_{4,4} & A^1_{4,5} & A^1_{4,6} \\ A^1_{5,1} & A^1_{5,2} & A^1_{53} & A^1_{5,4} & A^1_{5,5} & A^1_{5,6} \\ A^1_{6,1} & A^1_{6,2} & A^1_{63} & A^1_{6,4} & A^1_{6,5} & A^1_{6,6} \end{pmatrix} \begin{pmatrix} VolSug_{t-1} \\ SugPrice_{t-1} \\ Area_{t-1} \\ Precip_{t-1} \\ Temp_{t-1} \\ FertPrice_{t-1} \end{pmatrix} + \ldots +$$

$$\begin{pmatrix} A^p_{1,1} & A^p_{1,2} & A^p_{1,3} & A^p_{1,4} \\ A^p_{2,1} & A^p_{2,2} & A^p_{2,3} & A^p_{2,4} \\ A^p_{3,1} & A^p_{3,2} & A^p_{3,3} & A^p_{3,4} \\ A^p_{4,1} & A^p_{4,2} & A^p_{4,3} & A^p_{4,4} \\ A^p_{5,1} & A^p_{5,2} & A^p_{5,3} & A^p_{5,4} \\ A^p_{6,1} & A^p_{6,2} & A^p_{6,3} & A^p_{6,4} \end{pmatrix} \begin{pmatrix} VolSug_{t-1} \\ SugPrice_{t-1} \\ Area_{t-1} \\ Precip_{t-1} \\ Temp_{t-1} \\ FertPrice_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \\ \varepsilon_{6,t} \end{pmatrix} \qquad (9)$$

Where;

- ✓ t = time subscript,
- ✓ $VolSug_t$ = volume of sugar produced over time period t,
- ✓ $SugPrice_t$ = nominal price of sugar per kilograms observed over time period t, $Area_t$ = area in hectares devoted for sugarcane over time period t,
- ✓ $Precip_t$ = mean precipitation in milliliter observed over time period t,
- ✓ $temp_t$ = mean temperature in degree Celsius observed over time period t
- ✓ $FertPrice_t$ = mean temperature in degree Celsius observed over time period t,
- ✓ P = lag length
- ✓ $A_{i,j}$ = coefficients of the matrices associated to the VAR, the superscripts denote the order of that matrix,
- ✓ C_i = constants
- ✓ ε_t = the error terms

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In dealing with the series data, it is important to know whether changes in one variable will have an impact on the changes of another variable. Hence, this study proceeds to undertake Granger causality test.

✓ *Lag Length Determination*

To determine the appropriate lag length, choose the model which has the lowest Akaike Information Criterion (AIC) or the Schwartz Bayesian Criterion (SBC). The lag length derived in the estimation of the VAR using the data in levels are used in estimating the Vector Error Correction Model (VECM), as well as in determining the cointegrating rank. If the variables are not found to be cointegrated, then there is no need to specify for VECM. The VAR model is sufficient in itself.

- *Granger Causality Test*

One of the main uses of VAR models is forecasting. The structure of the VAR model provides information about a variable's or a group of variables' forecasting ability for other variables. The intuitive notion of a variable's forecasting ability is due to Granger (1969). If a variable, or group of variables, y_1 is found to be helpful for predicting another variable, or group of variables, y_2 then y_1 is said to Granger-cause y_2; otherwise it is said to fail to Granger-cause y_2. In this case, we would like to know whether the identified inputs can help forecast volume of production of sugarcane in the Philippines and can predict the relationship of inputs variables. In order to address this concern, the Granger-causality test is applied to test if past or historical values of one variable predict the future values of another. The test involves F-tests to examine whether lagged information on a variable x provides any statistically significant information about a variable y in the presence of lagged y. A test of causality is a test whether the lags of one variable enter into the equation for another variable. In a five-variable case, such as in this study, in which Aij (L) represents the coefficients of lagged values of variable j on variable i, variable j does not Granger cause variable i if all coefficients of the polynomial Aij (L) can be set equal to zero. Clearly, the notion of Granger causality does not imply true causality but only implies forecasting ability.

Testing for Granger causality between volume of produced sugarcane and input variables considered consists of checking the significance of a_{ij} coefficients.

- *Adequacy of Model*

Diagnostic tests for the residuals such as the Lagrange-Multiplier, Jarque-Bera and Eigenvalues stability condition tests were conducted to determine if the model is correctly specified.

➢ *Computing the Elasticities*

The supply responses through short-run and long-run elasticities were derived, using the coefficients obtained from the estimation of the quantity response using the VAR model. The obtained supply elasticities were estimated using this formula:

$$\eta_p^s = \frac{\Delta Q_s}{\Delta P} \times \frac{P_o}{Q_o}$$

The formula can also be expressed in the form (Griffiths, 1984):

$$\eta_p^s = \frac{\frac{\Delta E(y)}{E(y)}}{\frac{\Delta x}{x}} = \frac{\Delta E(y)}{\Delta x} \times \frac{x}{E(y)} = \beta_i \times \frac{x}{E(y)}$$

In the VAR setting, the short-run elasticity is expressed in this form:

$$\hat{\eta}_p^s = \beta_0 \times \frac{E(x_t)}{E(y)}$$

Where:

- *$E(x_t)$* = the expected (mean) value of the independent variable
- *$E(y)$*= the expected (mean) value of the dependent variable
- *β_0* = the regression coefficient at year t

It is expected that the short-run elasticity is lower than the long-run elasticity. Short-run is the time period of insufficient length to permit decision makers to adjust fully to change in market conditions (Bernardo, *et al.*, 1992).

Long-run is the period where producers can adjust fully in changing market conditions. The principal determinant of supply elasticity is the time involved in the ability of producers to respond to price changes. In the case of agricultural or farm products, it takes a long time to produce the products, the supply inelasticity, that's why it is expected that in rice production, the responses of farmers are highly inelastic (Fajardo, *et.al*, 2001).

- *Data Sources*

Time series data on Philippine sugarcane production (in metric tons), area (in hectares), sugarcane farm gate price, and price of corn were used in estimating the supply response functions. Data ranged from 1982-2020 and these were obtained from the Philippine Statistics Authority online website.

- *Estimation Procedure*

SHAZAM version 11.0 software is used to test for the presence of a unit root. It is an integrated, comprehensive, and complete statistical analysis that can execute simple and complex estimations. STATA 13 is used to compute its parameters of the model; this package provides a sophisticated data analysis and regression forecasting. GRETL software is used for lag length determination for VAR model.

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IV. RESULTS AND DISCUSSIONS

This chapter discusses the results and discussion of the study. It includes the presentation of trends of identified variables as inputs to production of sugarcane in the Philippines for 39 years from 1982 to 2020 using descriptive method with graphical presentation to describe the trends of the variables. The results of stationarity tests, the results of the Vector Autoregressive (VAR) estimation, and the Granger-causality test results are also discussed in this chapter.

A. Descriptive Analysis of Variables Used

- *Trend of Sugarcane Production and Area Used, 1982 – 2020*

The Philippine sugarcane industry did experience fluctuations in production from 1982 to 2000 as shown in Figure 2. During this period, there were several factors that affected the industry's production, such as changes in government policies, weather conditions, and global market demand.

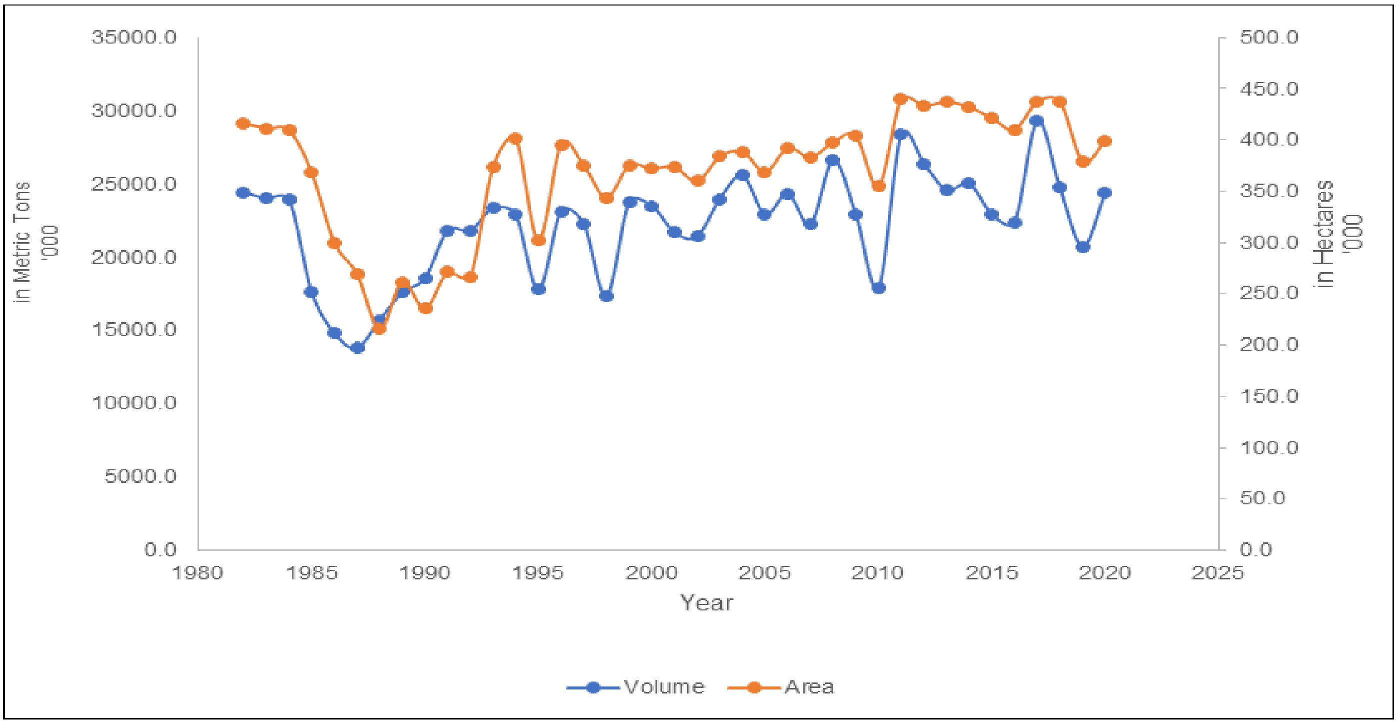

Fig 4 Trend of sugarcane production and area used, 1982-2020.
Source: Philippine Statistics Authority wee

One significant factor that affected the industry was the deregulation of the sugar industry in 1984, which removed the government's control over the industry's prices and production. This led to increased competition among sugar producers, and some smaller farms were forced to close due to the inability to compete with larger, more efficient operations.

Additionally, weather conditions also played a role in the industry's production during this period. Several severe typhoons and droughts in the 1990s caused significant damage to sugarcane crops and reduced the industry's production levels.

From 2001 to 2009, the Philippine sugarcane industry showed a stable performance as indicated by the increasing trend in total volume of production (Mallillin, 2019). However, a sharp decline in its production in 2010 is recorded. This decline is brought by several factors such as typhoons, pest infestations, and the conversion of sugarcane lands to other uses, particularly for the development of residential and commercial areas (Austria, 2019).

Typhoons and pest infestations have always been a significant threat to the sugarcane industry. In 2010, typhoons Ondoy and Pepeng, which hit the country in September and October of that year, respectively, caused severe damage to sugarcane crops in the Northern Luzon region (Philippine Daily Inquirer, 2010). Meanwhile, pest infestations such as the sugarcane borer and the yellow sugarcane aphid have also been a constant problem for sugarcane farmers, as they can significantly reduce crop yields and quality (Austria, 2019).

Figure 2 also shows the trend of area used or devoted for sugarcane production. As shown, it has mimic or has the same trend and pattern with volume of produced sugar. This suggests that the area used for sugarcane production has a direct impact on the industry's overall production. A decrease in the area used for sugarcane production may have contributed to the decline in the industry's production. Additionally, changes in weather patterns and market demand may have also played a role in the decline.

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➤ *Trend of Sugarcane Production and Own Price, 1982 – 2020*

An increasing trend of farm gate price of sugar is seen in Figure 3 from 1982 to 2010. This increase in farm gate price can be attributed to various factors, such as changes in government policies and market demand. For example, the deregulation of the sugar industry in 1984 may have contributed to an increase in competition among sugar producers, which in turn led to higher prices at the farm gate level.

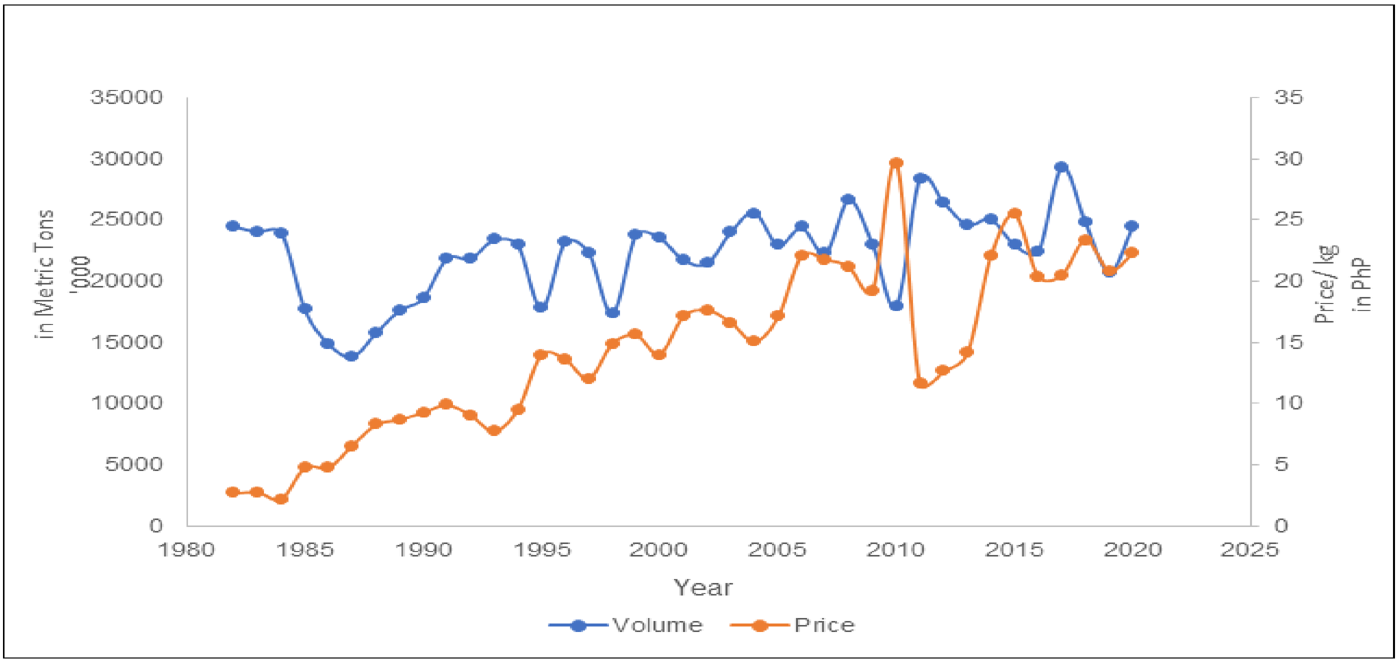

Fig 5 Trend of sugarcane production and farmgate price, 1982-2020
Source: Philippine Statistics Authority

In addition, changes in global market demand for sugar may have also influenced the farm gate price of sugar in the Philippines. As previously mentioned, the high demand for sugar in the 1980s and early 1990s led to an increase in production and likely contributed to higher prices for farmers.

However, it is important to note that while the farm gate price of sugar increased over this period, it may not necessarily have translated to higher profits for farmers. This is because increases in production costs and other factors, such as weather conditions, can also impact farmers' profitability.

As shown in the same figure, a sharp decline is observed in 2010 to 2013. The sharp decline in farm gate prices of sugar from 2010 to 2013 can be attributed to a number of factors. One possible factor is the influx of imported sugar into the Philippines during this period, which put downward pressure on domestic sugar prices.

Changes in government policies may have also played a role in the decline of farm gate prices during this period. For example, the removal of the quantitative restrictions (QRs) on sugar imports in 2012 may have contributed to an increase in imported sugar and a subsequent decrease in domestic sugar prices.

Moreover, weather conditions such as typhoons and droughts can also impact the production and supply of sugar, which in turn can affect farm gate prices.

It is worth noting that the decline in farm gate prices of sugar from 2010 to 2013 had significant impacts on farmers and the sugar industry as a whole. Some farmers were forced to sell their sugarcane at a loss, while others were unable to repay their loans and incurred debt. This highlights the importance of having policies and programs in place to support farmers during periods of market volatility.

Another factor that contributed to the decline in the industry's production in 2010 was the conversion of sugarcane lands to other uses, particularly for the development of residential and commercial areas. This conversion has been an ongoing issue in the Philippines, as agricultural lands are often targeted for development due to their strategic location and potential for higher profits (Llanto & Balboa, 2016).

➤ *Trend of Sugarcane Production and Price of Fertilizer, 1982 – 2020*

The increasing trend in the price of ammonia fertilizer from 1982 to 2020 can be observed in Figure 4. This trend may be attributed to several factors, such as changes in global demand and supply, production costs, and government policies. According to a report by the Food and Agriculture Organization (FAO) of the United Nations, the price of ammonia fertilizer is influenced by the cost of natural gas, which is a primary feedstock for ammonia production (FAO, 2018).

According to a study by Lamberte et al. (2019), the cost of inputs, including fertilizers, has been increasing in the Philippines, affecting the profitability of sugarcane farmers. The study also revealed that the cost of fertilizers, particularly urea and ammonium sulfate, has increased by 157% and 116%, respectively, from 2008 to 2018.

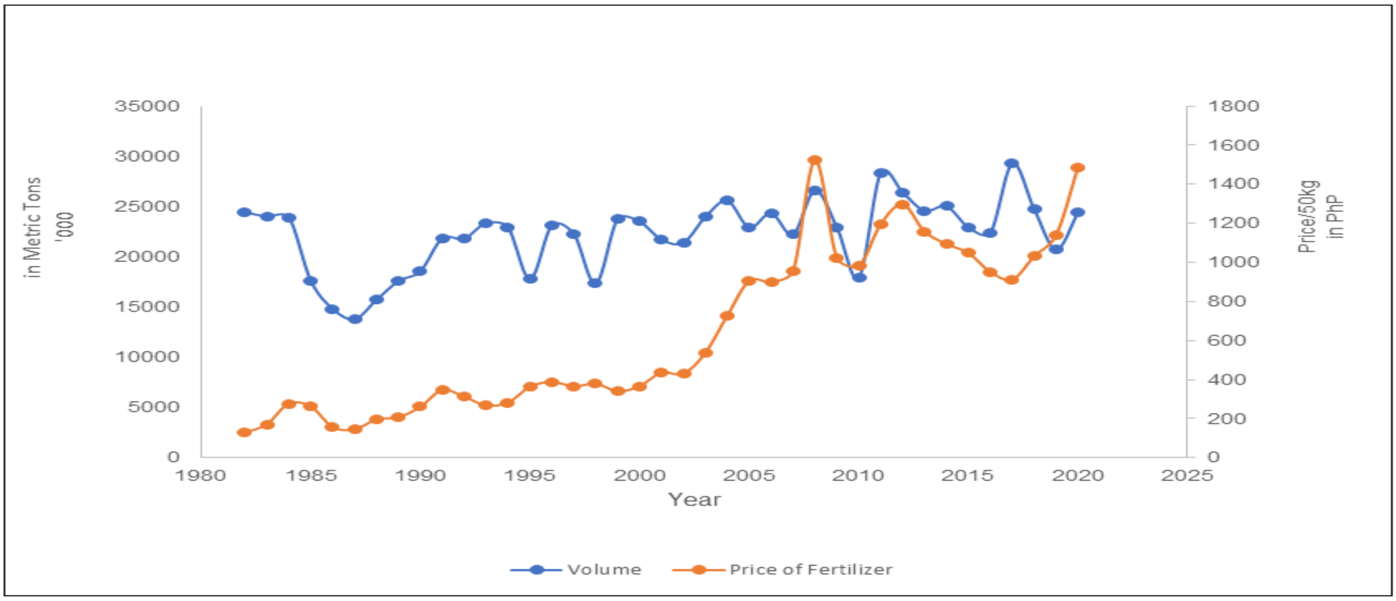

Fig 6 Trend of sugarcane production and ammonia price, 1982-2020
Source: Philippine Statistics Authority

The rising cost of fertilizers can be attributed to various factors, such as the volatility of international prices, the depreciation of the Philippine peso, and the increasing demand for fertilizers in the global market. As a result, sugarcane farmers in the Philippines are facing higher production costs, which can lead to lower profits and productivity.

➢ *Trend of Sugarcane Production and Mean Temperature, 1982 – 2020*

The mean temperature in the Philippines is a key factor that affects various industries, including agriculture. According to the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the average temperature in the Philippines from 1982 to 2020 has been observed to be volatile, with periods of above-average and below-average temperatures (PAGASA, 2020).

Climate change is one of the primary drivers of the volatile temperature in the Philippines. The Philippines is one of the countries that are most vulnerable to climate change, with its geographic location in the Pacific making it prone to tropical cyclones, floods, landslides, and droughts (Philippine Statistics Authority, 2020). The changing climate patterns in the country have affected agriculture production, including the sugarcane industry.

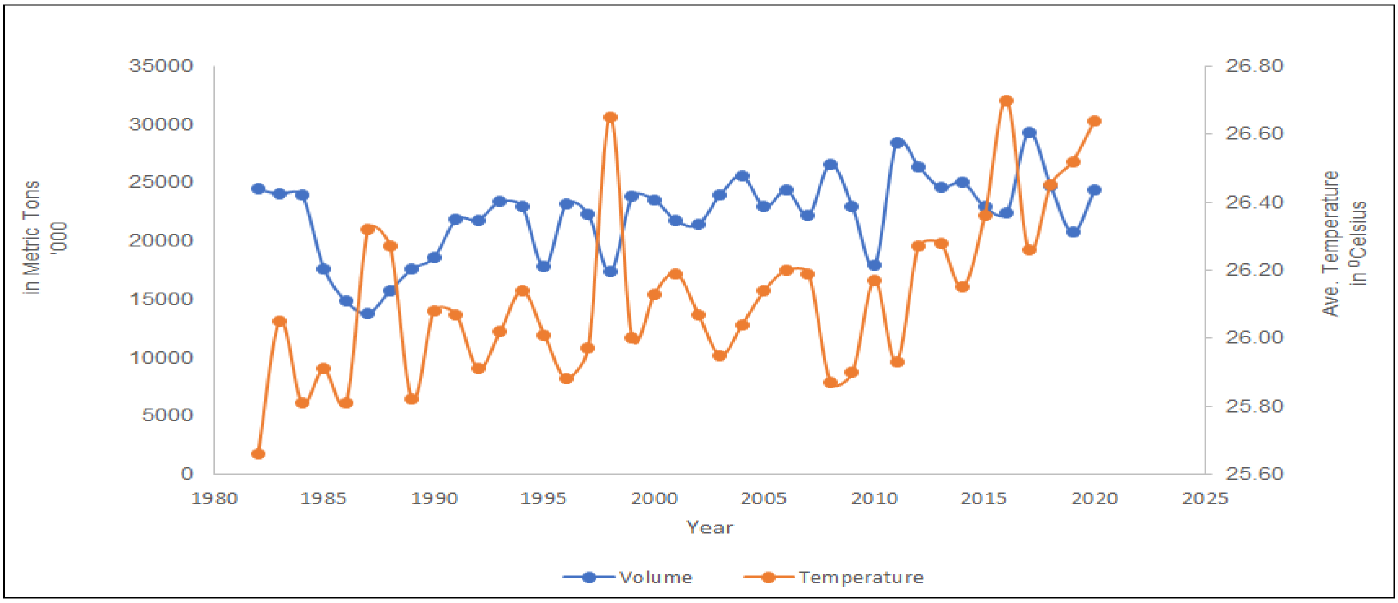

Fig 7 Trend of sugarcane production and mean temperature, 1982-2020
Source: Philippine Atmospheric Geophysical Astronomical Services Administration

For instance, as discussed earlier, the sugarcane industry in the Philippines experienced fluctuations in production due to various factors, including weather conditions. The extreme weather conditions such as typhoons, floods, and droughts, which are becoming more frequent and intense due to climate change, can negatively impact sugarcane production (Mallari et al., 2019).

The increase in temperature can also affect sugarcane growth and development, as it can impact the plant's photosynthetic rate and increase water requirements for irrigation, leading to increased production costs (Din et al., 2020). This can result in decreased sugarcane yield and quality. As shown in the Figure 4, there is an inverse relationship between temperature and volume produced.

- *Trend of Sugarcane Production and Mean Precipitation, 1982 – 2020.*

Sugarcane production and average precipitation in the Philippines exhibited a positive correlation between the two variables as shown in Figure 5. Basically, rainfall is a crucial factor in sugarcane production as it is essential for the growth of crops. The positive correlation suggests that higher levels of precipitation lead to more favorable growing conditions for sugarcane.

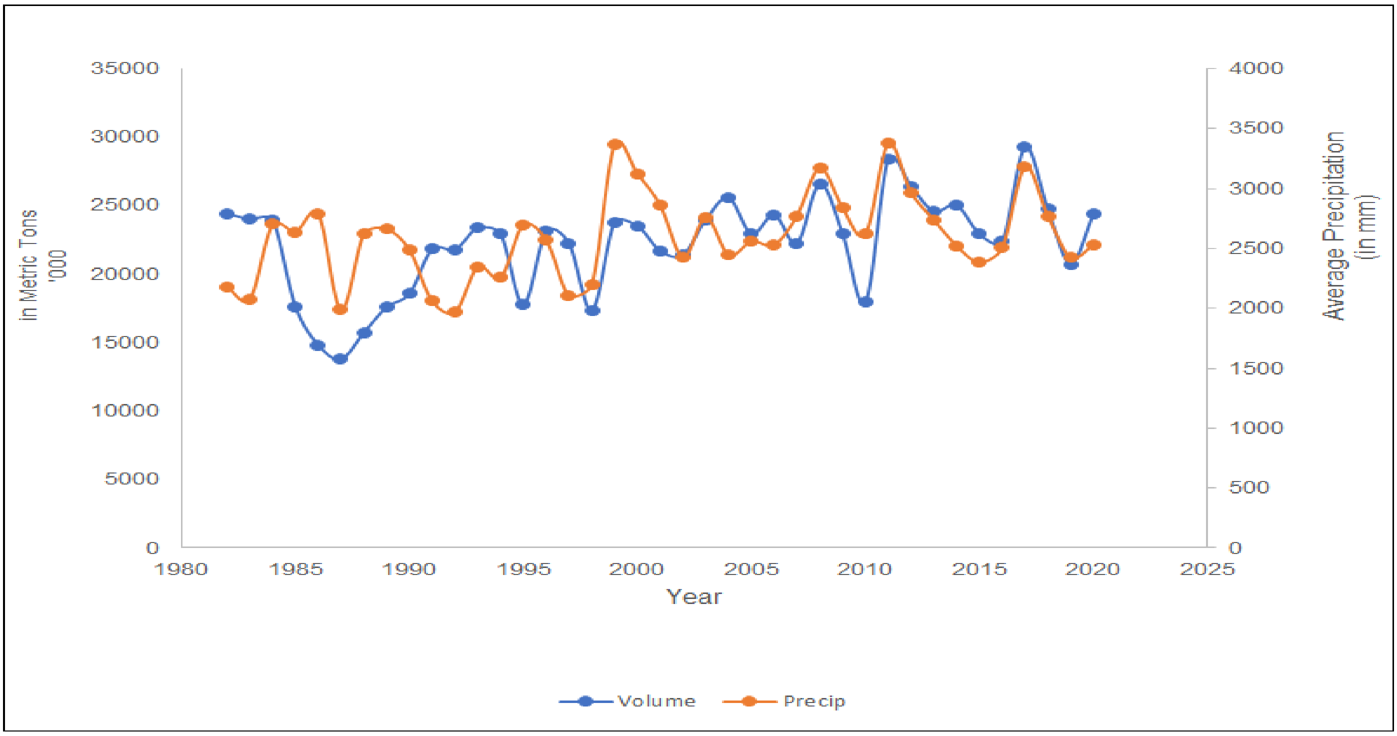

Fig 8 Trend of sugarcane production and mean precipitation, 1982-2020
Source: Philippine Atmospheric Geophysical Astronomical Services Administration

This finding is consistent with previous studies that have also identified rainfall as a key determinant of sugarcane production (Liu et al., 2018; Huang et al., 2019). By optimizing water use and adopting climate-resilient farming techniques, farmers can ensure consistent and efficient sugarcane production even in the face of changing weather patterns.

B. Vector Autoregressive Tests and Analyses

- *Stationarity Test*

In order to tests whether the series is stationary or not, the very first step that needed to be considered is the procedure of the autocorrelation function (ACF) and partial autocorrelation function (PACF) by detecting their correlograms. A correlogram helps to indicate whether the series is stationary or not. It is a commonly used tool for checking randomness in a data set. The randomness is ascertained by computing the autocorrelations for data values at varying time lags. If the data set is random, such autocorrelations should be near zero for any and all time-lag separators. Otherwise if the data set is non-random, then one or more of the autocorrelations will be significantly non-zero (*www.wikipedia.org*).

In this study, the autocorrelation correlograms (plots) of the ACF and PACF among the five variables were used to test for stationarity. These plots were extracted from the results using the STATA 13 as shown in Appendices ___. Results revealed that correlograms among the variables (sugar, farm gate price of sugar, fertilizer price, area, temperature, and precipitation) were somewhat slow to decay, an indication of nonstationary series. In addition, most of these variables considered in the study may have a lag order equal to 1 as shown in Table 2. The estimated lag orders refer to those where the PACFs were beyond the critical values and found to be significantly different from zero.

Table 1 Initial Lag Order Estimates for Sugarcane Produced, Farmgate Price, Price of Fertilizer, Area used for Sugarcane, Mean Precipitation, and Mean Temperature using Cointegration.

Variables	**Lag Order**
sugar	1, 2
price	0
fertprice	2
area	1 or 6
temperature	1, 2
precipitation	1, 2, 3

However, it is hard to differentiate the stationarity of the series by just looking at the correlogram alone. In order to test formally the stationarity of the series, the Phillips-Perron (PP) was applied.

Table 2 presents the Phillips-Perron (PP) test results for presence of unit roots. In this study, sugar, area, price, temp, and precipitation series are stationary since they did not contain unit roots. Price of fertilizer, however, contains unit root. In order to test the relationships among these variables, the next alternative way used in this study is the vector autoregressive (VAR) analysis.

Table 2 Phillips-Perron Test Results

Variable	**t-stat**	**MacKinnon p-value for Z(t)**
sugar	-3.624	0.01
Area	-3.268	0.07
Price	-4.456	0.00
FertPrice	-2.673	0.25
Temp	-5.452	0.00
Precip	-4.453	0.00

➢ *Lag Length Determination*

The appropriate lag length specification in VAR modeling is one of the important things to be considered since choosing inappropriate p reduces the precision of estimated coefficients in VAR (p) model. Table 4 presents the VAR model included in the study for selecting the VAR order using Gretl.

Table 3 Lag length determination for VAR (p) model

Lag Order	**AIC**	**BIC**	**HCQ**	**LR**
1	59.745196*	61.856554*	60.482116*	NA
2	59.938730	63.633608	61.228342	0.00214
3	60.208761	65.487157	62.051063	0.00423

- *Indicates lag order selection by the criterion*
- *LR: sequential modified LR test statistic (each test at 5% level)*
- *AIC: Akaike information criterion*
- *BIC: Schwarz Bayesian criterion*
- *HQC: Hannan-Quinn criterion*

For the VAR model, it can be seen that the AIC continues to increase while the BIC has its lowest at lag 1. In AIC, BIC, and HCQ test statistics, lag order 1 was significant at 5%. The lag length VAR (1) was then chosen to be lag order for the VAR model.

➢ *Vector Autoregressive Estimates*

VAR is a dynamic system of equations that examines the inter-relationships between economic variables which aims to provide good statistical representations of the past interactions between variables. There is no division between endogenous and exogenous variables in VAR. Here, a VAR describes the dynamic evolution of a number of variables from their common history.

The variables considered under this study are sugar (volume produced), farmgate price, price of fertilizer, area used, mean temperature, and mean precipitation having a VAR model with lag *p* equal to 1. In a tabular form, the VAR estimation outputs, and the standard errors are shown in Table 4. The results were obtained using *STATA13.*

The sign of a coefficient in a VAR model indicates the direction of the relationship between the current value of the variable and the lagged values of that variable and the other variables in the system. A positive coefficient indicates that an increase in the lagged value of the variable is associated with an increase in the current value of that variable and/or an increase in the values of the other variables in the system, while a negative coefficient indicates the opposite.

Table 4 Estimates of the Unrestricted VAR (1) Model.

	Sugar	**Area**	**Price**	**FertPrice**	**Temp**	**Precip**
Sugar (-1)	0.5078* *(0.2748)*	0.0064* *(0.0034)*	0.0002^{ns} *(0.0004)*	-0.0044^{ns} *(0.0166)*	0.000^{ns} *(0.000)*	-0.0241^{ns} *(0.0299)*
Area (-1)	-16.4378^{ns} *(18.2524)*	0.03410^{ns} *(0.2227)*	-0.0156^{ns} *(0.0234)*	-0.2831^{ns} *(1.1003)*	0.0001^{ns} *(0.0014)*	1.2515^{ns} *(1.9852)*
Price (-1)	187.6987^{ns} *(119.9785)*	2.3678^{ns} *(1.4638)*	0.2928* *(0.1539)*	-1.1407^{ns} *(7.2328)*	-0.0120^{ns} *(0.0095)*	12.8778^{ns} *(13.049)*
FertPrice (-1)	-1.2879^{ns} *(3.0969)*	-0.0048^{ns} *(0.0378)*	-0.0074* *(0.0040)*	0.6635* *(0.1867)*	-0.0002^{ns} *(0.0002)*	0.0015^{ns} *(0.3368)*
Temp (-1)	5775.047* *(2417.945)*	26.0961^{ns} *(29.4993)*	0.7800^{ns} *(3.1013)*	21.0512^{ns} *(145.763)*	0.0656^{ns} *(0.1908)*	700.9618* *(262.9791)*
Precip (-1)	-3.4306^{ns} *(1.3747)*	0.03397^{ns} *(0.0208)*	-0.0012^{ns} *(0.0022)*	-0.0429^{ns} *(0.1027)*	-0.0003* *(0.0001)*	0.6080* *(0.1852)*
Constant	-23814.93^{ns} *(70890.56)*	847.4252^{ns} *(864.8756)*	-198.2598* *(90.9259)*	-2564.984^{ns} *(4273.556)*	14.6095* *(5.5936)*	-2082.47^{ns} *(7710.19)*
R-square	0.6038	0.7914	0.7967	0.8917	0.4316	0.4970
RMSE	2778.59	33.8992	3.5639	167.504	0.2192	302.203
Log-likelihood		-1039.836				
Akaike information criterion		60.4234				
Hannan-Quinn criterion		61.6208				
Schwarz Bayesian criterion		63.8196				

*significant at 10% level
^{ns}not significant at 10% level

The estimates among the variables under the VAR model can then be used to explain the effect of each variable to another, as well as the effect of past values (one year before) of one variable to another. Results of this study revealed that the variation of these variables under the VAR (1) model can be explained by around 61%, 79%, 80%, 89%, 43%, and 50%, respectively.

The results pointed out that, for instance in the VAR (1) model, the present value for sugarcane production can be affected by the previous 1-year sugarcane production. Subsequently, the present farmgate price of sugarcane can be affected by the previous 1-year farmgate price of sugarcane. Then, the present price value for fertilizer can be affected by the previous 1-year price value of fertilizer. Moreover, the present level of mean precipitation can be affected by the previous 1-year level of mean precipitation. However, the present mean temperature is not affected by the previous 1-year mean temperature.

Consistent with the Law of Supply, the price of sugarcane positively affected the quantity of sugarcane production i.e., producers will produce and sell more of their product at a high price than at a low price, *ceteris paribus*. Price of fertilizer, mean precipitation, and area devoted to sugarcane negatively affected the quantity of sugarcane produced, *ceteris paribus*. Temperature, on the other hand, positively affected the quantity of sugarcane produced, *ceteris paribus*.

Results also revealed that volume of sugarcane production in the country is affected by the previous mean value of temperature. Meanwhile, the rest of the considered variables for sugarcane series do not have statistically significant effect for its previous values to present sugarcane production. This result is basically explained by the present system of inputs used to produce sugarcane.

- *Granger Causality*

Table 5 presents the causality results of the Granger causality test for the VAR (1) model. The relationship among the variables to the model is examined through causality testing. Test results under the VAR (1) model revealed that farm gate does Granger cause volume of sugar produced at 10% level of significance. This implies that farm gate price is said to be Granger caused by volume of sugarcane produced, *i.e.*, past values of farm gate price can help predict or forecast the effect of volume of sugarcane produced. Therefore, the results further pointed out that under the VAR (1) model, Granger's concept of causality is unidirectional.

Table 5 Granger Causality Test Result for VAR(1) Model

Null Hypothesis	**Obs**	**Probability > Chi2**
Sugar does not Granger Cause Area	39	0.02*
Area does not Granger Cause Sugar	39	0.01*
Sugar does not Granger Cause Price	39	0.02*
Price does not Granger Cause Sugar	39	0.23^{ns}
Sugar does not Granger Cause FertPrice	39	0.04*
FertPrice does not Granger Cause Sugar	39	0.54^{ns}

Sugar does not Granger Cause Temp	39	0.42^{ns}
Temp Sugar does not Granger Cause	39	0.19^{ns}
Sugar does not Granger Precip	39	0.47^{ns}
Precip does not Granger Sugar	39	0.48^{ns}

Moreover, price of fertilizer, mean temperature, and mean precipitation under the VAR (1) model revealed that it does Granger cause volume of sugar produced at 10% level of significance. This implies that price of fertilizer, mean temperature, and mean precipitation are said to be Granger caused by volume of sugarcane produced, *i.e.*, past values of price of fertilizer, mean temperature, and mean precipitation can help predict or forecast the effect of volume of sugarcane produced. It further pointed out that under the VAR (1) model, Granger's concept of causality is unidirectional.

➢ *Tests for Model Adequacy*

The Jarque-Bera test is performed on the variables used in the study. This test is a statistical test that is used to check whether a given sample of data has a normal distribution. Table 6 shows that all variables used are not significant, it is implying that the data is normally distributed, or at least, there is no strong evidence to reject the null hypothesis that the data is normally distributed.

Table 6 Jarque-Bera test

Equation	**Prob > chi2**
sugar	0.58457
area	0.77231
price	0.71742
fertprice	0.11589
temp	0.67105
precip	0.55345
ALL	0.74115

Moreover, using the Lagrange multiplier (LM), a statistical test used to check the goodness of fit of a model for VAR (1) whether there is any systematic pattern or structure in the residuals of the model. Results revealed that there is no evidence of autocorrelation in the residuals of the model. In other words, the residuals are not correlated with each other at any lag, and the model does not suffer from the problem of autocorrelation.

Table 7 Lagrange-Multiplier Test Result

lag	**Prob > chi2**
1	0.62650
2	0.56641

H0: no autocorrelation at lag order

Further, using the eigenvalue stability results of the VAR (Vector Autoregression) model, all values lie inside the unit circle and the model satisfies the stability condition. This means that the system is stable, and the dynamics of the system are well-behaved

Table 8. Eigenvalue stability condition

Eigenvalue	**Modulus**
0.9992568	0.999257
0.6937351 + 0.4084414i	0.805042
0.6937351 - 0.4084414i	0.805042
0.0792642 + 0.7185462i	0.722905
0.0792642 - 0.7185462i	0.722905
-0.6844543	0.684454
0.4505868	0.450587
0.2750239 + 0.3110035i	0.415164
0.2750239 - 0.3110035i	0.415164
0-.399105	0.399105
-0.1452468 + 0.03675249i	0.149824
-0.1452468 - 0.03675249i	0.149824

All the eigenvalues lie inside the unit circle.

C. Elasticities

Adaptive expectation means that farmers base their expectations of what will happen in the future based on what has happened in the past. Thus, they make production decisions in response to the previous market conditions.

Table 8 presents the summary of quantity response. As shown in Table 8, the estimated R^2 of quantity response models ranged from 64%. This means that 64% of the variability in the quantity of sugarcane produced can be ascribed to the unpredictability in prices of sugarcane.

The short-run quantity-sugarcane price elasticities was found 0.51; and, 14.83 in the long run. Sugarcane price elasticity was inelastic in the short and elastic in the long run, respectively. In terms of quantity response, sugarcane farmers do not respond to changes in sugarcane price in the short-run. Although the long-run elasticity is elastic, this means that farmers are sensitive to changes in sugarcane price in the long-run. This is justifiable in the sense that sugarcane farmers cannot immediately respond to price changes due to technical rigidities in production. The deterioration and poor performance of existing system is another common complaint that hinders the production of sugarcane. Or maybe while they may wish to expand production but capital is a constraint. Farmers lack farm credit to sustain their operation. Though technologies are available as "solutions" but these are often unprofitable for farmers without subsidies.

Table 9 Short-run relationship of identified variables for sugarcane production using VAR (1) model

Variable	**Short-Run Elasticity**	**R-Square**
Area	1.19	0.6484
Price	0.51	
FertPrice	1.25	
Temp	0.66	
Precip	1.58	

In terms of the area response of sugarcane, the short-run and long-run area response of sugarcane farmers are both elastic, 1.19 and 1.29, respectively. This means that a change in the area devoted to sugarcane will have a relatively large effect on the quantity of sugarcane produced in both the short run and the long run.

Specifically, the elasticities indicate that if the area devoted to sugarcane increases by 1%, the quantity of sugarcane produced will increase by 1.19% in the short run. In other words, sugarcane farmers are relatively responsive in the short-run but responsive to changes in the price of sugarcane, and they can adjust their production decisions by changing the quantity of land devoted to sugarcane production. The fact that both the short-run and long-run area responses are elastic suggests that sugarcane farmers can adjust their production decisions in both the short run and the long run to take advantage of changes in the price of sugarcane.

D. Forecast Values and Scenarios

The estimation and forecast for sugarcane production for the years 2021 to 2040 was accomplished using the time series regression coefficients estimates of the generalized least square estimates. Assumptions in the forecast was applied using the trend values of the exogenous variables used in the study, and by increasing and decreasing its values to present scenarios for the forecast values.

In order to verify that the projected model aligns with actual outcomes, the precision of the forecast was evaluated through computations of the mean absolute deviation (MAD), mean square error (MSE), and mean absolute percent error (MAPE).

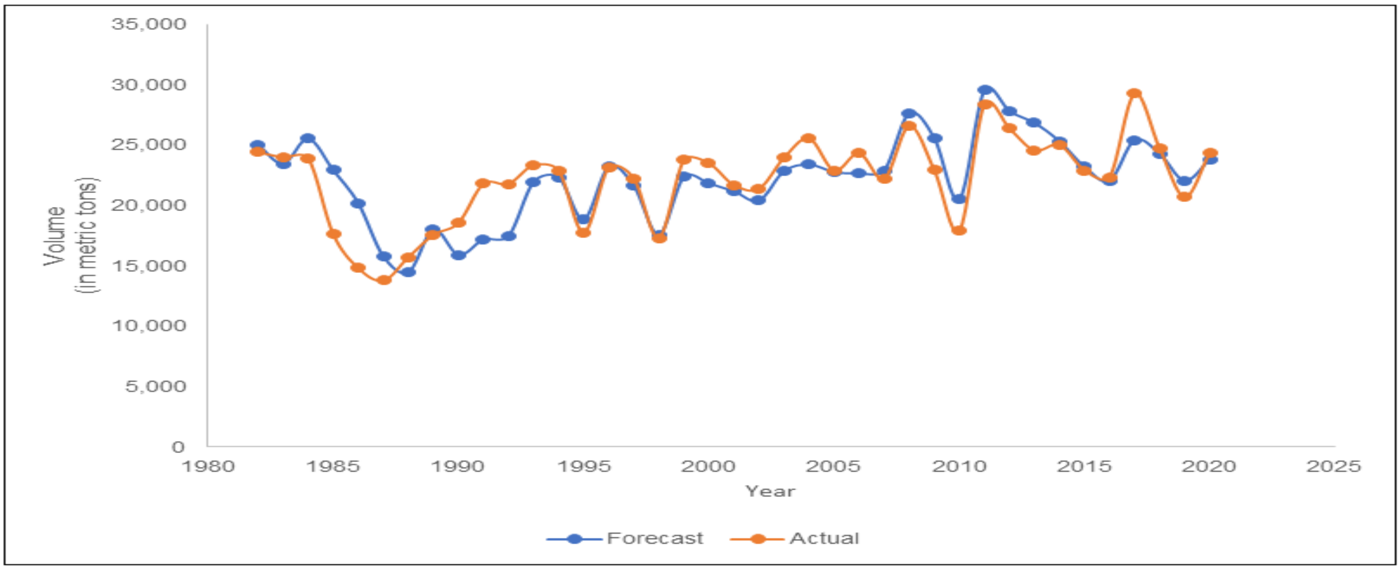

Fig 9 Actual values vs forecasted values of sugarcane produced.

$$\widehat{sug} = \widehat{97{,}995} + \widehat{41.37}Area + \widehat{4.20}Fert - \widehat{157.96}Price - \widehat{3{,}621}Temp + 1.20Precip$$

(48170) (7.30) (1.50) (81.86) (1813) (1.16)

MAD = 221.85 MAPE = 7.63

MSE = 4441534.381 Accuracy = 92.37%

Using the estimates of the GLS, the model for sugarcane yields 92.37% accuracy with mean absolute deviation of 221.85 as shown in Figure 6. These results suggest that the model is a reliable method for predicting sugarcane yields, with a high level of accuracy and a relatively low level of deviation between predicted and actual values.

Moreover, Figure 7 shows the forecast values of sugarcane production in the Philippines with three (3) different scenarios.

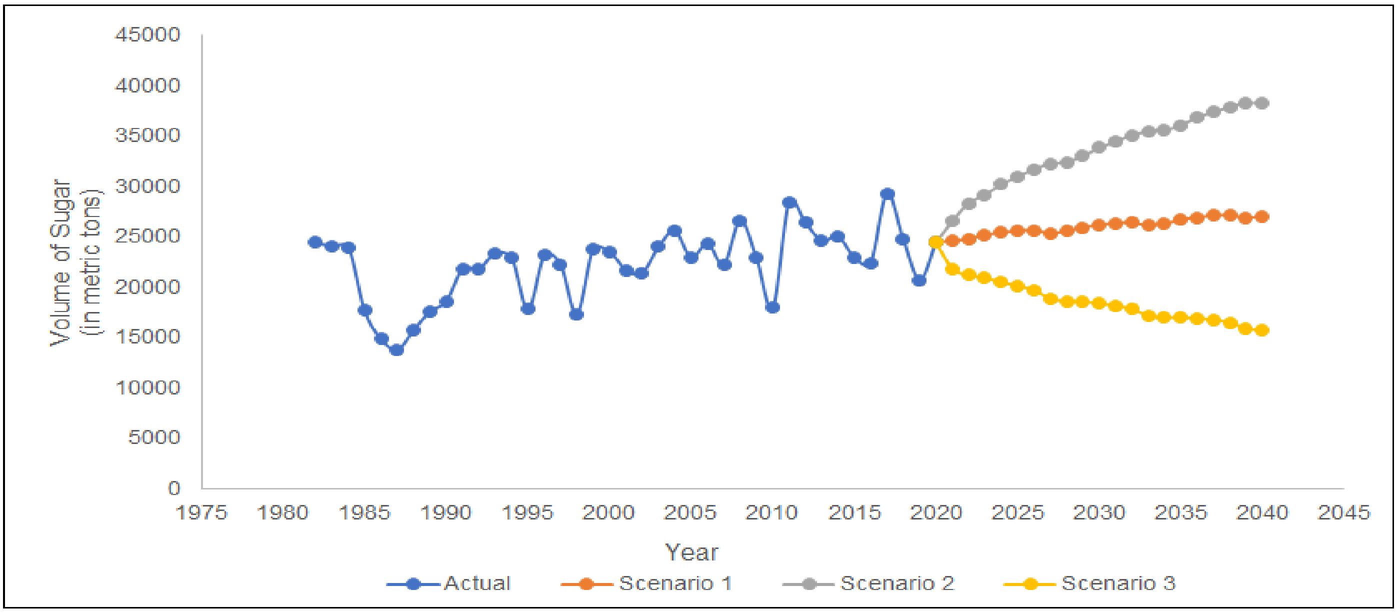

Fig 10 Scenarios of forecast values for sugarcane production in the Philippines

- *Assumptions:*

- *Scenario 1: Employs the trend patterns observed in the factors considered by the model.*
- *Scenario 2: Employs 20% increase in the factors considered by the model.*
- *Scenario 3: Employs 20% decrease in the factors considered by the model.*

The first scenario shows a little more reliable forecasts since it used average growth rates that are computed from the historical data. The second and third forecasts are somehow the presentation of the chosen regression model with 20% increase or decrease in the historical data of the predictors of the model.

V. SUMMARY, CONCLUSION, AND RECOMMENDATION

- *Summary and Conclusion*

This study provides valuable insights for policymakers who are developing price incentive policies aimed at boosting sugarcane production in the Philippines to address food security concerns. However, it is important to recognize that improving the efficiency of sugarcane production requires government support, as farmers alone cannot achieve this. The government's role in this effort could involve implementing price incentive policies that consider the different response behaviors of sugarcane farmers, as revealed by the study's estimated elasticities. By utilizing the price of sugarcane as an incentive to increase production, farmers' attitudes towards price can be changed, leading them to increase production during times of high prices and switch to other crops or more productive activities during times of low prices. Higher market prices would increase profits, creating a greater incentive for farmers to supply more sugarcane.

Furthermore, the study also conducted a causality test among the variables under the VAR model. Granger causality is a technique for determining whether a time series is useful in forecasting another. The question of whether these variables cause other variables and vice versa were analyzed. It should be noted that causality concept does not imply causation; rather it is useful in forecasting another.

The VAR framework of the study generated estimates which conform to the economic theory that explains sugarcane production. In this study, the previous year value of price and area, can positively influence the sugarcane

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production in the present year. This conforms with the adaptive expectations of the farmers that the previous value, especially price, can positively affect the present year value of production. Meanwhile, the previous year values of the price of fertilizer, area devoted, and mean rainfall precipitation negatively affects the present value of sugarcane production.

The Granger causality test conducted under the VAR (1) model pointed out at 10% level of significance. This means that price of fertilizer, mean temperature, and mean precipitation under the VAR (1) model revealed that it does Granger cause volume of sugar produced at 10% level of significance Therefore, causality in this case posits a unidirectional. The study was able to establish short-run for only since cointegration failed.

RECOMMENDATIONS

It has been shown that using the Philippine data for sugarcane, the quantity response results gave acceptable relationships among variables and results were in accordance with the theory of supply. However, it is necessary to consider the essential limitations of this study before recommendations are used. One limitation of this study is that this made use of the existing published data. Thus, the reliability of the result depends on the accuracy of data published by the agency from which the data were taken. Besides, the estimates of the elasticities are averages over the period considered and might be different from actual values.

➢ *Drawn from these Results of the Estimation, the following Recommendations are Prescribed:*

- *Invest in R&D initiatives focused on sugarcane breeding, disease and pest management, and agronomic practices.*
- *Allocate resources to improve infrastructure related to the sugarcane industry, such as irrigation systems, drainage networks, and farm-to-market roads.*
- *Establish credit facilities and financial support programs tailored specifically for sugarcane farmers. This can include low-interest loans, grants, and subsidies to enable farmers to invest in modern farming equipment, inputs, and technology*
- *Provide training and capacity-building programs for sugarcane farmers to enhance their skills and knowledge in modern farming techniques, crop management, and business practices.*
- *The government should extend financial assistance to farmers, specifically in the form of credit support. This measure would help eliminate intermediaries who take advantage of these farmers.*
- *Develop productivity programs to address the food security and self-sufficiency of sugarcane should be the key factor in attaining sustainability in the sugaracne industry.*
- *Accelerate distribution of lands through the Comprehensive Agrarian Reform Program (CARP) to address the issue of land ownership, including the provision of infrastructure support.*
- *Foster partnerships and collaboration among government agencies, research institutions, industry associations, and farmers' organizations.*
- *Develop strategies to help the sugarcane industry adapt to climate change impacts and mitigate its contribution to greenhouse gas emissions.*
- *Improve data collection and analysis systems to gather accurate and up-to-date information on sugarcane production, market trends, and industry performance.*

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