Sugarcane Supply Response in Eswatini

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ABSTRACT

The Kingdom of Eswatini's sugarcane production is a critical contributor to its economy, providing significant export earnings and employment. Despite its importance, there is limited empirical evidence on how sugarcane farmers respond to price and non-price factors, with previous studies suggesting a predominance of non-price influences in developing countries. The study aims to quantify the supply response of sugarcane farmers in Eswatini to variation in both price and non-price factors, hence providing important insights for policymaking. The study is grounded in Nerlove's adaptive expectations and partial adjustment framework. The Engle-Granger two-step approach for cointegration and Error Correction Model (ECM) has been employed in this to capture both long-run equilibrium relationships and short-run dynamics. Annual time series data from 2000 to 2022, comprising sugarcane area harvested, sucrose prices, maize prices (as a substitute crop), and fertiliser prices, were analysed. The empirical results reveal that the area harvested for sugarcane is significantly influenced by sucrose prices, maize prices, and fertiliser prices. The long-run model indicated that maize prices significantly influenced negatively sugarcane area harvested both current and lagged by two years, highlighting a strong substitution effect. Current fertiliser prices are also negative and significant. While the sucrose price was statistically insignificant in the long run, its lagged change had a positive and significant impact in the short run, indicating an adaptive and delayed response by farmers, likely due to biological and institutional constraints inherent in sugarcane production. The error correction term was negative and statistically significant, confirming a stable long-run cointegration relationship and a relatively rapid adjustment of short-run deviations back to equilibrium. Eswatini's sugarcane supply response is highly sensitive to relative crop profitability and input affordability. The findings show a necessity for integrated agricultural policies that consider the competitive dynamics with other crops, the mitigation of rising production costs, and ensure timely and credible price information. It is recommended that targeted input subsidies be implemented, promoting efficient irrigation technologies, strengthening extension services, and addressing land tenure constraints to enhance the sector's resilience and responsiveness.

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Table of Contents

List of Tables

List of Figures

CHAPTER ONE: INTRODUCTION

1. Background

1.1 Eswatini Background

The Kingdom of Eswatini, previously known as Swaziland, is a former British protectorate that gained independence on 6 September 1968 (Dlamini, 2017). The Kingdom's name was changed to its ancient name, Eswatini, during the 50th independence anniversary (2018). King Mswati III mentioned that this was an attempt to distinguish the country's name from other nations, such as Switzerland (Ncube, 2019). Eswatini is landlocked, located in Southern Africa, bordered on the north, west, and south by the Republic of South Africa and on the east by Mozambique. Eswatini covers an area of 17,364 square kilometres and has two major towns: Mbabane, the capital city, and Manzini (Dlamini & Dlamini, 2002). The country has four distinct agroecological regions: the Highveld, the Middleveld, the Lowveld, and the Lubombo region see Figure 1.1 (Munyaka et al., 2024). Eswatini has a population of 1.2 million people, with about 70% of the population relying on agriculture for their livelihoods (Dlamini & Ngulube, 2024).

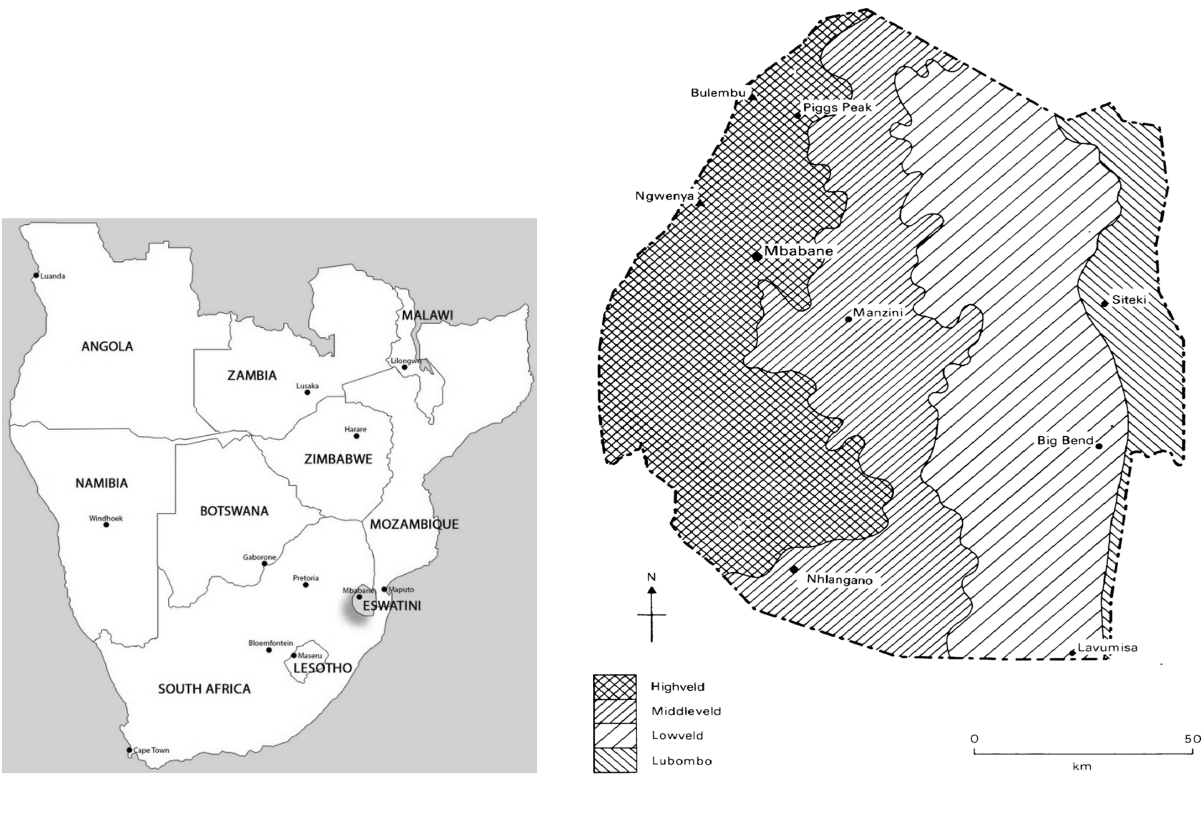

Figure 1.1: The Four Agro-Ecological Regions and Eswatini's Location in Southern Africa

In 2023, the Kingdom of Eswatini was reported to have a Gross Domestic Product (GDP) of US$4.6 billion and a per capita GDP of US$3,823 (World Bank, 2023). The country's economy is divided into three sectors which are the Primary sector (agriculture and forestry, crop production, animal production, and mining and quarrying), the Secondary sector (manufacturing, electricity supply, water supply, and construction), and the Tertiary sector (wholesale and retail trade, transportation and storage, information and communication, tourism, and health) (Central Bank of Eswatini, 2024). Eswatini has been slowly shifting its output and employment from agriculture to services as the share of services in GDP rose from 45.6% in 2000 to 53.5% in 2023. On the other hand, the primary sector, particularly in agriculture, has seen a decline from 12.3% to 8.1% (see Figure 1.2). The secondary sector has declined from 39.1% to 33%. Notably, the manufacturing industry is mainly focused on food and beverages in the country (African Development Bank, 2024).

1.2 Eswatini's Agricultural Sector

The agricultural sector in Eswatini is perceived as one of the key drivers of economic growth, poverty reduction, and inequality eradication. The sector has proved crucial for the economy as it provides raw materials used by other sectors. About 75% of the country's export earnings come from agricultural-based commodities. Hence, its inclusion in main policy documents, such as the National Development Strategy, has shown the sector's importance (Mashinini et al., 2019). Furthermore, the sector supports the livelihood of people living in rural areas since about 70% of the country's population lives in rural areas (World Bank, 2011). The agricultural sector contributed 7.7% to GDP, whilst employment created in agriculture is 12.2% (FAO et al., 2022). The figures suggest that the sector has seen a decline in its relative performance in recent years (Ministry of Economic Planning and Development, 2014).

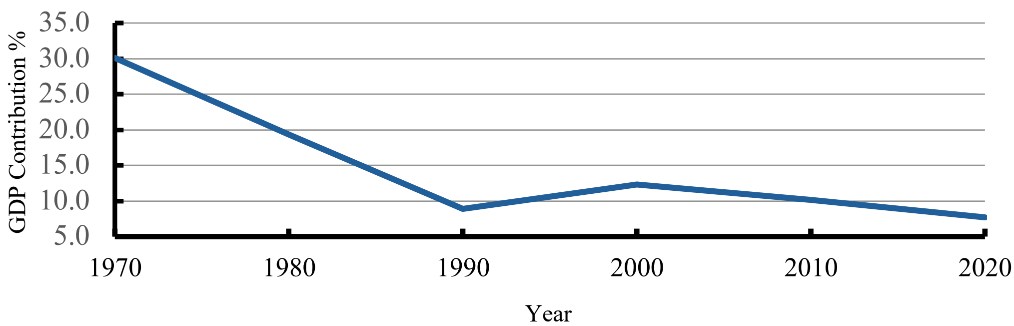

Figure 1.2: Share of Agriculture Contribution to Gross Domestic Product (GDP) 1970 to 2020
Source: (World Bank, 2023)

Eswatini operates under a dualistic land tenure system: Title Deed Land (TDL) and Swazi Nation Land (SNL). SNL accounts for 75% of the total land, and TDL accounts for 25%. Land governance in the SNL is done by chiefs who are referred to as traditional land administrators, whilst the urban local administration and central government govern TDL (Manyatsi & Singwane, 2019). In 2016, TDL contributed an estimated 80% to the agricultural sector, while SNL contributed an estimated 10%, with the difference being a contribution attributed to livestock and forestry. However, most of Eswatini's farmers are smallholder farmers who predominantly operate under SNL and mainly practice subsistence farming, while in TDL, large-scale commercial farms are predominant (Rugube et al., 2019). This is because TDL is market-driven and employs a great deal of modern technology, such as advanced irrigation systems, high-yielding seed varieties, and machinery, while SNL is subsistence-oriented, relies heavily on rainfall, and has low input use (Dlamini, 2019).

Eswatini's smallholder farm household size averages eight people, and the average farm size is 3 hectares (Rugube et al., 2019). Smallholder farmers grow mostly maize crops for home consumption and sell surplus within communities and to the National Maize Corporation. Hence, the country is a net importer of maize and heavily reliant on South Africa to satisfy the demand for maize in the country since the commercially grown maize in TDL is insufficient to meet the self-sufficiency levels of the country (Singh et al., 2020). Moreover, the country is also a net importer of wheat, rice, fruits, and vegetables. However, commercially, Eswatini is a net exporter of sugar, canned fruit products, and beef.

Despite the downturn of the share of agricultural contribution to Eswatini's GDP, the sugar sector continues to be a leading export agricultural product and has created about 20,000 jobs. The agricultural sector is seeing growth as sugarcane production is forecast to increase by 4% despite smallholder farmers facing rising production costs, including energy for irrigation. Eradicating the rising production costs is constrained by access to credit since in Eswatini most of the smallholder farmers operate under SNL which limits their ability to have their farmlands as collateral in accessing credit from formal finance institutions to finance their production costs and expansion. With this challenge at hand smallholder sugarcane farmers face disparities in production output when compared to large commercial estates which are predominantly under TDL and have better access to credit for financing better technology and other significant means of production that help increase their output and increase area under cultivation (Maziya, 2019). However, besides sugarcane being at the forefront in production in the country, significant strides are taken to revive other agricultural crops and products as Eswatini is reviving and expanding the production of industrial crops such as cotton, cassava, strawberries, melons, and sunflowers to supply the domestic industry with inputs for processing (International Trade Administration, 2024).

The transformation of subsistence farming to commercial farming continues to form a major part of policy agendas in most developing countries (Ume, 2023). Eswatini, being one of the developing countries, has most of its population operating under subsistence farming for income and self-sufficiency. Initiatives to transform subsistence farms into commercial farms in the Lowveld region have proven to be noteworthy initiatives, as the farms primarily grew maize, the country's staple crop, and were being converted to commercial sugarcane farms to help foster improvement in income and standard of living of rural farm households (Nhlengetfwa & Mamba, 2024).

1.2 Problem statement

Improvements in irrigation water supply, an increase in sugarcane planted area, and a recovery in yields of sugarcane production in Eswatini are expected to increase by 9%. Domestic sugar consumption has been trending upwards and is forecasted to rise to 73,000 metric tonnes. Population growth, a stronger local economy, and greater market access in remote areas are expected to increase sugar consumption per capita to 40.2 kg/hd/yr (Eswatini Sugar Association, 2024b). Furthermore, the industry is expected to enjoy competitive prices due to weaker exchange rates, strong global demand, and expanding market access, and exports are anticipated to increase by 10%. Increasing production and adoption of new technologies are necessary for sugarcane production to accommodate and support the demand for sugar (Eswatini Sugar Association, 2024b). With this favourable outlook in prices, the assumption would be that farmers would increase their production. However, this hypothesis does not have enough evidence to support it. This study attempts to quantify the supply response of sugarcane farmers to price changes in sugarcane. However, past studies reveal that producers in developing countries don't respond to price changes, and non-price factors are predominant. This is due to limited access to technology and poor rainfall distribution (Shoko et al., 2016).

1.3 Motivation of the study

The importance of sugarcane in Eswatini is elevating food security and improving the livelihoods of smallholder farmers and households through employment and income. The investigation of farmers' production decisions is important. Hence, providing knowledge of the responsiveness of sugarcane farmers to variations in price and non-price factors could help policymakers formulate better policies to elevate the economy and the sugar industry. The focus of the study is to ascertain the farm decision response to economic incentives, which are believed to be of main concern to policymakers.

1.4 Purpose of the study

The study aims to quantify the supply response of sugarcane farmers in Eswatini.

1.5 Objectives of the study

I. Quantify Eswatini's sugarcane farmers' supply response to the price of sugarcane.
II. Estimate the supply response of sugarcane growers to variations in non-price factors.

1.6 Hypotheses

Null Hypotheses (H_0)

- H_{01}: Price incentives have no significant effect on the area harvested for sugarcane in Eswatini.
- H_{02}: Own-price factors have no significant effect on the area harvested for sugarcane in Eswatini.

Alternative Hypotheses (H_1)

- H_{11}: Price incentives significantly influence the area harvested for sugarcane in Eswatini.
- H_{12}: Own-price factors significantly influence the area harvested for sugarcane in Eswatini

1.7 Research questions

I. How do sugarcane farmers respond to price changes?
II. How do sugarcane farmers respond to non-price changes?

CHAPTER TWO: LITERATURE REVIEW

In this section, the author will review the literature on sugarcane production of Eswatini. The chapter will review sugarcane physiology, factors that affect sugarcane production, its value chain, and challenges faced by smallholder farmers in sugarcane farming.

2.1 Sugarcane Physiology and Production

Sugarcane is a monocotyledon and a member of the family Gramineae tribe Andropogoneae and is classified in the genus *Saccharum* (Julien et al., 1988). Commercially, the crop is cultivated in the tropical and subtropical regions of more than 90 countries. Sugarcane thrives in varied climatic conditions, requiring 1500-2500 mm of rainfall per season and performing best in temperatures between 25-33 ^{0}C (Silva et al., 2014). Sugarcane is a tall perennial tropical grass that tillers to produce unbranched stems 2 to 4 m tall and approximately 5 cm in diameter (James, 2008). Sugarcane is harvested several times before replanting. One planting of sugarcane is estimated to allow three to six annual harvests before replanting (Salassi et al., 2002). The first cycle is called the plant crop; subsequent crops are ratoons. The size of yield loss is a main criterion for farmers when deciding when to replant sugarcane (Marin et al., 2019). Moreover, various factors such as climate, seed variety, and management practices influence the number of harvests. Harvesting in Eswatini is done when the crop is 12 months of age, and the harvesting period happens for 9 months (April to December). Harvesting is segmented into three harvesting times, namely, early season (April to June), mid-season (July to September), and late season (September to December) (Dlamini et al., 2024b).

Sugarcane production and profitability are dependent on different factors, which include the ratooning variety. To commercialise sugarcane production, a wide ratooning variety is preferred, and the ratooning ability is one of the factors that are taken into consideration when choosing a variety. Furthermore, the ratoon crop must be able to achieve high yields, produce several economically rewarding ratoon crops, and be resistant to pests and diseases (Dlamini et al., 2024a). In Eswatini, sugarcane production started in the Big Bend area of Eswatini in 1956, which is in the Lowveld region of the country (see Figure 1.1). The area of production has increased over the years; at present, over 70,000 hectares are under sugarcane production (Tfwala et al., 2022). Currently, sugarcane is grown on more land than any other crop. Sugarcane irrigation consumes about 10,000m^3/ha of water (Mhlanga et al., 2006). Furthermore, sugarcane production mainly occurs in the Lowveld region of Eswatini, where the annual mean rainfall is 400 mm, with temperatures of 37 ^{0}C during summer and a low of 7

^{0}C in winter (FAO, 2018). Sugarcane is grown commercially in the region, and agrochemical usage is extensive during the growing season to realise high yields and good-quality crops.

In 1956, sugarcane was only grown on estates owned by the millers until 1962, when about 257 smallholder farmers started to produce sugarcane under the Vuvulane Irrigation scheme located in the Lowveld of Eswatini. Furthermore, the Eswatini Sugar Association and the government have facilitated the expansion of sugarcane production by enacting the Komati Downstream Development Project (KDDP) and Lower Usuthu Smallholder Irrigation Project (LUSIP) in 2002 and 2003, respectively. The initiative has seen an increase in sugarcane production from smallholders, as in the growing season of 2014/15, the total area under sugarcane production was over 14,000 hectares and yielded 686,778 tonnes of sugar. The involvement of smallholder farmers in the industry has redistributed the dependency on sugarcane production from large-scale growers (Kibirige & Singh, 2021).

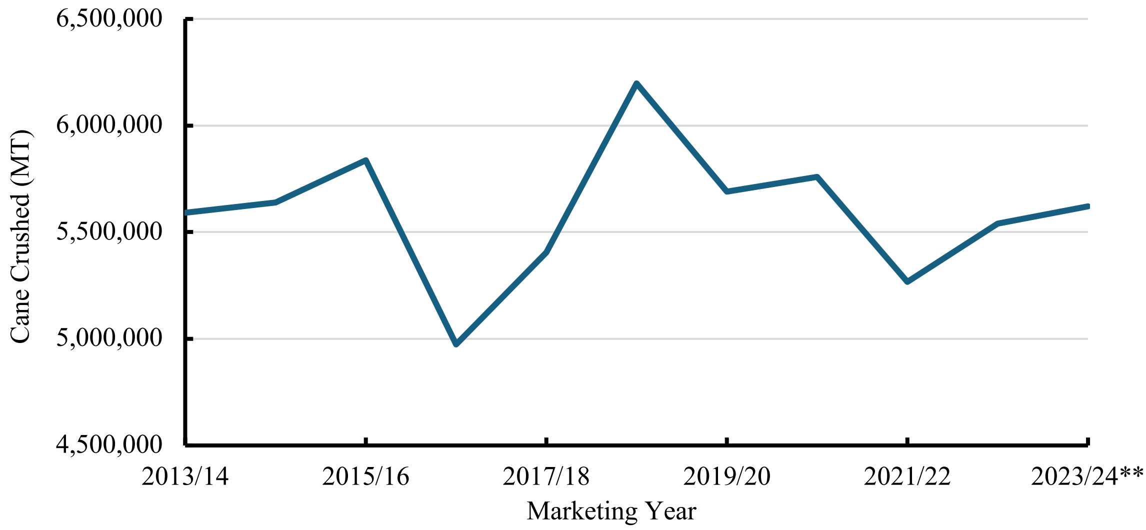

Figure 2.1: Cane Crushed in Eswatini 2013/14 to 2023/24

Source: (United State Department of Agriculture, 2023)

Eswatini’s sugarcane growers are divided into three categories: small-scale, medium-scale, and large-scale growers. The total number of producers is 469, and 444 are small-scale growers (Eswatini Sugar Association, 2024b). Small-scale growers operate on a total land area of less than 50 hectares. In the year 2023/24, small-scale growers contributed 29% of total production, coming second to large-scale growers who operate in farms greater than 1,000 hectares, contributing 62% of the total production. The total production in the reported year stood at 625,361 tonnes, as shown in Table 2.1 below, whilst, on the other hand, crushed sugarcane in that year was 5,539,396 tonnes (see Figure 2.1). Eswatini sugar industry products are sugar (raw sugar, direct consumption sugar, refined sugar), molasses, and ethanol (Eswatini Sugar Association, 2020b).

Table 2.1: Sugar Produced in Eswatini 2013/14 to 2023/24.

Marketing Year	Sugar produced (MT)	Sugar/Cane Ratio (Percentage)
2013/14	653,337	11.68
2014/15	686,778	12.18
2015/16	695,408	11.91
2016/17	586,086	11.78
2017/18	650,126	12.03
2018/19	746,983	12.05
2019/20	673,369	11.83
2020/21	684,562	11.89
2021/22	613,895	11.66
2022/23*	625,361	11.29
2023/24**	652,057	11.60

Source: (United State Department of Agriculture, 2023)

2.1.1 Climate Variability Risks

Eswatini's variable weather patterns have been causing challenges for sugarcane farmers, such that it has lowered yield potential and increased yield variability in sugarcane (Nalley et al., 2019). Eswatini is further divided into four main administrative regions: Hhohho, Manzini, Shiselweni, and Lubombo. The Highveld and Middleveld are formed by the Hhohho, Manzini, and Shiselweni regions, whilst the Lowveld and Lubombo are under the Lubombo region. The Highveld and Middleveld receive more rainfall compared to the Lubombo region (see Figure 2.2). Recently, climatic events in Eswatini caused a 16% reduction in sugar output (Swaziland Sugar Association, 2016). Notably, 586,086 tonnes of sugar were produced in the marketing year of 2016/17, as shown in Table 2.1. This was due to the 2015/16 El Niño drought, which has been recorded as the worst drought experienced in the country since 1992.

Furthermore, in the 2015/16 season, rainfall received in the Lubombo region was 590 mm lower than the long-term means (see Figure 2.2).

This resulted in some rivers running dry and dam levels being lowered, which negatively impacted sugarcane production. This situation further prompted the rationing of irrigation due to less water availability, resulting in short and medium-term negative effects (Swaziland Cane Growers Association, 2017).

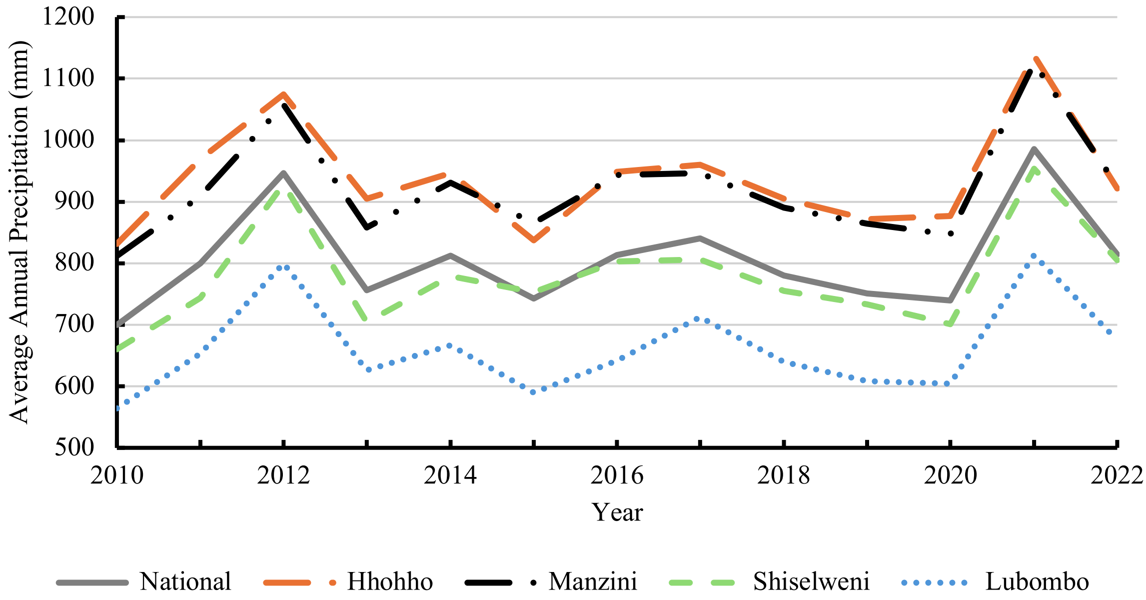

Figure 2.2: Average Rainfall Distribution of Eswatini from 2010 to 2022 in the four main administrative regions

Source: (The World Bank Group)

Knox et al. (2010) simulated possible outcomes based on the historical Eswatini weather data. Predictions were that the existing irrigation structures would fail to maintain the current levels of production, even when considering unrestricted water availability. This further indicates that as climate change intensifies, the variability and intensity of extreme heat events could cause changes to traditional rainfall distribution and amounts. The sugarcane industry in the country is set to face long-term sustainability issues in terms of increasing output and profitability. For instance, whilst irrigation is important for the industry, late rains during the sucrose production growth stage have the potential to negatively impact the amount of sucrose in the cane, which in turn reduces farmers' earnings. Hence, as weather patterns become more unpredictable, a complex relationship between weather and profitability creates a new set of challenges for

Eswatini's sugar industry and the population that depends on farming for their livelihood (Nalley et al., 2019).

2.1.2 Irrigation

Sugarcane's yield is significantly determined by its stalk height and circumference, and this is highly dependent on the plant's access to water (Bhingerdeve et al., 2017). The crop is negatively affected by water stress conditions, which results in a reduction of its height and yield. Eswatini smallholder sugarcane farmers have been performing poorly when compared to their large-scale counterparts, and this has been largely due to inefficient irrigation systems. Most farmers use sprinkler irrigation systems. However, smallholder farmers are still facing technical challenges that involve using incorrect irrigation intervals, which can result in under-irrigation or over-irrigation. This can impact the crop negatively since under-irrigation can cause water stress conditions, whilst over-irrigation can result in misuse of water, leaching of fertilisers, and increased electricity costs, which all can impact the overall production of sugarcane (Bhebhe, 2020). Adoption of a proper irrigation interval can help smallholder farmers increase their water use efficiency and productivity (Masuku, 2011).

Increasing drought events have resulted in water shortages for irrigation, causing a complex issue which has challenged the farming sector to come up with a proper strategy for applying water that will necessitate appropriate irrigation intervals and, at the same time, conserve water to ensure long-term sustainability (Dlamini & Masuku, 2013). This has prompted the government to invest in irrigation to benefit smallholder sugarcane growers by improving water access, which would enhance irrigation efficiency (Mamba & Shongwe, 2022). Furthermore, the Government of Eswatini formed the Eswatini Water and Agricultural Development Enterprise (EWADE), formerly known as Swaziland Water and Agricultural Development Enterprise (SWADE), in 1999 to promote participation of smallholder farmers in irrigated commercial agriculture to combat poverty in the country and increase land under sugarcane production (Terry & Ogg, 2017).

The country has four major rivers: the Komati, Mbuluzi, Usuthu, and Ngwavuma rivers. These rivers are shared with South Africa upstream and Mozambique downstream (see Figure 2.3). The Komati and Usuthu rivers originate from South Africa and flow out through Eswatini into Mozambique, whilst the Mbuluzi and Ngwavuma rivers originate from Eswatini and flow through Mozambique and South Africa (see Figure 2.3). EWADE initiated irrigation projects called the Lower Usuthu Smallholder Irrigation Project (LUSIP), which was actioned in two phases: LUSIP I and LUSIP II, sourcing the irrigation water from the Usuthu River.

The project's mission was to construct two dams, intake structures, canals and pipelines that are solely for irrigation. The objective was to transform farmers who relied on rainfed practices into commercial irrigated sugarcane farms (Mkhonta, 2016). Furthermore, the organisation, in efforts to adapt to climate change, has migrated from sprinkler irrigation systems to drip irrigation systems. EWADE has further added eight small and medium earth dams strategically constructed in different areas of the country to ensure increased water harvest activities. The earth dams are to benefit 3000 hectares of irrigation area (Eswatini Water And Agricultural Development, 2023).

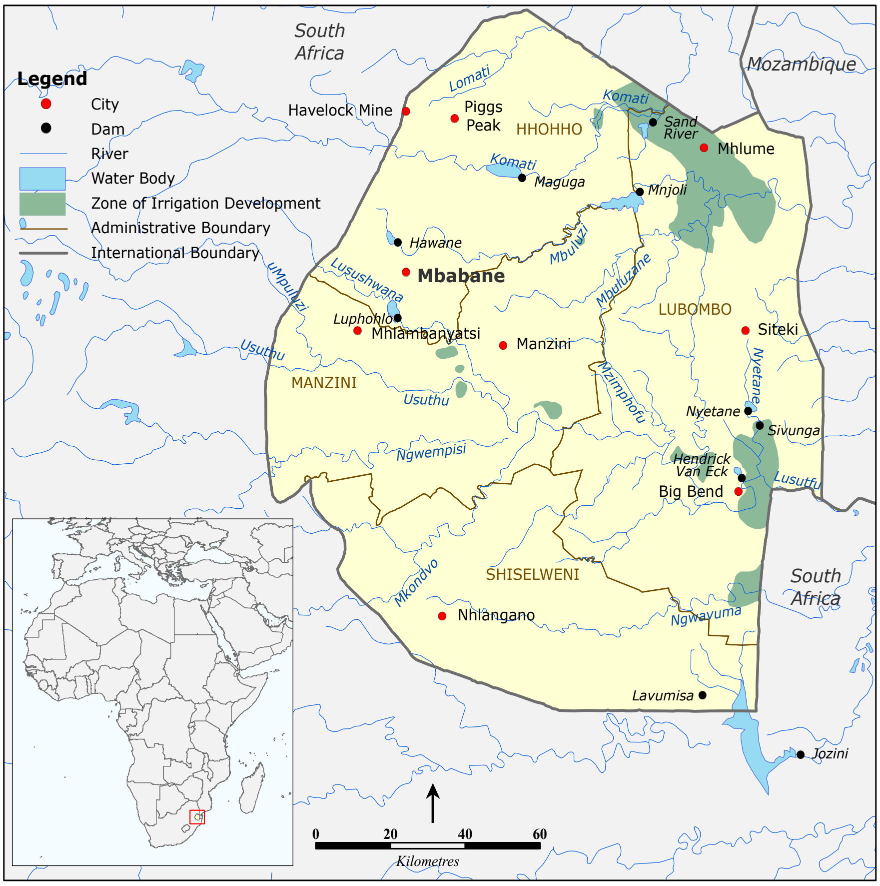

Figure 2.3: Eswatini's Major Rivers, Dams, and Irrigation Areas

Source: (Food and Agriculture Organization of the united Nations, 2005).

2.1.3 Electricity Costs

The electricity industry is actively seeking self-generation alternatives, as in 2018, data shows that the Electricity Supply Commission's (ESKOM) peak demand was 187.39 MW during the day, which correlated with farmers' irrigation patterns since they irrigate their sugar cane farms during the day. Eswatini imports 80% of its electricity from South Africa, and the sugar cane industry contributes significantly to the utility demand revenue as consumption by the sector in 2018 was 434 GWh, accounting for 30% of total consumption (Dlamini & Bekker, 2019).

Eswatini's average electricity price has been increasing over the years from US$ 0.11/kWh in 2013 to US$ 0.14/kWh in 2023 (see Figure 2.4). Furthermore, the Eswatini Electricity Company (EEC) has recently applied for another overall tariff increase of 25.51% for the year 2025. However, the Eswatini Energy Regulation Authority (ESERA) has been awarding EEC a lower tariff than the proposed tariff. The highest EEC has ever been awarded recently was an average of 15% (Eswatini Electricity Company, 2024).

Eswatini's sugarcane farmers are faced with increasing irrigation pumping costs, attributed to the annual increases in electricity tariffs from EEC. Furthermore, from June to August, sugarcane farmers' electricity usage is at a peak. This is also the period when electricity tariffs are adjusted to higher rates, which results in high pumping costs for the sugarcane growers. This not only reduces their income but also threatens the long-term survival of their farms. As a result, farmers have been advised to adopt energy-saving practices, which include irrigation scheduling, maintaining pumps, maintaining electrical equipment (e.g. pressure gauges, voltmeters, and current meters), and installing Power Factor Correction Devices (PFCD) (Eswatini Sugar Association, 2020a).

Solar-powered irrigation is becoming an attractive option for sugarcane farmers as the cost of fuel and standard grid electricity continues to increase, whilst the cost of establishing solar-powered systems is on a decline. The location of the sugarcane farmers is ideal as they receive enough solar radiation to harness sufficient energy to make solar-powered irrigation feasible (Eswatini Sugar Association, 2024a). Moreover, the Eswatini Sugar Association is supporting the use of solar energy by growers as it has facilitated the adoption of solar energy for irrigation and initiated an industry-wide solar power study. The organisation's support has seen thirteen growers with installed solar having no reported incidents of failed irrigation systems. Also, they have rolled out the installation of renewable energy by adopting solar and biomass energy at the millers (Eswatini Sugar Association, 2022). Despite the declining cost of establishing solar power systems, there are still calls for the government to subsidise solar-powered installations as the cost of acquisition and installation is relatively expensive for some farmers (Eswatini Sugar Association, 2018).

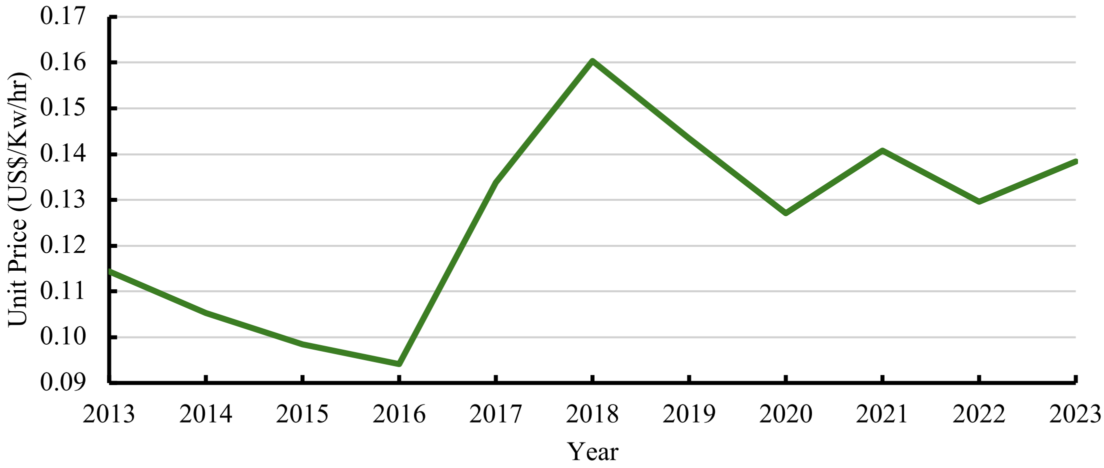

Figure 2.4: Average Electricity Per Unit of Eswatini

2.1.3 Fertiliser

In the sugarcane industry, fertiliser application is one of the important management determinants that need to be closely monitored for farmers to increase yield and realise profit. However, fertiliser costs have a negative relationship with profit, as an increase in fertiliser costs usually results in a decrease in profits. Small-scale growers are recommended to form cooperatives so that they can buy fertiliser in bulk and receive discounts to reduce costs on fertiliser (Dlamini & Masuku, 2013). Recently, farmers have been greatly concerned about the exponential rise in fertiliser prices. In 2020, the price of diammonium phosphate (DAP) and urea rose from May 2020 to August 2021, where DAP increased by 124% while Urea increased by 107%. These fertilisers are highly used in sugarcane production. The significant increase was caused by increased global demand for fertiliser and increased production costs (Eswatini Sugar Association, 2021).

2.2 Eswatini Sugarcane Value Chain and Trade

Eswatini's sugar industry has several segments that play a pivotal role in the success of its value chain, as shown in Figure 2.5. The sugar industry in Eswatini is regulated and overseen by the Eswatini Sugar Association (ESA). The roles of the association are marketing all sugar and molasses produced in the country, and supporting the entire sugar industry value chain, including agricultural research, cane testing, warehousing, distribution, and policy advocacy. Furthermore, the ESA governs the millers and cane growers in the country (Anderson, 2018). Concerning the sugarcane growers in the country, the organisation plays an important role in regulating various issues that involve cane varieties to be grown, pest and disease control, and allocation of sucrose quotas. The association also oversees the millers to ensure sugar quality is maintained. Also, the ESA is heavily involved in international trade negotiations (Ministry of Agriculture, 2015).

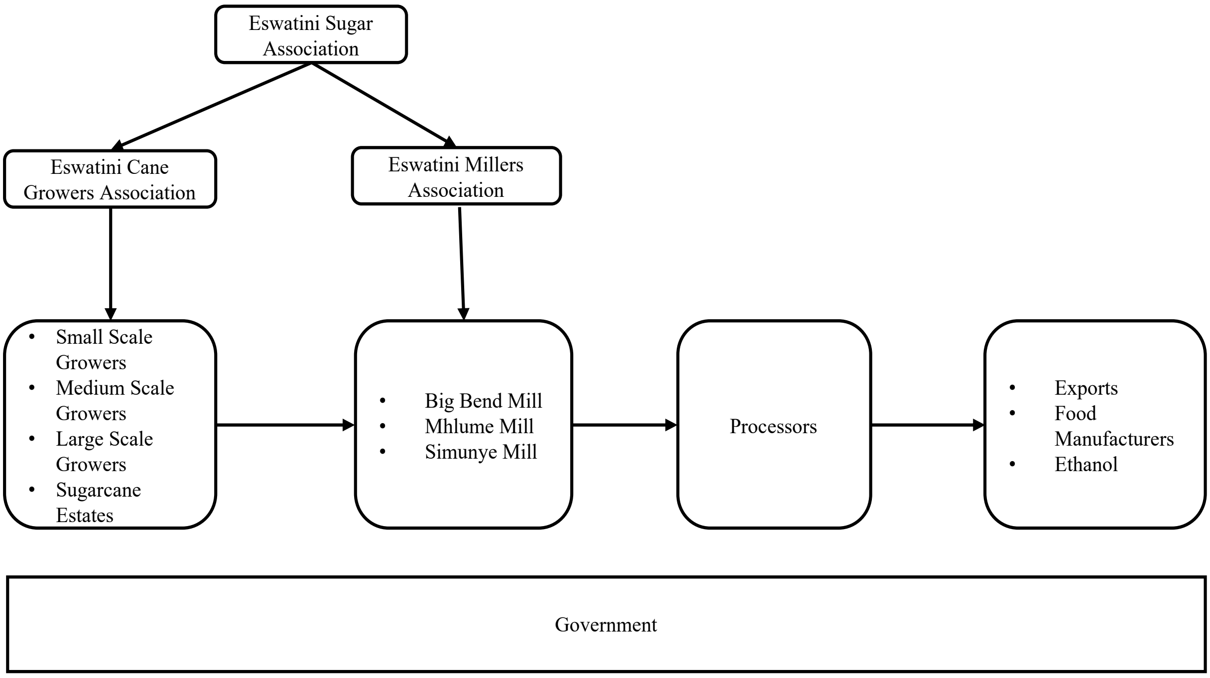

Figure 2.5: Eswatini Sugarcane Industry

In Eswatini, sugarcane is grown by Estates, Small-scale, Medium-scale, and Large-scale growers. Growers are part of the Eswatini Cane Growers Association (ECGA), a non-governmental organisation (NGO) established in the Kingdom through the Cane Growers Act No.12 of 1967. Membership in the association is open to any sugarcane grower possessing a legal permit or quota approved by the ECGA Executive Committee. However, ECGA membership prohibits growers with direct links to the sugar mills or who are members of associations other than the ECGA, such as the Simunye Sugar Estate owned by the Simunye Mill (Eswatini Cane Growers Association, 2024a). The association was founded solely to represent, promote, and advocate for the farmers' collective interests in sustaining the industry and ensuring its progress. Under the Act it was formed, the Ministry of Agriculture must impose an annual levy on all growers under the recommendation of the Association. ECGA charges a levy per ton of sucrose supplied to and accepted by the millers. As a Non-Profit, ECGA largely depends on the collected levy for its operations (Government of Eswatini, 2003). Farmers in recent years have seen a constant increase in the levy charged by the Ministry of Agriculture from year to year, as in 2020, the levy on sucrose per tonne was charged at US$0.40, whilst in 2021, the Government announced a 13% increase in the levy with a new charge of US$0.52

(Nzima, 2021b). Moreover, in 2022, the levy was further lifted by 4.4% to US$0.54 (Nzima, 2021a).

The production and processing of sugarcane into sugar mainly happen at the mills. Eswatini has three mills, Simunye, Mhlume, and Big Bend Mills, as shown in Figure 2.5 above. After harvesting the sugarcane, growers supply the cane to the mills, where it is tested and taken for processing into sugar, which is the main product of sugarcane. Sugarcane processing creates two main by-products essential in the value chain: bagasse and molasses. Bagasse is the fibrous material left after crushing sugarcane in the extraction of its juice (Loh et al., 2013). It is used for power generation, which is used within the mills for their operations, and any surplus is sold to the national grid, as shown below in Figure 2.6. Molasses is a thick, dark syrup that consists of fermentable carbohydrates and several non-sugar organic materials (Valli et al., 2012). The syrup is mainly used for ethanol production, and a small amount goes to animal feed. The mills in the country produce different forms of sugar: Very High Polarised (VHP) brown sugar, refined sugar, Demerara, and Nucane. The sugar produced is mainly for human consumption and manufacturing, as shown below in Figure 2.6. Eswatini enjoys strong sugar demand from food and beverage manufacturers who use it as one of their main ingredients. Trade statistics show that the impact of artificial sweeteners on sugar consumption has thus far been insignificant; hence, per capita consumption in the country was forecasted to increase to 40.2kg/hd/yr from 40kg/hd/yr in 2022/23 MY.

The main food and beverage manufacturers that utilise sugar are Bromor Foods, Kraft Foods (previously Cadbury), Ngwane Mills, Parmalat, Swazican, and two boutique companies producing limited quantities of rum, vodka, and craft gin (Masego & Wood, 2023). Most of the sugar in the country is exported to the Southern African Customs Union (SACU), the European Union (EU), and the United States (US) (Dlamini & Dlamini, 2019). Eswatini was one of the countries that benefited from the protected EU sugar industry before 2006 through the African, Caribbean, and Pacific Group (ACP)-EU partnership, which allowed less efficient producing countries to experience gains from this export market. However, after 2006, the EU liberalised the sugar industry, which has seen an increase in the supply of EU sugar on the world market, reducing imports from Africa and causing a decline in sugar prices within the EU (Mabeta & Smutka, 2023). On the other hand, ethanol products produced in the country are sold to the SACU (20%), Southern African Development Community (SADC) (15%), East Africa Market (EAC) (37%), and EU markets (28%) (Royal Eswatini Corporation, 2019).

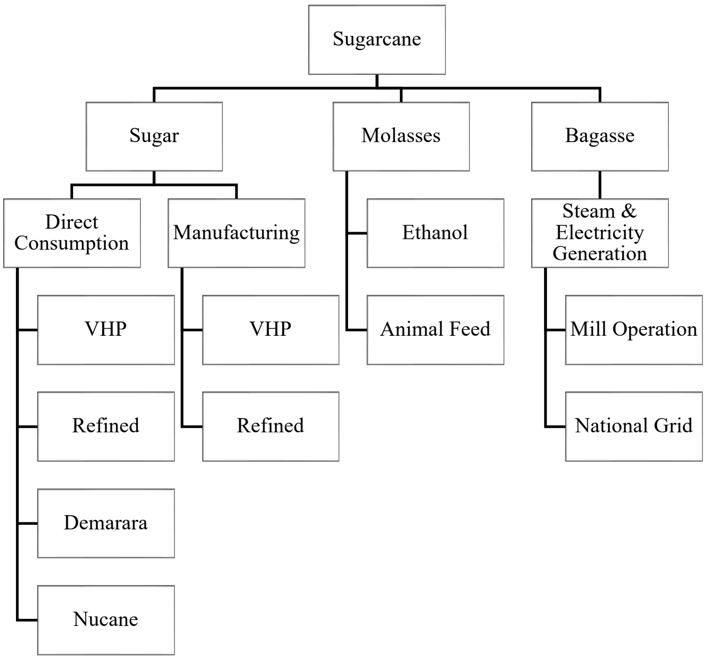

Figure 2.6: Eswatini's Sugarcane Value Chain

The ESA is responsible for the marketing of all sugar and molasses, as mentioned earlier. After marketing the products, the association makes payments to the millers, who then pay the growers according to the amount of sucrose in the cane delivered by the grower. This also includes the grower's share of the net sugar and molasses sales proceeds (Swaziland Sugar Association, 2014). As illustrated in Equation (1) below, this depicts the payment process for sugarcane; the cane is first delivered by the growers for processing. Following processing, the sugar and molasses are shipped to the ESA warehouse in preparation for sale in the market. Subsequently, the ESA receives payments from the markets, which then pay the millers and account for financial costs. Payments to the millers are made weekly, while growers receive their share of payments at the end of the financial year, once all accounts have been settled. The prices paid to both the millers and the growers should be expressed per ton. The price allocated to the growers is calculated using the following formula:

$$P_s = \frac{\left\{[P-(A+B)]\times\frac{C\times 10\%}{(C\times 10\%)+(D\times 12\frac{1}{2}\%)}\right\}}{R} \quad (1)$$

Where:

P_s = Price per ton of sucrose.

P = Price per ton of 96 ° pol equivalent sugar paid to each miller.

A = Notional cost of producing the cane required to manufacture one ton of 96 ° pol sugar, calculated by multiplying the notional cost of producing one ton of cane by the rolling three-year weighted average cane/96 ° pol sugar ratio of the two mills.

B = Notional cost of manufacturing one ton of 96 ° pol sugar.

C = notional capital employed to produce the cane required to manufacture one ton of 96 ° pol sugar, calculated by multiplying the notional capital employed to produce one ton of cane by the rolling three-year weighted average cane/96 ° pol sugar ratio of the two mills.

D = Notional capital employed to produce one ton of 96 °C pol sugar.

R = Rolling three-year weighted average sucrose/96 ° pol sugar ratio of the two mills.

The final price payable to the growers by the millers, as mandated by the Sugar Act of 1967, is derived by adding together the price per ton of sucrose, calculated using the price formula above, and the value of molasses expressed as an amount per ton of sucrose. The value of molasses is calculated by dividing the due proportion of total net molasses proceeds at the mill by the total tons of sucrose delivered to that mill during the season. Payments to the growers are usually made within thirty days after the date on which the net average price of raw sugar is determined and paid to the miller by the Sugar Association; the same applies to the payment of molasses. Payment for bagasse is not made so long as the millers are using the by-product as boiler fuel for the exclusive production of sugar, because this saves on milling expenses. In any case, bagasse is used for commercial purposes. The value attributed to the product shall be assessed, and the proceeds attributed to it shall be shared amongst the cane growers affiliated with that particular mill (Legislation, 1998). Figure 2.6 below shows the financial model of the sugar industry and clearly details how payments are made to different stakeholders in the sugar industry. This shows that the ESA is responsible for marketing and making payments to farmers for sugar and other products sold in the market.

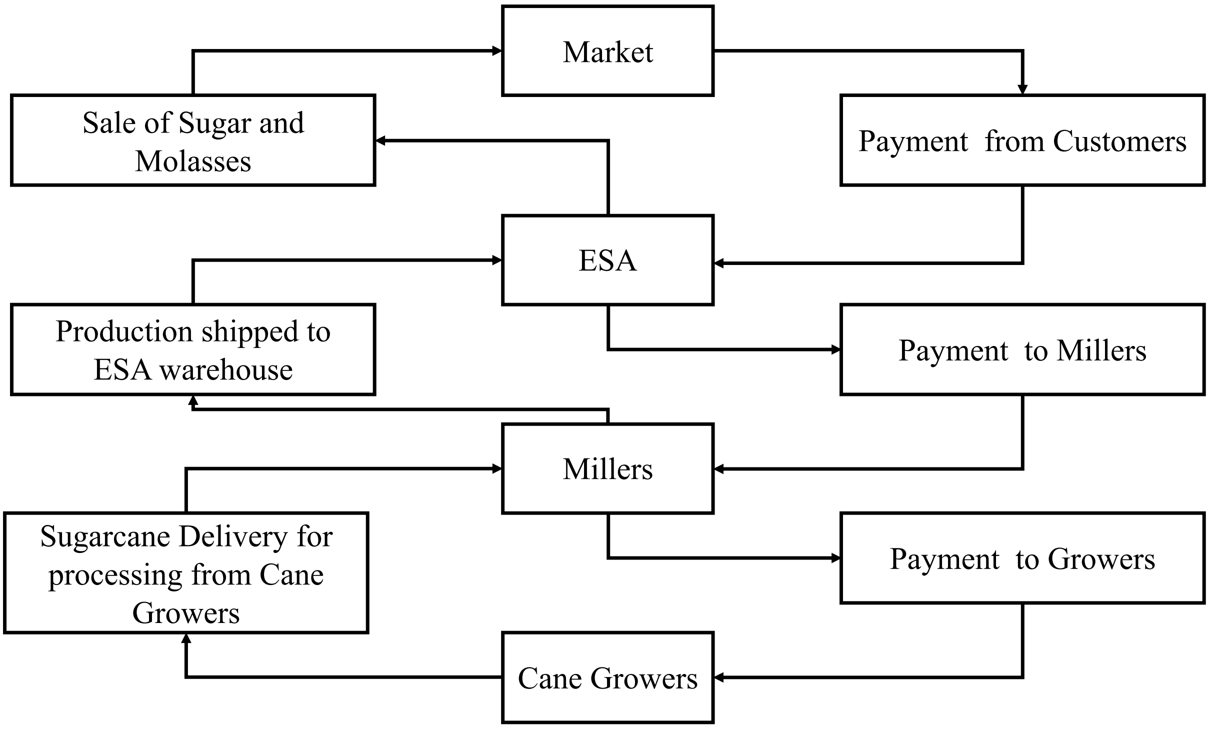

Figure 2.6: Eswatini's Sugarcane Financing Model

Since early 1990, the currency of Eswatini, the Lilangeni, has been depreciating compared to the US dollar. Reasons for the depreciation could be attributed to the 1-1 fixed exchange rate regime between the South African Rand and the Eswatini Lilangeni. Besides South Africa having a bigger economy than Eswatini, it is also a major trading partner of the country. This means that not only is Eswatini a net importer from South Africa, but some of the negative and positive shocks experienced by South Africa are passed on to Eswatini, which impacts the exchange rate due to the currency peg formalised by the Common Monetary Agreement. Furthermore, in recent years, the weakening of the Kingdom's currency has also been attributed to the COVID-19 pandemic, causing a drastic decline in the Lilangeni against developed economies(Simelane, 2021). The impacts of the weakening local currency have also been felt by the sugarcane growers in the Kingdom, as shown in Figure 2.7 below. In the harvest season of 2017/18, farmers experienced a decline in world prices and a sudden strengthening of the local currency against major currencies, which brought about approximately a 4% drop in the sucrose price year on year. Beforehand, farmers were in a difficult period where the El Niño drought (2015/16 season) had affected their production output. This harmed the output of the 2016/17 season, where farmers recorded a record low of 13% yield. This pushed the season's price up to US$291.05 from a low of US$212.14 the previous year. However, corrections to the prices happened after the 2016/17 season (Swaziland Cane Growers Association, 2018). Despite the continued depreciation of the local currency against major economies, the sucrose price has been on an upward trend as recently, in the 2023/24 season, it increased by 25%, which has saved the farmers from an intense economic turmoil which could have resulted in dismal yields. The sucrose price is further expected to be significantly higher in the following years, with farmers expecting to enjoy gains on improved prices (Eswatini Cane Growers Association, 2024b).

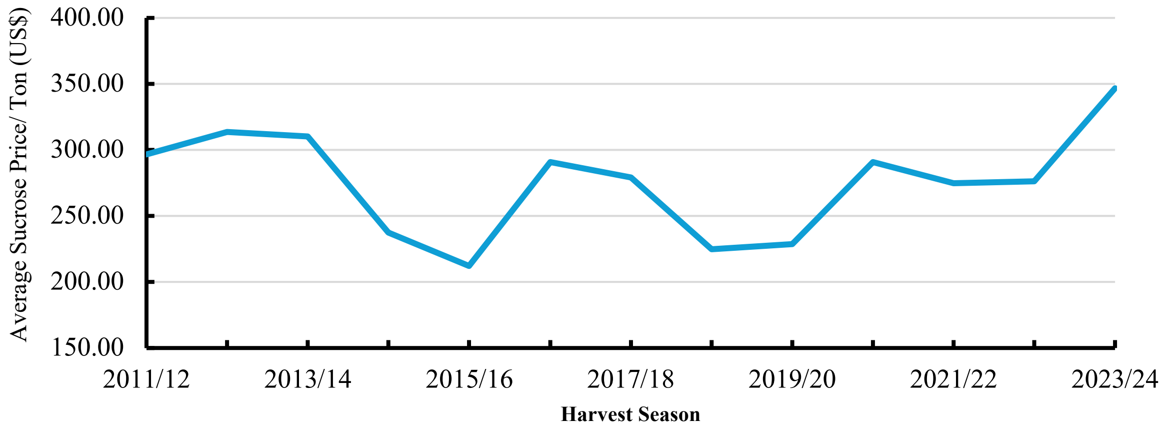

Figure 2.7: Eswatini's Sucrose Price Trends Over The Past Ten Years

Source: (Eswatini Sugar Association)

In conclusion, the literature reviewed in this chapter provides a clear understanding of sugarcane production in Eswatini, highlighting the crop's physiology, climatic requirements, and the evolving dynamics of the industry. While sugarcane remains an important economic crop cultivated in the Lowveld, its productivity and profitability are heavily dependent on climate variability, irrigation efficiency, rising input costs, and electricity tariffs. Moreover, smallholder farmers face challenges such as limited access to irrigation technologies and rising production costs. However, the government and institutions have invested their efforts in the expansion of irrigation infrastructure, promoting renewable energy, and the value chain managed by the ESA plays a crucial role in supporting sustainable production and marketing integration. Despite external shocks such as droughts, exchange rate fluctuations, and international trade policy changes, Eswatini's sugarcane industry remains resilient, with strong potential for inclusive growth and enhanced competitiveness if challenges are effectively addressed.

CHAPTER THREE: SUPPLY RESPONSE MODEL SPECIFICATION

This chapter establishes the theoretical, conceptual, and empirical foundations guiding the analysis of sugarcane supply response in Eswatini. Beginning with the theoretical framework, which will elaborate on the classical economic theories of supply and demand, discussions will follow on the factors that affect supply and how demand plays a role in influencing supply. Furthermore, the section will discuss the Nerlove Model, distributed lags, the Engle-Granger two-step procedure and other important models recognised in literature. Moreover, a discussion of the conceptual framework will be presented, drawing on theories that have been widely discussed within the theoretical framework. The importance of this discussion is to create a solid foundation in building a reliable estimable model for sugarcane supply response; hence, the empirical framework is based on the underpinnings of the theoretical and conceptual frameworks that will be discussed in this chapter.

3.1 Theoretical Framework

3.1.1 Determinants of Agricultural Supply: Price and Non-Price Factors

In economic theory, the concept of supply and demand explains how prices and quantities of goods and services are formed by the interaction of buyers and sellers in a market. Demand is described as the quantity of a good that buyers are willing to purchase at a series of alternative prices, in each market, during a given period, holding all other things constant. On the other hand, supply is defined as the quantity of a good that sellers are willing to offer at a series of alternative prices, in a given market during a given period of time, holding all other things constant (Dummond & Goodwin, 2010). Note that the definition of both demand and supply is similar, except that supply is concerned with the relationship between price and quantity that sellers are willing to offer in the market. Hence, a more appropriate definition of supply is the relationship between the price of a good and the amount of a good available at a given location and at a given time (Barkley & Barkley, 2016). The concept of supply and demand can be briefly explained by three propositions, which are highlighted by Lowe (1942) taking from H.D. Henderson's Handbook :

1. If demand exceeds supply at the price ruling, the price tends to rise. Conversely, when supply exceeds demand, the price tends to fall.
2. A price rise tends, sooner or later, to decrease demand and to increase supply. Alternatively, a fall in price tends sooner or later, to increase demand and to decrease supply.

3. Price reaches equilibrium when demand is equal to supply.

The three propositions form the law of supply and demand and are viewed as the cornerstone of economic theory. They are the framework in which all analyses of special, detailed problems must be fitted, since their scope is vast (Henderson, 1922). Based on these propositions, a further discussion can be made on the relationship between supply and demand. Attention is now turned to the concept of supply, as it applies to farm commodities, since they have unique features that require the underlying economic principles to be adapted to these features. Given that this study focuses on the supply response of sugarcane in Eswatini, it is essential to adapt general supply principles to the specific characteristics of agricultural production. Establishing a solid conceptual foundation of supply concerning farm commodities enables a better understanding of the relationship between price and quantity in agricultural markets. Farm commodities are characterised by seasonality, production lags, biological constraints, perishability, and vulnerability to environmental shocks (Gardner, 1992; Tweeten & Quance, 1969) In this context, agricultural supply can be defined as the quantity of an agricultural product offered for sale within a specified period, whereby the farm firm utilises a range of resources in agricultural production to generate the supply of agricultural products (Ritson, 1977). If farmers produce to maximise profits, their supply function would look like the following:

$$Q_s = f(T, P_p, P_{i\ldots n}, I_{j\ldots m}) \qquad (2)$$

Where Q_s is the quantity of product.

T is the technological conditions of production.

P_p is the price of the agricultural product.

$P_{i \text{ to } n}$ are the prices of substitute products and complements.

$I_{j \text{ to } m}$ are the prices of inputs.

A key distinction in the theory of supply lies between movements along the supply curve and shifts of the supply curve. This means that a movement along the supply curve is the change in the quantity supplied resulting from a change in the price of the product itself (P_p), holding other factors constant (Varian, 2014). However, in agricultural markets, supply is also affected by various non-price factors such as technological changes, price of substitute products, input prices, or weather conditions, which cause the entire supply curve to shift (Doll & Orazem, 1992). For instance, a rise in fertiliser costs (I_j) may lead to a decrease in supply at all price levels, shifting the curve to the left. Conversely, advancement in technology (T) or favourable climatic conditions could increase output capacity, shifting the supply curve to the right. These shifts are crucial to understanding agricultural supply behaviour, especially for perennial crops such as sugarcane, which are sensitive to input costs, rainfall variability, and intertemporal production decisions (Binswanger, 1989).

Having established the basic framework of supply theory and its application to agriculture, it is important to shift focus to how supply responds to various influencing factors. For better understanding, a distinction between movements along the supply curve, which reflect responses to changes in the product's own price, and shifts of the supply curve, which are caused by changes in own-price determinants, must be made. Clarifying this distinction is essential for analysing supply behaviour in agricultural contexts, where both price and own-price factors interact in complex ways to shape producer decisions.

Movements along the supply curve occur when there is a change in the quantity of the product supplied as a direct result of a change in the price of the product itself, holding other factors constant. This reflects the law of supply, which states that a price increase tends to increase the quantity supplied, and a price decrease tends to reduce it (Samuelson & Nordhaus, 2009). For instance, sugarcane is a perennial crop with a long growth cycle (up to 12-18 months before harvest), which limits immediate adjustments. From a farmer's perspective, price acts as a signal. When the market price of a commodity, such as sugarcane, increases, producers are encouraged to increase their production either by intensifying input use, reallocating land, or harvesting a larger portion of the planted area. However, in the short run, their ability to respond fully may be constrained by biological, input use, and seasonal factors. This is especially the case in areas like Eswatini, where smallholder sugarcane farmers comprise family farms using family labour, land, and many forms of capital, which are fixed inputs in the short run; in the going concern of a family farm, the cost of these inputs does not change appreciably whether they are used or not, hence they are fully employed. Conversely, if the product price is decreasing, farm labour, land, and sunk capital lack alternatives; hence, the return of these resources falls along with product prices, and they continue to be employed on the same farms (Cochrane, 1955). This suggests that in the short run, resources remain fully employed and total output will vary modestly with changes in price levels. A higher price may influence decisions about ratoon maintenance, fertiliser use, or the area to be planted in the next season, representing a movement along the supply curve. On the other hand, a fall in sugarcane prices reduces the incentive to maintain or expand production, leading to a reduction in quantity supplied. However, due to the production lags and sunk costs as mentioned earlier, such as already planted or fixed contracts, farmers may still supply sugarcane to avoid losses, though with reduced intensity (Binswanger & Rosenzweig, 1986).

While movements along the supply curve are driven solely by changes in the product's own price, agricultural producers do not operate in isolation from other market forces. Farmers make production decisions within an environment influenced by non-price factors, among which the prices of substitute and complementary products are significant. These related goods influence supply decisions by affecting the opportunity cost of allocating land and other inputs to crop cultivation. Changes in these prices do not result in movement along the existing supply curve; rather, they cause the supply curve to shift outward (an increase in supply) or inward (a decrease in supply), depending on whether the use of alternative resources becomes profitable. Therefore, examining how these non-price factors, beginning with substitutes and complements, shape agricultural supply is essential for understanding the broader dynamics between price and quantity beyond the narrow confines of price alone.

Substitutes are commodities that can be produced using the same resources or inputs. For example, in Eswatini, the substitute crop for sugarcane is maize. If producing maize becomes more profitable, the supply curve will shift outward. However, if maize becomes less profitable to produce compared to sugarcane, the supply curve will shift inward (Colman & Young, 1989). This can happen if the price of the competing commodity rises relative to sugarcane or if the costs of producing the substitute crop decrease relative to sugarcane. The latter may occur if a new technology increases the maize yield relative to sugarcane. Therefore, relative changes in prices, yields, or efficiency can alter the relative profitability of different crop fields (Tomek & Kaiser, 2014).

Another significant non-price determinant of agricultural supply is the cost of inputs such as seeds, fertilisers, chemicals, irrigation, labour, and machinery. Input price influences producers' profitability and directly affects the quantity of output that farmers are willing and able to supply. When input costs rise, the cost of production increases, reducing the marginal profitability of cultivating a crop like sugarcane. This discourages expansion and can lead to an inward shift in the supply curve. Conversely, a fall in input prices can reduce production costs, making farming more profitable and leading to an outward shift in supply (Doll & Orazem, 1984).

Eswatini's smallholder sugarcane farmers often rely on purchased inputs such as fertiliser and herbicides, as well as contracted labour. If the price of fertiliser increases significantly, these farmers may reduce application rates, affecting yields and supply. Furthermore, access to credit markets also influences how input prices affect supply. Farmers with constrained access to finance, moderate increases in input costs can severely impact production decisions (Key et al., 2000). Input supply constraints also interact with risk perceptions. Farmers may be reluctant to invest heavily in inputs if they perceive weather variability or market prices as uncertain. This reflects how input prices and supply responses are not just a mechanical cost-return relationship but are also shaped by farmers' expectations and risk behaviour (Just & Pope, 1979).

Beyond the cost factor, input demand also plays a crucial role in shaping how agricultural supply responds. Movements along the supply curve occur when the current market price of sugarcane changes, incentivising farmers to adjust the quantity they supply, holding input usage constant. For example, a higher current price may prompt farmers to sell more of the crop they can already produce, holding factors such as fertiliser, labour, and irrigation constant. On the other hand, shifts of the supply curve arise when factors other than the current price, particularly expected future prices, influence input demand. When farmers anticipate higher sugarcane prices, they are likely to increase usage of inputs such as fertiliser, labour, or irrigation to expand productive capacity. Additional input investment allows more output to be supplied at any given current price, resulting in an outward shift of the supply curve (Chambers & Lichtenberg, 1994). However, if the increased demand for inputs leads to higher input prices, the cost of production rises, which can offset the intended expansion in supply. For example, a surge in fertiliser demand can drive up fertiliser prices, resulting in an increase in production costs, which can potentially reduce the quantity supplied at each price level. This dynamic illustrates the complex interplay between input demand, input prices, and supply responsiveness (Barkley & Barkley, 2016). In Eswatini, fluctuations in the international price of sugar or changes in domestic regulations, such as miller-cane contracts or pricing schemes, can influence how much farmers are willing to invest in production. While commercial farmers may adjust input usage more easily in response to price signals, smallholders, facing constraints such as limited working capital, higher transaction costs, and exposure to climate risks, often display lower responsiveness. As a result, input demand elasticity and supply responsiveness are similar across farming systems (Binswanger & Rosenzweig, 1986; Kirsten & Van Zyl, 1998). The variations in supply responsiveness between large commercial estates and smallholders arise because commercial farmers often have better access to credit, bulk purchasing, and economies of scale that help mitigate input price volatility. Meanwhile, smallholders tend to operate under tight liquidity constraints and are more vulnerable to price and climate shocks, making their supply response more sensitive to changes in the input market (Dorward et al., 2005).

Technological change is a crucial factor in agricultural supply, influencing both the productivity of resources and the production cost structure. Advances in crop varieties, irrigation methods, pest and disease control, mechanisation, and information systems enhance the efficiency of input use, potentially leading to increased yields at lower costs (Alston et al., 2010; Hayami & Ruttan, 1985). In the context of sugarcane farming, the adoption of high-yielding varieties, drip irrigation systems, or integrated pest management can significantly improve output. These improvements can shift the supply curve outwards, allowing producers to supply more sugarcane at the same price levels. However, the adoption of such technologies often depends on farm size, education, access to extension services, and capital availability (Eswatini Sugar Association, 2020b; Poulton et al., 2006). Eswatini's sugar industry has made some strides in promoting technological adoption among smallholders, particularly through miller-cane grower partnerships and capacity-building programs. Nevertheless, disparities in access to these innovations persist, limiting the overall responsiveness of supply to price signals (Mnisi, 2019).

Beyond technological innovations, agricultural supply is also heavily influenced by climatic and biological variables, which introduce a unique layer of uncertainty to production. Although much of Eswatini's sugarcane sector relies on irrigation, climatic conditions such as rainfall and temperature still play an important role, especially for farms with limited or supplementary irrigation or during periods when water availability is constrained. Unpredictable rainfall patterns, droughts, or extreme weather events can adversely affect yields, leading to supply fluctuations despite favourable market prices (Barrett, 1996). Moreover, sugarcane's perennial nature and its reliance on ratooning practices mean that adverse climatic events can have lingering effects on production across multiple seasons. For instance, drought during the planting or establishment phases can impair the productivity of ratoons in the following years.

As such, supply decisions are not only driven by anticipated market returns but must also consider environmental risks and resilience capacity (Tschirley & Benfica, 2001).

In addition to technological and environmental factors, institutional and policy contexts play a critical role in shaping agricultural supply behaviour. Institutional arrangements such as land tenure systems, access to credit, market infrastructure, and government policies determine farmers' incentives and ability to respond to price signals. Secure land rights, for example, encourage investment in productivity-enhancing technologies and practices, whereas insecure tenure may discourage such investments and dampen supply responsiveness (Deininger, 2003; Place & Hazell, 1993). In Eswatini, the predominance of communal land tenure under the SNL system presents challenges for sugarcane expansion, especially among smallholders without formal titles (Dlamini & Dlamini, 2012). Furthermore, access to extension services, input subsidies, contract farming arrangements, and price support mechanisms influences farmers' capacity to adjust production levels (Poulton et al., 2006). While regulatory frameworks such as quotas and guaranteed pricing can provide income stability, they may also reduce incentives for producers to respond flexibly to changing market conditions (Eswatini Sugar Association, 2020b). Understanding these institutional dynamics is therefore essential for interpreting observed supply patterns and for designing effective policies to enhance supply responsiveness.

3.1.2 Supply Response Theory: Marc Nerlove Supply Response Theory

While the classical supply theory provides insights into the general relationship between price and quantity supplied, it lacks the temporal dimension required to capture the delayed responses characteristic of agricultural production. This is where the concept of supply response becomes essential.

Supply response is the change in output in response to price variations. (Siegle et al., 2024). The concept of supply response encompasses the traditional notion of supply but goes further to account for its dynamic nature. It is concerned with how output adjusts to changes in prices, whether through increased resource use, technological improvements, or expansion of productive capacity. Unlike the static framework of classical theory, supply response emphasises the role of shifting supply curves, particularly in response to evolving economic conditions (Cochrane, 1955).

This dynamic perspective becomes even more critical in agriculture, where production decisions are made under conditions of uncertainty, biological lags, and institutional constraints. Farmers often adjust their output over time due to the time it takes to gather information, access inputs, and implement changes in cropping patterns. To capture this gradual adjustment process, a more sophisticated framework is required, which will recognise both the adaptive behaviour of producers and the lagged effects of prices (Askari & Cummings, 1977b).

Thus, Nerlove's (1958) work on the partial adjustment model provides a coherent theoretical and empirical foundation for analysing agricultural supply response. An extension of supply theory was done by Nerlove to incorporate both expectations and adjustment lags into a formal econometric model (Nerlove, 1958). His approach assumes that producers do not instantly adjust output to price changes, but they respond partially in the current period and complete the adjustment gradually over time. Making it highly suitable for understanding farmer behaviour under dynamic market conditions.

The Nerlove Model is based on three core assumptions, which are:

1. Adaptive expectations: Farmers are uncertain of the future price, so they base their expected price on a weighted average of past prices. This implies a lag in the formation of expectations, capturing the inertia in decision-making.
2. Partial adjustment Mechanism: Producers adjust area under cultivation or output only partially toward the desired level due to constraints such as capital limitations, information asymmetries, and risk aversion. The adjustment coefficient (λ) measures the speed of convergence.
3. Separation of long-run and short-run elasticities: The Nerlove Model allows estimation of both short-run and long-run supply elasticities, which is essential for policy analysis and forecasting.

Mathematically, the model can be represented in three equations:

$$A_t^D = \alpha_0 + \sum_{i=1}^{I} \alpha_i P_{t-i} + \sum_{i=1}^{I} \alpha_i Z_{t-i} + \varepsilon_t \tag{3}$$

$$P_t^e = + \sum_{i=1}^{I} \beta_i (P_{t-i} - P_{t-i}^e) \tag{4}$$

$$A_t = A_{t-i} + \sum_{i=1}^{I} \lambda_i (A_t^D - A_{t-i}) \tag{5}$$

Where: A_t = actual area under cultivation at time t,

A_t^D = area desired to be under cultivation at time t,

P_{t-i} = Lagged own prices (reflecting past price signals),

Z_{t-i} = Lagged own price factors (e.g. substitute price, fertiliser cost),

P_t^e =Expected own price at time t,

ε_t = Random error term

β_i, λ_i: are the expectation and adjustment coefficients, respectively.

Equation (3) represents a distributed lag formulation of the desire acreage function where the current supply decision is influenced by a combination of past prices and non-price variables such as inputs or weather conditions (Griliches, 1960). This then allows the model to account for gradual information absorption and the cumulative effect of prior price periods' price signals.

Equation (4) extends the adaptive expectations mechanism by relaxing the assumption of immediate expectation updates. Instead, it shows that farmers may form expectations by weighing multiple prior deviations between actual and expected prices, recognising that price volatility and uncertainty are persistent (Nerlove & Fornari, 1998).

Equation (5) simplifies the partial adjustment process, suggesting that actual acreage decisions adjust incrementally toward the desired level over time. This process reflects institutional constraints, financial limitations, and other real-world frictions that prevent instant change.

The Nerlove model has been adopted and adapted in various ways in actual empirical work, which can be grouped into three categories. First is the modification of the affecting variables used by Nerlove; second is the inclusion of factors of particular interest in the situation under investigation, corresponding to the variable z in equation (3); lastly, attempts to represent quantitatively factors not considered by Nerlove, especially on perennial or slow-maturing crops (Askari & Cummings, 1977b; Muth, 1961; Nerlove, 1958). These refinements are essential for accurately modelling agricultural supply response in settings like Eswatini, where market access, rainfall variability, and land tenure constraints influence producers' ability to respond to price signals in a single season.

Critics argue that the Nerlove model's reliance on linearity and constant parameters may oversimplify real-world supply behaviour (Muth, 1961). It also assumes rational expectations only in adaptive form, which may not hold under volatile conditions. Subsequent extensions have incorporated non-linear adjustments, time-varying elasticities, and rational expectations frameworks (Nerlove & Bessler, 2001).

The model's flexibility has allowed researchers to adapt it to various contexts, including developing countries and perennial crop production. For example, Askari and Cummings (1977) revised the model by modifying the set of price and non-price factors, while others extended it to account for credit access and infrastructure variables, which can be relevant in the context of developing countries like Eswatini (Binswanger et al., 1993; Zulu et al., 2024).

3.1.3 Distributed Lag Model in Supply Response Analysis

While the Nerlove Partial Adjustment Model provides a foundational structure for modelling agricultural supply behaviour, particularly using adaptive expectations and partial adjustment mechanisms, it remains restrictive in capturing the full complexity of farmers' responses to economic stimuli. The emergence of Distributed Lag Models to address these limitations has offered a more flexible econometric framework. They allow for a richer and more empirically driven characterisation of lagged relationships between agricultural output and its determinants, without imposing a rigid behavioural structure.

A Distributed Lag Model expresses the dependent variable (e.g. area planted or yield) as a function of current and multiple lagged values of independent variables, including both price and non-price factors. Unlike the Nerlove Model, which imposes specific assumptions about the formation of expectations and the speed of adjustment, Distributed Lag Models estimate the lag structure from the data, without assuming partial adjustment or adaptive expectations (Johnston & DiNardo, 1997; Maddala, 2001)

A simple distributed lag model can be expressed as:

$$Y_t = \alpha_0 + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_k X_{t-k} + \varepsilon_t \tag{6}$$

Where: Y_t = the agricultural output (e.g. area planted or area harvested) at time *t*,

X_t = the explanatory variable (e.g. commodity price or fertiliser cost) at time t,

X_{t-1}, X_{t-2}, X_{t-k} = the lagged values of the explanatory variable from the previous year's capturing the delayed effects of past price or cost conditions,

β_0, β_1, β_2,...., β_k = short-run coefficients measuring the impact of each lag on output

α_0 = intercept term,

ε_t = Error term.

The long-run effect of the explanatory variable is calculated as the sum of the lag coefficients:

$$\text{Long-run multiplier} = \sum_{i=0}^{k} \beta_i$$

Use of distributed lag models can be attractive in agricultural supply modelling when the true lag structure is unknown or variable, producers face multi-seasonal influences and delayed decision making, and there is no clear theoretical guidance on the speed of form of supply adjustment. For instance, in sugarcane production in Eswatini, where decisions may be influenced by weather variability, input costs, market access issues, and other constraints, the distributed lag framework provides the empirical flexibility to better capture the complex timing and magnitude of supply response to price and non-price factors. This has been highlighted in agricultural supply studies in similar contexts, where time lags often arise from biological cycles, seasonal credit availability, and planning uncertainties (Behrman, 1968; Bond, 1983).

Moreover, distributed lag models offer a conceptual and empirical bridge to more advanced time series models, particularly the Autoregressive Distributed Lag (ARDL) approach. ARDL models integrate distributed lag regressors with lagged dependent variables, allowing for simultaneous estimation of short-run and long-run relationships. They can be beneficial, especially when dealing with a small sample or with variables possessing mixed integration orders (Nkoro & Uko, 2016; Pesaran & Shin, 1995).

3.1.4 Autoregressive Distributed Lag (ARDL) and Autoregressive Moving Average (ARMA) Models in Agricultural Supply Response

Even though distributed lag models provide a framework for capturing delayed responses of agricultural output to changes in explanatory variables, they often rely on the assumption of stationarity and do not address long-run equilibrium relationships. As agricultural time series data are usually non-stationary, more flexible models such as the ARDL and ARMA models have become increasingly important in empirical supply response analysis (Maddala, 2001).

In time series modelling, it is important to determine whether the variables are stationary, meaning their mean and variance remain constant over time. If variables are non-stationary, regressions involving them may lead to spurious results. Integration order helps classify the stationarity properties of a time series. If a variable is said to be I(0), it is stationary in levels, and if it is I(1), it becomes stationary after first differencing. Tests such as the Augmented Dicky-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) are used to check for stationarity and integration order of time series variables (Dickey, 2015; Dickey & Fuller, 1979; Lee & Schmidt, 1996; Witt et al., 1998).

However, when individual series are non-stationary, they may exhibit cointegration, implying a stable long-run equilibrium relationship between them. This is relevant in agricultural economics, where variables like crop area, expected prices, and rainfall often move together in the long run. For instance, farmers may adjust planting decisions based on a long-term expectation of profitability, linking harvested area and price trends over time.

The ARDL model can handle variables that are a mix of I(0) and I(1), without requiring all time series to be integrated to the same order. This makes ARDL suitable for empirical studies with a small sample size and mixed stationarity.

An ARDL model can be written as:

$$Y_t = \alpha_0 + \sum_{i=1}^{I} \phi_i Y_{t-i} + \sum_{j=0}^{J} \beta_j X_{t-j} + \varepsilon_t \qquad (7)$$

Where: Y_t = Dependent variable,

Y_{t-i} = lagged dependent variable,

X_{t-j} = current and lagged independent variables,

ϕ_i and β_j = short-run dynamic coefficients,

ε_t = error term.

i = 1…. I,

j = 1… J

The specified model enables researchers to estimate both short-run and long-run effects in a unified framework. The bounds' testing approach is to test for the existence of cointegration among variables in the ARDL model (Hassler & Wolters, 2006).

On the other hand, ARMA models are applied to univariate stationary time series. An ARMA model can be specified as:

$$Y_t = \alpha + \sum_{i=1}^{I} \phi_i Y_{t-i} + \sum_{j=1}^{J} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (8)$$

Where:

Y_t = Dependent variable at time *t*.

α = Intercept term or constant.

ϕ_i = Autoregressive coefficients, capturing the influence of lagged values of Y on its current value.

Y_{t-i} = Lagged dependent variable at time *t – i,* where *i* = 1…, I.

θ_j = Moving average coefficients, capturing the effect of past error terms on current Y_t.

ε_{t-j} = lagged error terms at time *t – j,* where *j* = 1…, J.

ε_t = White noise or current-period error term, assumed to be normally distributed with mean zero and constant variance.

Here, the AR (autoregressive component captures persistence in the dependent variable, while the MA (moving average accounts for serial correlation in the error terms. Generally, ARMA models are used in forecasting variables like crop yield or prices rather than estimating structural relationships. However, they play a complementary role in analysing the dynamics of agricultural output when combined with explanatory variables in Autoregressive Integrated Moving Average (ARIMA) or Autoregressive Integrated Moving Average with exogenous variables (ARIMAX) frameworks (Box & Jenkins, 1976).

When residuals are serially correlated, they can undermine the reliability of statistical inference; this econometric issue of autocorrelation can be addressed by incorporating lagged terms of both the dependent and error variables (Wooldridge, 2016). Multicollinearity is another issue in supply response models, which arises when independent variables are highly correlated. This can inflate the standard errors of the estimated coefficients. The ARDL model mitigates this issue by distributing the effects of collinear variables across different lags, thereby improving the precision of the estimation (Gujarati & Porter, 2009).

3.1.5 The Engle-Granger Two-Step Procedure: Cointegration and Error Correction

The Engle-Granger Two-Step method, introduced by Engle and Granger (1987), is a seminal approach for analysing cointegrated time series. It allows for the estimation of both long-run and short-run relationships through an Error Correction Model (ECM). The technique is relevant in agricultural supply response studies, where adjustments in variables often unfold gradually due to biological and behavioural lags.

The first step of the Engle-Granger procedure involves estimating a long-run relationship among non-stationary variables that are integrated of the same order I(1). The equation is estimated using Ordinary Least Squares (OLS). Although OLS is applied to non-stationary series, the method remains valid for cointegration analysis because the focus lies in testing whether the residuals from the regression are stationary (Engle & Granger, 1987). While the traditional Engle-Granger framework uses contemporaneous values of explanatory variables, it is often beneficial to include lags to account for adjustment delays. This is because in agricultural supply, decisions are not instantaneous; farmers may respond to past prices or environmental conditions. The inclusion of lagged independent variables acknowledges the distributed lag nature of agricultural production and decision-making (Sadoulet et al., 1996). After estimating the long-run regression, the residuals are tested for stationarity using unit root tests such as the ADF test. The null hypothesis is that residuals have a unit root (no cointegration), and the alternative hypothesis is that the residuals are stationary (cointegration exists). If the residuals are stationary, it indicates that the variables share a stable long-run relationship despite being non-stationary individually (Engle & Granger, 1987). The second step involves modelling the short-run dynamics and incorporating the Error Correction Term (ECT) to account for deviations from the long-run path. The ECT is the lagged residual from the long-run cointegration regression:

$$ECT_{t-1} = \mu_{t-1} = A_{t-1} - (\beta_0 + \beta_1 P_{t-1} + \beta_2 M_{t-1} + \beta_3 F_{t-1}) \quad (9)$$

Where:

A_{t-1} = area under sugarcane harvested at time $t - 1$.

P_{t-1} = sucrose price (proxy for sugarcane price) at time $t - 1$.

M_{t-1} = maize price (proxy for substitute crop) at time $t - 1$.

F_{t-1} = fertiliser price (proxy for input cost) at time $t - 1$.

β_0 = intercept.

$\beta_1, \beta_2, \beta_3$ = long-run coefficients that capture elasticities of area harvested with respect to sucrose price, maize price, and fertiliser price, respectively.

This lagged residual becomes a regressor in the ECM, capturing how much of the deviation from the long-run equilibrium in the previous period needs to be corrected in the current period. The estimated ECM with distributed lags will look like this

$$\Delta A_t = \alpha_0 + \sum_{i=1}^{I} \alpha_{1i} \Delta P_{t-i} + \sum_{j=1}^{J} \alpha_{2j} \Delta M_{t-j} + \sum_{k=1}^{K} \alpha_{3k} \Delta F_{t-k} + \lambda ECT_{t-1} + \epsilon_t \quad (10)$$

Where:

ΔA_t = Change in area under cultivation (dependent variable).

ΔP_{t-i}, ΔM_{t-j} ΔF_{t-k} = Lagged changes in sucrose price, maize price, and fertiliser price (dependent variable)

α_0 = Intercept.

α_{1i} α_{3k} = Short-run coefficients on each lag.

λ = Speed of adjustment coefficient (should be negative and significant).

ECT_{t-1} = Lagged error correction term derived from the cointegrating relationship.

ϵ_t = Error term.

i = 1… I,

j = 1… J,

k = 1… K.

Moving on to Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. In many agricultural time series analyses, especially in developing countries, price volatility and weather-related shocks lead to heteroskedastic residuals. This violates the classical assumption of constant error variance, which can bias inference. To address this, GARCH models are employed. Introduced by Bollerslev (1986), the GARCH model captures time-varying volatility in the error term:

$$\varepsilon_t = z_t\sqrt{h_t,}\ z_t \sim N(0,1)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{11}$$

Where:

h_t = Conditional variance at time *t*.

α = ARCH effect (sensitivity to recent shocks)

β = GARCH effect (persistence of past volatility)

ω = Constant.

GARCH models are commonly estimated as a second stage, with residuals from the ECM used as input. This enables researchers to analyse not only mean relationships but also the variance dynamics, which is vital when agricultural decision-making is sensitive to risk and uncertainty (Engle, 1982; Nyankori, 1996)

3.2 Conceptual Framework

The conceptual framework for this study is grounded in the theory of supply response, particularly Nerlove's (1958) adaptive expectations and partial adjustment model, which is employed in agricultural economics. It provides a systematic structure for understanding how farmers respond to both price and non-price factors in making production decisions. About Eswatini, sugarcane production is characterised by long gestation periods, contract-based out grower arrangements, and input costs. As such, farmers are unable to respond immediately to market signals due to various constraints. Thus, aligning with the assumptions of the Nerlove model, which highlights that supply response is lagged and subject to partial adjustment

(Askari & Cummings, 1977b; Griliches, 1960). The following key concepts are what guide the study:

Key Concepts

a) Lagged Adjustment in Supply

Farmers adjust their cultivated area in response to prices over multiple periods. This is due to immobility, fixed cropping calendars, and risk aversion in the face of climate uncertainty (Ellis, 1993).

b) Adaptive Expectations

Agricultural producers form expectations of future prices based on past prices, which affects their decisions in allocating land. The assumption is that expectations adjust gradually rather than immediately (Femenia & Gohin, 2011).

c) Price and Non-Price Determinants

Agricultural supply is influenced not only by the price of the crop, but also by other variables such as input costs (e.g. fertiliser prices), opportunity costs (e.g. price of substitutes such as maize), and exogenous variables (e.g. rainfall and institutional factors).

d) Institutional and Technological Constraints

Factors like land tenure arrangements, access to irrigation, market agreements, quotas, and advanced seed. Technology and machinery should be considered when estimating supply response, especially for developing countries, since many farmers, for instance, in Eswatini face constraints in accessing capital for purchasing advanced technology to maximise their output. Considering the partial adjustment, they are most likely to adjust their production practices over time to accommodate technological advancement. This influences the amount supplied by the farmers and must be captured in the supply response model (Barrett, 2010; Diao et al., 2007).

e) Perennial Crop Dynamics

Sugarcane is a perennial crop with multiple harvests (without replanting) and a long gestation period, which introduces biological lags. Considering the biological lags in the supply response model helps gain an understanding of how farmers adjust and allocate their land resources in response to prices and non-price factors when natural lags are considered (McKay et al., 1999).

The conceptual framework, therefore, incorporates lagged behavioural responses, dynamic expectations, and both price and non-price influences to better understand land allocation decisions in sugarcane cultivation. This forms the basis for the empirical model specified below.

3.3 Empirical Framework

Building on the conceptual foundations, the empirical framework aims to quantify the relationship between sugarcane area harvested and its determinants using a time series econometric approach. The study employs the Engle-Granger (1987) two-step method to test for a long-run relationship and an ECM to capture short-run adjustments.

3.3.1 Long-Run Model Specification

The long-run model is specified as a distributed lag function where the area harvested responds to past values of key explanatory variables. This reflects that farmers adjust their resource allocation decisions over time in response to past changes in both economic and environmental factors. The model can be expressed in general form as:

$$A_t = \alpha_0 + \sum_{i=1}^{I} \alpha_{1i} P_{t-i} + \sum_{j=1}^{J} \alpha_{2j} M_{t-j} + \sum_{k=1}^{K} \alpha_{3k} F_{t-k} + \varepsilon_t \qquad (12)$$

Where:

A_t = Area of sugarcane harvested at time *t.*

P_t = Sucrose price (own price) in period *t.*

M_t= Maize price (cross price) in period *t.*

F_t = Fertiliser price (input cost) in period *t.*

ε_t = Error term

α_0 = Intercept term

$\alpha_1, \alpha_2, \alpha_{3,} \alpha_4$ = Long run elasticities or coefficients capturing the magnitude and direction of the relationship between the explanatory variables and sugarcane area.

i = 1… I,

j = 1… J,

k = 1… K.

This equation captures how past values of prices and rainfall influence farmers' decisions to allocate land for sugarcane. Lagged values account for time delays in adjustment due to the perennial nature of sugarcane, planting constraints, and information asymmetries.

3.3.2 Stationarity Testing

Before estimating the model, unit root tests are conducted to determine the order of integration of each variable using the ADF, PP, and KPSS tests. Employing these tests helps identify whether the variables are stationary or non-stationary, which is crucial when selecting an appropriate model strategy. Variables that are integrated of order I(1) are retained for cointegration testing. This is essential to prevent spurious regressions that can occur when non-stationary variables are used in OLS regression models, leading to misleading results (Enders, 2008). Although the long-run model can be estimated with non-stationary variables, ensuring that the variables are stationary after first differencing is necessary for applying cointegration techniques such as the Engle-Granger or Johansen methods, which require the variables to be stationary at first differencing (Engle & Granger, 1987; Johansen, 1991).

3.3.3 Cointegration and Error Correction Model

If the variables are integrated of the same order I(1), the next step is to test for cointegration by using the ADF test to check for stationarity on the residuals extracted from the long-run model. If residuals are stationary (I(0)), it implies that a long-run equilibrium relationship exists among the variables. This enables the estimation of the short-run supply relationship using the ECM method, and the general form of the model takes the functional form:

$$\Delta A_t = \beta_0 + \sum_{i=1}^{I} \beta_{1i} \Delta P_{t-i} + \sum_{j=1}^{J} \beta_{2j} \Delta M_{t-j} + \sum_{k=1}^{K} \beta_{3k} \Delta F_{t-k} + \phi ECT_{t-1} + \mu_t \qquad (13)$$

Where;

Δ = First difference operator.

ECT_{t-1} =lagged error correction term from the long-run model.

ϕ = Measures the speed of adjustment back to equilibrium

μ_t = is the short-run error term.

β_0 = The intercept.

$\beta_{1i}, \beta_{2i}, \beta_{3k}$ = Short-run coefficients measuring immediate effects.

The role of the error correction term is to reconcile short-term disequilibria with the long-term relationship. The coefficient ϕ is expected to be negative and statistically significant, confirming that deviations from the long-run equilibrium are corrected over time (Hendry & Juselius, 2000).

3.3.4 Diagnostic and Model Evaluation Tests

The robustness of the ECM is essential and must be evaluated using different diagnostic tests to ensure that the classical linear regression assumptions are not violated and the model provides reliable and unbiased estimates. These tests are used to assess the validity of residual behaviour, model specification, multicollinearity and parameter stability. These components are critical in model analysis to provide accurate results. Table 3.1 below summarises the choice of diagnostic tests, their purpose, rationale for their inclusion, and their expected results.

Table 3.1: Summary of Diagnostic Tests

Test	Purpose	Rationale for inclusion	Expected results
Durbin-Watson Test	For autocorrelation of residual	Serial correlation inflates standard and biases test statistics (Durbin & Watson, 1992).	No autocorrelation ($p>0.05$)
Shapiro-Wilk Test	For normality of residuals	Normality is a classical assumption for valid inference and small-sample properties. The test is to assess whether the sampled data comes from a normally distributed population (Shapiro & Wilk, 1965).	Residuals are normally distributed
Breusch-Pagan Test	For heteroskedasticity of residuals	Heteroskedasticity is when the variance of the error terms is not constant across all levels of the independent variables. Heteroskedastic errors invalidate standard errors in regression models.	Homoscedastic residuals

		Hence, validation of results must be ensured (Halunga et al., 2017).	
Variance Inflation Factor	For Multicollinearity	When two or more independent variables are highly correlated with each other, and difficult to separate their individual effects on the dependent variable, they normally exhibit multicollinearity. High collinearity can distort the standard errors and their significance making it hard to distinguish which variables are truly significant predictors (Thompson et al., 2017).	VIF<10
Ramsey RESET Test	For functional form misspecification	Helps detect omitted variables or incorrect functional form. Which means that it accurately reflects the relationship between variables. It mainly assesses whether the model might be missing non-linear relationships or if the assumed functional form is appropriate (Ramsey, 1969).	Insignificant test statistic
CUSUM and CUSUMSQ	For stability of regression coefficients over time	Detects changes or shifts in a sequence of data points over time. The method ensures coefficients are stable over time and not regime dependent. It is helpful in identifying structural breaks in time series data and assessing parameter stability in econometric models (Brown et al., 1975).	Plot stays within 5% boundaries

These tests are essential for diagnosing econometric issues that could invalidate the findings of the study. For example, autocorrelation and heteroskedasticity are common issues in agricultural time series data, due to seasonality, shocks, or structural changes in production behaviour (Hill et al., 2018). Addressing these issues using appropriate tests helps to ensure that the model is robust and captures the true underlying relationships without being biased by econometric flaws.

3.3.5 Data

Table 3.2: Description of variables

Variable	Definition	Measurement	Expected sign	Data Source
A_t (Area harvested)	Area under sugarcane harvested	Hectares	_	United States Department of Agriculture (USDA)
S_t (sucrose price)	Sucrose price (proxy for sugarcane price)	US Dollar/Ton	Positive (+)	Eswatini Sugar Association (ESA)
M_t (Maize price)	Maize price (proxy for substitute crop)	US Dollar/ Ton	Negative (-)	National Maize Corporation, FAOSTAT
F_t (Fertiliser price)	Fertiliser price (proxy for input costs)	US Dollar/Ton	Negative (-)	FAOSTAT
ECT_{t-1} (Error correction term)	Error correction term (residual from long run model)	Unitless	Negative (-)	Computed from OLS residuals

As shown in Table 3.2, appropriate data relating to sugarcane production are important in this study to carry out an econometric analysis that is based on the objectives of the study. The study has made use of historical time series data obtained from various reliable sources for the period 2000 to 2022. The data acquired was annual data, which included area harvested sourced from the United States Department of Agriculture annual reports. Sugarcane prices were sourced from the Eswatini Sugar Association, and maize prices were sourced from the National Maize Corporation's annual reports and Food and Agriculture Organisation Statistics (FAOSTAT). The study has also included fertiliser prices, which were sourced from FAOSTAT. The sugarcane and maize prices were obtained in the local currency and later converted to US Dollars for data uniformity. Furthermore, all the prices included for analysis were deflated using the Consumer Price Index obtained from the World Bank, with 2010 being the base year. This was done to derive the real prices of the variables in preparation for analysis.

3.3.6 Empirical examples

The application of distributed lag models and ECMs to investigate supply response has been supported by empirical studies. Contributions by Askari and Cummings (1977b) investigated the supply response of major crops in India and Pakistan using the Nerlovian adaptive expectations model. The findings were that agricultural supply responses are inelastic in the short run but increase in magnitude over the long run due to partial adjustment processes. They highlighted the importance of including non-price factors such as rainfall and inputs, which are critical for modelling in developing countries with structural constraints.

Vitale et al. (2009) Estimated the supply response of cotton producers in West Africa (Mali). The study adopted the Nerlovian supply response model showing that the price responsiveness was relatively inelastic for Mali cotton farmers, with supply elasticities only about one-half of those estimated for producers in developed countries. To improve responsiveness to prices, policy reforms were suggested as a mechanism to also increase the average productivity levels.

Bateman (2017) reviewed different empirical work related to the supply function for tree crops, and general models that can be applied to perennials such as cocoa, rubber, lemons, and coffee. The study highlighted two main points of interest for developing supply models for perennials, which are ascertaining what forces motivate the farmer to plant, and what is the relationship between acres planted and output harvested. However, Ady (1968) reviewed various models of cocoa studies Bateman (1965) and came up with an alternative approach that had alternative assumptions about producer price expectations to allow for the effect of statutory marketing. The resultant model was used to test for Uganda coffee and Nigerian cocoa, which assumed that producer price expectations at the time of planting were influenced by last year's price and partly by the course of world prices. The findings suggested the influence of world prices does not take a distributed lag form, since the results were more successful when using the deflated last year's price than a 3-year moving average. The results further showed a strong positive reaction of planting to real prices, and a strong positive response to prices at harvesting was recognised in both Uganda coffee and Nigerian cocoa. However, a strong inverse relationship was indicated between cocoa's output and current prices.

Dowling (1979) Analysed the supply response of Thailand based on the Nerlove model and the distributed lag model. The study used the relative price of rubber to rice instead of the real price of rubber, which resulted in more satisfactory statistical results. However, inconsistencies between the theoretical model and the empirical results were partially due to the lack of reliable estimates for the area planted function. Data limitations are a common issue in supply response studies, especially in developing countries, which limits the accuracy and omission of key variables.

3.3.7 Modelling Limitations

While the empirical strategy adopted in this study is grounded in the Nerlove partial adjustment framework, it is subject to several limitations which must be acknowledged. These limitations relate to data constraints, estimation challenges, and model specification decisions.

The time series data used in the study comprises only 23 observations, which limits the degrees of freedom when estimating lagged models like ECM. It is suggested that for more precise observations should be above 30. However, 20-30 observations are acceptable, but extreme caution in the interpretation of the output must be taken. This is because in small samples, coefficient estimates (particularly dynamic ones) may lack precision and robustness, increasing the risk of overfitting or unstable inferences.

Including a lagged error correction term in the ECM is theoretically acceptable, but in small samples, its coefficients can behave erratically. For instance, the speed of adjustment may be less than -1, which may indicate overshooting. The problem of overshooting may be due to limited observations or model misspecification. However, testing for stability is recommended to understand the cause of overshooting and tests like the CUSUM, CUSUMSQ, and M-fluctuation are utilised. If the model passes the tests, then the overshooting might be predictable and consistent. Furthermore, the assumption for overshooting might be reflecting real economic behaviour whereby farmers overreact to price shocks, especially with lags or uncertainty (Saghaian et al., 2002).

The study has further used multiple stationarity tests to check the stationarity of the variables. Since dealing with small sample sizes, the use of different stationarity tests is recommended, as some tests may have low power to precisely check for stationarity; hence, the triangulation of results improves robustness, and inconsistencies between tests may introduce ambiguity in determining the integration order of some variables. Combining multiple tests helps address this issue, but full reliability cannot be guaranteed in small samples (Brooks, 2014).

Due to data limitations, the study has excluded important variables such as labour, credit constraints, and government interventions (subsidies, quotas, or zoning, which directly shape planting choices). Supply response models that exclude variables related to input use, risk preferences, and institutional risk, attributing their effects to weather, leading to misleading estimates (Askari & Cummings, 1977b).

Lastly, the study has not modelled structural breaks and external shocks. Naturally, supply response models often assume a stable economic environment, but sudden changes in the underlying relationship can occur due to reasons such as policy regime changes (e.g., liberalisation, new land laws), climate shocks such as prolonged droughts or floods affecting perennial crops long-term. Furthermore, pets and disease outbreaks, and global price volatility can cause external shocks. Given that sugarcane in Eswatini is an export crop, omitting global price volatility can affect the precision of the supply response model estimate. This is because open economies like Eswatini often form supply decisions based on expected export prices, which can be highly volatile due to global market fluctuations, currency exchange movements, trade policies, tariffs, and subsidies in importing countries. Since the expectations are adaptive, they can lead to farmers overreacting to sudden price surges or drops, causing the earlier discussed issue of overshooting in the area harvested (Frankel, 1986). Moreover, since Eswatini's sugarcane industry is made up of smallholder farmers, they are more likely to lack access to real-time market information, face delays in input access or credit, and be vulnerable to price misperceptions, which is a more common issue in developing economies. This, in turn, makes them more reactive than being adaptive (Barrett et al., 2010).

CHAPTER FOUR: RESULTS AND DISCUSSION

This chapter presents the empirical results and discussion of the study. The analysis was grounded on the theoretical and empirical framework outlined in the previous chapter, which combined classic supply theory with Nerlove's adaptive expectations model, distributed lags and cointegration (ECM). Sugarcane farmers adjust their production based on past price and non-price factors, subject to distributed lags and expectations. The choice of variables used for estimation was guided by economic supply theory. The study has employed area harvested as a proxy area under cultivation, since it serves as a practical substitute when accurate data on planted area is unavailable or unreliable (French & Matthews, 1971). Moreover, the area harvested is closely aligned with farmers' decision-making processes, since it directly reflects the choices about land use in response to economic incentives. However, yield is influenced by exogenous factors such as weather conditions, pest outbreaks, and soil fertility, which lie largely outside the control of the farmer (Weersink et al., 2010). Thus, investigating producers' reactions to price changes, using area harvested, provides a more behaviourally consistent indicator of resource allocation decisions. Furthermore, the study has used the sucrose price as a proxy for own price since this is the farm gate price producers receive for their output, which has been discussed in chapter two. Maize prices were also used as a proxy for a substitute crop. The inclusion of the substitute crop is based on supply theory, as farmers are likely to reallocate their resources towards the substitute crop if prices are relatively higher or producing it is more profitable. This is important since it captures the shifts in the supply curve alongside input costs such as fertiliser prices, which have been included in the estimation. This has been done to capture the dynamics of input costs on how farmers react when there is a variation. Due to data availability, careful consideration had to be taken in including the parameters since with small sample sizes, the addition of many variables limits degrees of freedom, which in turn will affect the analysis of the model. This could also bring about problems of overfitting; hence, other variables were not included in this analysis (Pandey & Bright, 2008).

The estimated long-run model was based on the general model presented below:

$$A_t = \alpha_0 + \sum_{i=1}^{I} \alpha_{1i} P_{t-i} + \sum_{j=1}^{J} \alpha_{2j} M_{t-j} + \sum_{k=1}^{K} \alpha_{3k} F_{t-k} + \varepsilon_t \quad (13)$$

Adaptations of the general model were done to get a more satisfactory model. The alternative model specifications presented in the appendices were not retained for discussion as some long-run estimations failed cointegration tests (see Appendix C), suggesting spurious relationships (see Appendix A), while certain ECM outputs displayed overshooting beyond plausible bounds (see Appendix B). These shortcomings rendered the results unreliable, and therefore, the main analysis focused on the final ECM, which satisfied diagnostic checks and aligned with theoretical expectations. Hence, the following model was formed for final estimation:

$$A_t = \alpha_0 + \beta_1 P_{t-2} + \beta_2 M_t + \beta_2 M_{t-2} + \beta_3 F_t + \varepsilon_t \quad (14)$$

Where:

A_t: Area under sugarcane (dependent variable),

P_{t-2}: Sucrose prices at t-2

M_t, M_{t-2}: Maize price (substitute crop) at time t and t-2

F_t: Fertiliser price at time t

ε_t: Random error term

Equation (14) has been used to estimate the long-run effect, and its residuals were employed to test for cointegration. The cointegration test was necessary to determine whether the variables were cointegrated or not. Furthermore, this also acts as a check to ensure that the regression analysis is not spurious and does not produce false results; therefore, identifying cointegration in the results validates the relevance of the long-run estimate outcomes and is suitable for discussion. After identifying cointegration, an ECM was developed. The formulation of the estimate was based on the general equation below:

$$\Delta A_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta P_{t-i} + \sum_{j=1}^{q} \beta_{2j} \Delta M_{t-j} + \sum_{k=1}^{r} \beta_{3k} \Delta F_{t-k} + \phi ECT_{t-1} + \mu_t \quad (15)$$

Descriptions of the general short-run equation have been previously discussed in the former chapter. The estimated equation model is as follows:

$$\Delta A_t = \gamma_0 + \alpha_1 \Delta P_{t-2} + \alpha_2 \Delta M_t + \alpha_3 \Delta M_{t-2} + \alpha_4 \Delta F_t + \emptyset EC_{t-1} + \mu_t \quad (16)$$

Where:

ΔA_t First difference of area harvested for sugarcane

ΔP_{t-2}: First difference of lagged sucrose price

ΔM_t , ΔM_{t-2}: First difference of current and lagged maize price

ΔF_t: First difference of fertiliser price

EC_{t-1}: Lagged error correction term derived from the residuals of the long-run equation

$\emptyset$: speed of adjustment coefficient (expected to be negative and significant)

μ_t: Error term

4.1 Stationarity and Cointegration Tests

The study has tested stationarity using the ADF, PP, and KPSS tests to confirm stationarity of the variables and order of integration. The rationale for using different statistical tests was to ensure robustness and solve issues of inconclusive results on different tests. The thumb rule is that when two or three of the tests suggest stationarity, we assume the variable to be stationary. Furthermore, a cointegration test was performed using the ADF test on the residuals of the long-run model. The results of stationarity are as follows:

Table 4.1: Stationarity Results at Level

Variable	ADF P-value	PP P-value	KPSS P-value	Conclusion at Level
Area	0.0846	0.6113	<0.01	Non-stationary
P	0.1698	0.5185	0.0119	Non-stationary
M	0.2790	<0.01	<0.01	Non-stationary
F	0.6745	0.0668	0.0481	Non-stationary

Table 4.2: Stationarity Results at 1st Difference

Variable	ADF P-value	PP P-value	KPSS P-value	Conclusion at 1st difference
Area	0.148	<0.01	>0.1	Stationary
P	0.043	0.146	>0.1	Stationary
M	<0.01	<0.01	>0.1	Stationary
F	0.246	0.013	>0.1	Stationary

The results shown in Table 4.1 show that all variables are non-stationary at the level, as all the ADF and PP tests fail to reject the null hypothesis of non-stationarity, and the KPSS confirms non-stationarity on all variables. This concludes that the variables at the level are non-stationary. A further analysis of the root test has been done, as first differences of the variables were taken to be tested for stationarity. According to Table 4.2, the variables were stationary since some variables, such as area and fertiliser price (F), had mixed results, but since two of the three tests confirmed stationarity, we assumed that they are stationary and appropriate for the cointegration test.

Table 4.3: Cointegration Test Results

Test Type	Test Statistic	Lag Order	P-value	Conclusion
ADF on residuals	-3.7404	2	0.03997	Residuals are stationary

An ADF test was applied to the residuals of the estimated long-run relationship. The p-value was 0.03997, rejecting the null hypothesis of non-stationarity as shown in Table 4.3. This suggests that the residuals are stationary and thus the variables in the long-run model are cointegrated. The findings of the cointegration test suggested that an ECM is feasible.

4.2 Estimation Results

4.2.1 Long-run Model Results

The long-run estimation results, as presented in Table 4.4, show key insights into the variables influencing sugarcane supply response in Eswatini. The dependent variable, area harvested, was regressed on lagged sucrose prices (P_{t-2}), current and lagged maize prices (M_t and M_{t-2}), and current fertiliser prices (F_t), guided by the Nerlove adaptive expectations framework and the broader supply response literature.

The adjusted R-squared of the model is 0.8115, suggesting that approximately 81% of the variation in area harvested is explained by the included independent variables. This is a reasonably good fit for the model, which validates the theoretical underpinning that both price and non-price factors influence agricultural supply decisions. According to the findings, maize price both in the current period and two years ago is statistically significant at 1% level and harms the area harvested for sugarcane. In the current period, a unit increase in maize price reduces area harvested by 26.2 hectares; a unit increase two years ago reduces area harvested by 26.5 hectares.

Table 4.4: Long-run estimates for the sugarcane supply response model

Sugarcane Long-run Model				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
P_{t-2}	11.464	12.250	0.936	0.3632
M_t	-26.157	6.613	-3.955	0.0011 ***
M_{t-2}	-26.528	7.516	-3.529	0.0028 ***
F_t	-5.154	2.619	-1.968	0.0667 *
R-squared	0.8492	**Adjusted R-squared**	0.8115	
Significance	p< 0.01***	p<0.05**	p<0.1*	

The findings show the competitive relationship between maize and sugarcane, whereby increases in the profitability of maize will likely cause farmers to divert their resources away from sugarcane cultivation. This indicates the substitution effect in supply, which assumes that farmers are likely to respond to returns of alternative crops. The findings provide strong empirical evidence for the substitution effect between sugarcane and competing crops. This is consistent with the findings of Griliches (1960) and the work of Wickens and Greenfield (1973) who observed that competing crops significantly influence farmers' land allocation decisions in the long-run due to changes in their profitability.

Current fertiliser price is also statistically significant at 10% level and negatively affect area harvested of sugarcane. This indicates that a unit increase in fertiliser price reduces the area harvested by 5.2 hectares. Which means that a rise in input costs can discourage farmers from expanding or maintaining sugarcane acreage. Given that sugarcane is a relatively input-intensive crop, particularly with fertiliser requirements, this reflects a cost-push constraint on supply. An increase in input costs raises production costs, hence reducing returns from sugarcane production, discouraging supply (Tweeten & Quance, 1969).

4.2.2 Short-run Model Results

The results in Table 4.5 show the estimated short-run dynamics of sugarcane supply in Eswatini using an ECM. The model included differenced independent variables to capture the short-run changes and included the lagged error correction to reflect the speed of adjustment towards the long-run equilibrium. The dependent variable is explained by approximately 70% of the variation of the independent variables.

Table 4.5: Short-run estimate for the sugarcane ECM Model

Sugarcane Short-run Model				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
ΔP_{t-2}	33.2112	7.5221	4.415	0.0013 ***
ΔM_t	-27.7242	5.2589	-5.272	0.0004 ***
ΔM_{t-2}	-26.9901	6.5022	-4.151	0.0020 ***
ΔF_t	-4.9291	1.4329	-3.440	0.0063 ***
ECT_{t-i}	-0.7589	0.2580	-2.941	0.0148 **
R-squared	0.7969	**Adjusted R-squared**	0.6953	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Lagged change of sucrose price is positive and significant at level 1%. A unit change in the sucrose price two years ago increases the area harvested by 33.2 hectares in the short-run. This may reflect adaptive expectations and planning cycles, where producers adjust supply only after confirming persistent price trends. Farmers may wait to observe if the price changes are persistent before committing additional resources, especially where crop replanting involves high fixed costs and irreversibility (Muth, 1961; Nerlove, 1958). Again, in the short-run both current and two-period lagged changes in maize price are negative and statistically significant at 1% level. This also confirms the substitution effect between maize and sugarcane, where short-run increases in maize prices divert resources away from sugarcane. According to the results, a unit increase in current maize price reduces area harvested by 27.7 hectares, and a unit increase in maize price two years ago reduces area harvested by 27 hectares. The significant magnitude of these coefficients suggests that farmers in Eswatini are highly responsive to relative crop profitability in the short term. The findings reiterate that sugarcane supply is sensitive not only to its own price incentives but also to substitute crops. This is consistent with the theoretical foundation that farmers maximise short-term expected returns by adjusting land allocation between crops as relative profitability changes (Askari & Cummings, 1977a)

Current fertiliser price is also significant at 5% level with a coefficient of -4.9291. This means that a unit increase in current fertiliser prices reduces the area harvested by 4.9 hectares. The findings suggest that rising input costs in the short run discourage planting decisions. Farmers, especially smallholders, are often constrained by inadequate liquidity or access to subsidised inputs, making them vulnerable to input price volatility (Key et al., 2000). The results highlight. The critical role that production costs and liquidity constraints play in agricultural production decisions is noted in studies by Dorward et al. (2002) and Fan et al. (2008).

As expected, the error correction term is negative and statistically significant at 5% level. The coefficient implies that 76% of the previous period's deviations are corrected in the current period, reflecting a rapid adjustment to the long-run equilibrium. The significance of the error correction term validates the long-run cointegration relationship and that short-run shocks to the area harvested are not persistent, as the system tends to revert to its long-run equilibrium.

For instance, in a Tanzanian study using ECM, the coefficient on the error-correction term was significant and indicated that a part of the gap is closed each year (Mbua, 2020). For example, if about 40-50% of the deviation is corrected per year, that implies a moderate speed of adjustment, which suggests that farmers take a couple of years to adjust to a new equilibrium after a price shock. A slower speed of adjustment would suggest protraction, maybe due to severe constraints.

The results presented from the short-run ECM provide valuable insight into the supply responsiveness of sugarcane farmers to price and input cost changes in the study area. The significant positive response of area harvested to lagged changes in sucrose price is consistent with the Nerlove partial adjustment theory, which emphasises that past prices affect current agricultural supply decisions due to adjustment lags and biological constraints, especially when dealing with semi-perennial and perennial crops like sugarcane.

4.2.3 Diagnostic check

A Durbin-Watson test was conducted to test for the presence of first-order autocorrelation in the residuals. The results, as shown in Table 4.6, depict that the DW statistic was 1.79 and the p-value was 0.3604, suggesting that the null hypothesis of autocorrelation was not rejected. The DW statistic is close to 2, suggesting that there is no autocorrelation. The residuals of the ECM model show no significant autocorrelation. This is important since autocorrelation can lead to inefficient estimates and biased standard errors.

Table 4.6: Autocorrelation Test

Test	**DW Statistic**	**P-value**	**Decision**
Durbin-Watson Test	1.7889	0.3604	No evidence of autocorrelation

To test for normality, a Shapiro-Wilk test was applied. The results are shown below in Table 4.7, as the p-value of 0.5213 is greater than 0.05, indicating that the residuals are normally distributed. These results satisfied the normality assumption required for valid hypothesis testing in OLS models. This ensured the reliability of the p-value and confidence intervals of the regression output.

Table 4.7: Normality Test

Test	**W Statistic**	**P-value**	**Decision**
Shapiro-Wilk Test	0.95196	0.5213	Residuals are normally distributed

For heteroskedasticity, a Breusch-Pagan Test was conducted, and the p-value was 0.9232, failing to reject the null hypothesis of homoscedasticity. This indicated that there was no evidence of heteroskedasticity in the model.

Table 4.8: Heteroskedasticity

Test	**BP Statistic**	**Degrees of Freedom**	**P-value**	**Decision**
Breusch-Pagan Test	1.4104	5	0.9232	No evidence of heteroskedasticity

Furthermore, the model was tested for multicollinearity, and the VIF for all variables was between 1.28 and 2.73, which means that multicollinearity among the independent variables was not present. This was a good measure, suggesting that the estimated coefficients were stable and reliable.

Table 4.9: Multicollinearity Test

Variable	VIF
Lagged P	1.282
M	1.947
Lagged M	2.726
F	2.309
ECT	1.896

The Ramsey RESET Test was used to evaluate whether the model was correctly specified by testing for omitted variables or incorrect functional form. The high p-value (0.7347) suggested there was no evidence of misspecification in the model.

Table 4.10: Model Specification Test

Test	RESET Statistic	Degrees of Freedom	P-value	Decision
RESET Test	0.32042	(2,8)	0.7347	No model specification errors

Lastly, for structural stability, the OLS_CUSUMSQ test was used to test whether the model remains stable over the sample period. The p-value, as shown in Table 4.11 below, was 0.6926, suggesting that there are no significant structural breaks. This means that relationships between the variables remain stable throughout the sample.

Table 4.11: Structural Stability Test

Test	DW Statistic	P-value	Decision
OLS_CUSUMSQ (M-fluctuation Test)	1.099	0.6926	No evidence of structural breaks

The results from this study provided an understanding of sugarcane response in Eswatini. Guided by the Nerlove adaptive expectations framework and rooted in classical supply theory, both the long-run and short-run models confirm that sugarcane farmers adjust their area harvested in response to substitute crop profitability and input costs rather than own-price alone. While the sucrose price was found to be statistically insignificant in the long run, it had a positive and significant impact in the short run, which indicates a delayed and adaptive response likely from biological and institutional constraints in sugarcane production. However, maize prices (substitute crop) were constantly significant and negatively affected sugarcane acreage across both models, implying a strong substitution effect. Fertiliser prices also had a negative and significant effect in both models, revealing cost-related issue to supply expansion. The error correction term confirmed the existence of a long run equilibrium relationship, with a relatively high speed of adjustment, indicating that deviations are corrected within a short time frame. Furthermore, diagnostic tests validated the robustness, reliability and structural stability of the model. Overall, the results point to the importance of relative prices, input affordability, and timely price signals in shaping farmers' land allocation decisions. These findings carry important policy implications for improving the responsiveness of sugarcane supply to economic incentives.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study examined Eswatini's sugarcane farmers' supply responses, considering both price and non-price factors. The survey results highlight the vital role of the sugarcane sector in Eswatini's economy, as it is the leading agricultural exporter and a major source of employment. The study found that substitute crops and input costs influence farmers' decisions about the area they harvest. The profitability of substitute crops (maize) and costs of key inputs such as fertiliser significantly impact harvested area more than the price of sugarcane itself. Although the long-term effect of sucrose prices was statistically insignificant, it had a positive and significant impact in the short term. This suggests that responses are delayed and adaptive due to biological and institutional constraints within sugarcane production. Additionally, rising fertiliser prices consistently had a negative and significant effect in both the long- and short-term models of sugarcane supply, indicating that input costs present a major challenge to expanding production. The error correction term confirmed a long-term equilibrium among the variables, as it was negative and significant, as expected based on theory. The speed of adjustment was relatively rapid, meaning deviations from equilibrium are corrected quickly. Furthermore, Eswatini's sugarcane sector faces notable challenges, including climate variability risks, inefficiencies in irrigation systems, especially among smallholder farmers and rising electricity costs linked to irrigation. Adoption of modern technology, such as solar-powered irrigation, remains a barrier for smallholder farmers. While such technology is crucial for efficiency and sustainability, high initial costs for purchase and installation hinder its widespread use. Lastly, institutional factors, such as the dualistic land tenure system and the annual levies imposed by the ECGA, influence farmers' production decisions and overall profitability.

5.2 Recommendations

Based on the findings of the study, recommendations are proposed to enhance the responsiveness and sustainability of sugarcane supply in Eswatini. Developing and implementing integrated agricultural policies, considering the strong competitive relationship between sugarcane and staple crops like maize, can help involve targeted support mechanisms that can make sugarcane cultivation consistently more attractive. Eswatini farmers are burdened with input costs, especially smallholder farmers. Creation of cooperatives can increase farmers' purchasing power through bulk purchasing of inputs such as fertiliser at discounted rates. The government should also consider introducing input subsidies or other financial assistance programs that will help farmers manage their rising costs of fertilisers. Furthermore, considerations should be made for technology adoption through promotion and education on the benefits of using modern farming technologies. Price information dissemination should be timely, and reviews of the existing payment structures to growers should be conducted to improve farmers' responsiveness to sugarcane prices. This could also enhance farmers' liquidity and their ability to react to market signals. Lastly, the need for further research is imperative as future studies should aim to overcome the limitations of this study by utilising a larger dataset and incorporating unobserved critical variables such as labour, access to credit, and government policies (e.g. quotas) to provide a more comprehensive and robust understanding of sugarcane supply response. Environmental and weather variability risks are also critical to ascertaining a broader spectrum of sugarcane supply response in Eswatini.

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Appendices

Appendix A: Long-Run Model Specifications

Appendix A1: Long-Run Model 1 (Inconsistent signs, non-stationary residuals- spurious)

Sugarcane Long-run Model 1				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
P_t	-6.591	18.142	-0.363	0.7271
P_{t-1}	3.186	21.713	0.147	0.8875
P_{t-2}	39.040	20.792	1.878	0.1025
P_{t-3}	-6.925	16.882	-0.410	0.6939
M_t	-19.907	7.513	-2.650	0.0330 **
M_{t-1}	-7.006	6.849	-1.023	0.3404
M_{t-2}	-15.455	5.720	-2.702	0.0306 **
M_{t-3}	-10.562	6.313	-1.673	0.1383
F_t	-4.154	2.393	-1.736	0.1261
F_{t-1}	-3.948	2.134	-1.851	0.1067
F_{t-2}	-2.419	1.908	-1.268	0.2454
F_{t-3}	-1.694	2.175	-0.779	0.4614
R-squared	0.9781	**Adjusted R-squared**	0.9405	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Appendix A2: Long-Run Model 2 (Inconsistent signs, non-stationary residuals- spurious)

Sugarcane Long-run Model 2				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
P_t	-5.5357	28.7991	-0.192	0.8511
P_{t-1}	23.2703	40.3665	0.576	0.5759
P_{t-2}	1.0184	28.1175	0.036	0.9718
M_t	-23.8798	13.0300	-1.833	0.0940 *
M_{t-1}	-15.4392	9.9882	-1.546	0.1504
M_{t-2}	-25.9865	10.3724	-2.505	0.0292 **
F_t	-4.0692	4.1697	-0.976	0.3501
F_{t-1}	1.0422	3.8356	0.272	0.7909
F_{t-2}	-0.1316	3.6756	-0.036	0.9721
R-squared	0.8821	**Adjusted R-squared**	0.7856	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Appendix A3: Long-Run Model 3 (Inconsistent signs, but stationary residuals)

Sugarcane Long-run Model 3				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
P_t	-6.783	27.560	-0.246	0.8092
P_{t-1}	9.491	37.697	0.252	0.8049
P_{t-2}	5.888	26.046	0.226	0.8244
M_t	-23.760	12.245	-1.940	0.0727 *
M_{t-2}	-25.439	9.183	-2.770	0.0150 **
F_t	-5.608	3.802	-1.475	0.1624
R-squared	0.85	**Adjusted R-squared**	0.7857	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Appendix A4: Long-Run Model 4 (Inconsistent signs, but stationary residuals)

Sugarcane Long-run Model 4				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
P_t	-0.8394	13.7708	-0.061	0.9522
P_{t-2}	11.5489	12.7257	0.908	0.3785
M_t	-25.8146	8.8414	-2.920	0.0106 **
M_{t-2}	-26.3831	8.1171	-3.250	0.0054 ***
F_t	-5.0691	3.0425	-1.666	0.1164
R-squared	0.8493	**Adjusted R-squared**	0.799	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Appendix B: Error Correction Model (ECM) Specifications

Appendix B1: ECM Specification 1 (Inconsistent coefficient signs, Overshooting-implausible adjustment speed)

Sugarcane Short-run Model 3				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
ΔP_t	-27.7431	12.1570	-2.282	0.0519 *
ΔP_{t-1}	14.6321	10.6118	1.379	0.2053
ΔP_{t-2}	22.5923	7.9722	2.834	0.0220 **
ΔM_t	-25.3450	4.8232	-5.255	0.0008 ***
ΔM_{t-2}	-34.7300	7.0332	-4.938	0.0011 ***
ΔF_t	-7.1058	1.7559	-4.047	0.0037 ***
ECT_{t-i}	-1.2134	0.3505	-3.462	0.0085 **
R-squared	0.8686	**Adjusted R-squared**	0.7537	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Appendix B2: ECM Specification 2 (Inconsistent coefficient signs, Overshooting-implausible adjustment speed)

Sugarcane Short-run Model 4				
Variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
ΔP_t	-22.5189	10.5348	-2.138	0.0613 *
ΔP_{t-2}	30.7677	6.6667	4.615	0.0013 ***
ΔM_t	-28.1305	4.5496	-6.183	0.0002 ***
ΔM_{t-2}	-34.0557	6.5472	-5.202	0.0006 ***
ΔF_t	-6.1072	1.3643	-4.476	0.0015 ***
ECT_{t-i}	-1.2825	0.3348	-3.831	0.004 **
R-squared	0.8686	**Adjusted R-squared**	0.7537	
Significance	p< 0.01***	p<0.05**	p<0.1*	

Appendix C: Diagnostic Check (Cointegration results)

Appendix C1: ADF Test 1 (Long-Run Model 1 residuals)

Test Type	Test Statistic	Lag Order	P-value	Conclusion
ADF on residuals	-1.006	2	0.9197	Residuals are non-stationary

Appendix C2: ADF Test 2 (Long-Run Model 2 residuals)

Test Type	Test Statistic	Lag Order	P-value	Conclusion
ADF on residuals	-3.49	2	0.06527	Residuals are non-stationary

Appendix C3: ADF Test 3 (Long-Run Model 3 residuals)

Test Type	Test Statistic	Lag Order	P-value	Conclusion
ADF on residuals	-3.762	2	0.03843	Residuals are stationary

Appendix C4: ADF Test 4 (Long-Run Model 4 residuals)

Test Type	Test Statistic	Lag Order	P-value	Conclusion
ADF on residuals	-3.742	2	0.03986	Residuals are stationary