ESTIMATION OF SORGHUM SUPPLY ELASTICITY IN SOUTH AFRICA

BY

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MINI-DISSERTATION submitted in partial fulfilment of the requirements for the degree

of

Master of Science

in

Agriculture (Agricultural Economics)

in the

Faculty of Science and Agriculture

(School of Agricultural and Environmental Sciences)

at the

University of Limpopo

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2019

ABSTRACT

Studies have indicated that sorghum hectares in South Africa have been decreasing over the past decades. This has resulted in a huge importation of the grain sorghum by the country. This study was undertaken due to sorghum production variability in South Africa. The objectives of this study were to estimate elasticity of sorghum production to changes in price and non-price factors, as well as estimating the short-run and long-run sorghum price elasticity. The study used time series data spanning from 1998 to 2016. This data was obtained from the abstracts of agricultural statistics and verified by South African Grain Information Services. Variance Error Correction Model (VECM) was employed to address both objectives. A number of diagnostic tests were performed to ensure that the study does not produce spurious regression results.

This study estimated sorghum supply elasticity using two dependent variables being the area and yield response functions as model one and two respectively. The results have shown that area response function was found to be a robust model as most of the variables were significant, responsive and elastic. Maize price as a competing crop of sorghum negatively influenced the area allocation; however, the remaining variables positively influenced the area allocation in the long-run. In this model, all variables were statistically significant at 10% and 1% in the short and long-run respectively.

In the yield function, most of the variables were insignificant, not responsive and inelastic, therefore, this model was found not to be robust and hence not adopted. Thus, it was concluded that sorghum output in South Africa is less sensitive to changes in price and non-price factors.

The findings further indicated that error correction term for area was -1.55 and -1.30 for yield response function. This indicated that the two models were able to revert to equilibrium. Therefore, it was concluded that the area response function was more robust, while the yield response function was not. Furthermore, it was concluded that sorghum production was more responsive to area allocation than yield function.

Based on the findings, the study recommends that amongst other methods to enhance sorghum output, producers could use improved varieties or hybrids, as this action would result in allocation of more land to sorghum production, following price change.

Keywords: Sorghum, Supply, Elasticity, Error Correction Model, South Africa

DECLARATION

I declare that the mini-dissertation hereby submitted to the University of Limpopo for the degree of Master of Science in Agriculture (Agricultural Economics) has not previously been submitted by me for a degree at this or any other university; that it is my own work in design and execution, and that all material contained herein has been duly acknowledged.

______________________________ ______________________________

Surname, Initials (title) **Date:**

ACKNOWLEDGEMENTS

Let me take this opportunity to pass my special gratitude to the almighty God for energising me throughout this research project, as well as to keep me focused on my education against all odds. To my Supervisor, Professor Abenet Belete and Co-supervisor Dr Jan Hlongwane, I thank you very much for the assistance provided in this study, it was indeed a pleasure to work with you.

I would also like to thank my friends and family for the continued support especially my mother Mogaladi Mojapelo, my uncle Abram Mojapelo and my sister Phillipine Mashiane for the financial support, you are indeed angels and keep brightening up the family. My life partner Ngoanamoshadi Florence, thank you for the support you gave me at the time when I needed it the most.

My Master's programme lecturers, colleagues and classmates, I thank you for the knowledge we have shared in the past years. Mr Makgoka Lekganyane, let me thank you for the provision of data as well as Mr Tozamile Lukhalo for the guidance on how to access the data.

Finally, let me thank everyone who provided support to this project either directly or indirectly.

DEDICATION

I dedicate this research project to my beloved son Mathibedi and his mother Ngoanamoshadi Florence.

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LIST OF ACRONYMS

ADF	Augmented Dickey Fuller
ADL	Autoregressive Distributed lag Model
DAFF	Department of Agriculture, Forestry and Fisheries
ECM	Error Correction Model
EU	European Union
GDP	Gross Domestic Product
ML	Maximum Likelihood
NAMC	National Agricultural Marketing Council
OLS	Ordinary Least Square
PPI	Producer Price Indices
SACU	Southern African Customs Union
SADC	Southern African Development Community
SAGIS	South African Grain Information Services
VAR	Vector Autoregressive Model
VECM	Variance Error Correction Model

CHAPTER 1: INTRODUCTION

1.1 Background

Sorghum is a tropical cereal crop that has been cultivated in southern Africa for over 3 000 years (Sorghum South Africa, 2006). Globally the production is approximately 70 million tons of grain from about 50 million hectares of land (Department of Agriculture, Forestry and Fisheries [DAFF], 2015). It is the dietary staple for more than 500 million people in more than 30 countries. Today, sorghum is cultivated across the world in the warmer climatic areas (National Agricultural Marketing Council [NAMC], 2007). Sorghum is still largely a subsistence food crop, but it is increasingly becoming the foundation for successful food and beverage industries. Sorghum is the 5th most important crop after wheat, maize, rice and barley (DAFF, 2010). The sorghum farming community in South Africa can be conveniently divided into the smallholder and commercial farmers owing to the differences in farm sizes, production and marketing methods.

Economic theory postulates that there is a direct relationship between the price of the commodity and the quantity supplied of that commodity, *ceteris paribus* (the law of supply). This means that an increase in the price of sorghum will result in an increase in the quantity supplied and vice versa; quantities respond in the same direction as price changes (Gujarati & Porter, 2009). According to DAFF (2015) major production areas of sorghum are the Free State province which is South Africa’s largest sorghum producing area and produces on average 54% of the total domestic sorghum crop. Mpumalanga is the second largest sorghum producing province (28%), followed by Limpopo (7%), North West Province (5.8%) and Gauteng (5%). The following four provinces are part of sorghum producing areas: Eastern Cape, Kwazulu-Natal, Northern Cape and Western Cape.

In South Africa, the total quantity of sorghum produced annually fluctuated between 450 000 and 150 000 tons, depending on the total area planted and the yields obtained (Sihlobo & Kabuya, 2015). Sorghum cultivation in Africa is still mainly characterised by traditional farming practices with low inputs (no inorganic fertilisers or pesticides) and traditional varieties. Such low yields mean that there is often no surplus sorghum, without which processing industries cannot be created. However, where intensive agriculture is practised with improved varieties or hybrids, yields are much higher and become comparable to other major cereals.

1.2 Problem statement

The idea that the responsiveness of the agricultural market is uncertain concerns the majority of South Africans who are reliant on sorghum for different purposes. These include breweries, feed producing companies and food industries. Reviewed literature has explicitly indicated that there are uncertainties in terms of the magnitude of both the short-run and long-run elasticity of supply of individual agricultural commodity. According to Nmadu (2010) the price of the product plays a significant role in determining the extent of elasticity of supply of a particular agricultural commodity.

Swarts (2016) reported that sorghum planting has decreased by 8,000 hectares, compared to the 70,500 hectares in the previous year (2015). Hence, South Africa was expected to import about 90,000 tonnes of sorghum in the 2016/17 production year, to cater for the shortfall of sorghum, which is most commonly used in beer production and animal feed, but also as a replacement of maize when necessary. Given this scenario, it was critical to investigate sorghum supply elasticity, more especially by focusing on short-run and long-run price elasticity. According to NAMC (2007) the major production areas of sorghum in South Africa are the Free State, Mpumalanga, Limpopo, North West and Gauteng provinces. Therefore, this study attempts to bridge the information gap as far as the research problem is concerned, which makes the investigation on this subject to be very imperative. The study has explained both short-run and long-run elasticity of supply of sorghum and estimated the response of sorghum production to changes in price and non-price factors.

1.3 Rationale

Given that sorghum is the 5th most produced crop in South Africa, this implies that a large proportion of the population in the country consumes it (DAFF, 2010). Sorghum is a staple food crop for more than 500 million people in more than 30 countries (NAMC, 2007). This further implies that it contributes to food security, Gross Domestic Product and it serves as a source of income for sorghum producing farmers. Unlike the top four crops namely, maize, wheat, rice and barley, studies on sorghum have not been given adequate attention. Thus, knowledge of elasticity of sorghum product supply and related demand functions would improve government intervention in the sorghum industry.

Swarts (2016) estimated that there is an expected increase in imports of sorghum, that is linked to reductions in hectares of sorghum planted in South Africa. This is in the context of taking into consideration the notion of increasing imports attributed to by a number of factors including low rainfall received in 2015 (AgriSA, 2016). Therefore, it was important to analyse the response of sorghum industry to changes in price and non-price factors. This has assisted in providing in-depth understanding of the changes in the supply patterns of sorghum in South Africa. Howai *et al.* (2013) investigated supply response of cocoa farmers in Trinidad and suggested that the most important measure of supply in most countries is increased export despite the rising export price.

Mutua (2015) applied Error Correction Model to estimate sugarcane supply response in Kenya using one dependent variable. Contrary to that, this study has use two dependent variables to provide extensive knowledge on whether area or yield response function play a significant role in determining the supply of sorghum in South Africa. Ehirim *et al.* (2017) undertook a study on soybean supply response to price and non-price factors in order to explain the state of food security in Nigeria. The study suggested that planned supply does not always equate actual supply. Hence, the need to investigate the speed of response of planned supply of soybean to actual supply is imperative. Furthermore, this study takes into consideration the suggestions made by Poulomi *et al.* (2016) which states that milk supply is responsive to price incentives and hence price support and subsidy programmes for dairy farmers become critical to improve government intervention. This study attempts to improve agricultural policy interventions with respect to the state of elasticity of supply of sorghum in South Africa. Given the limited literature pertinent to the context of South Africa, thus, investigations on this study was inevitable.

1.3.1 Aim of the study

This study seeks to investigate sorghum supply elasticity in South Africa.

1.3.2 Objectives

The objectives of the study were to:

i. To estimate elasticity of sorghum production to changes in price and non-price factors.
ii. To estimate the short-run and long-run sorghum price elasticity.

1.4 Hypotheses

i. Elasticity of sorghum production in South Africa does not respond to changes in price and non-price factors.
ii. The short-run and long-run sorghum price is not elastic.

1.5 Outline of the dissertation

This dissertation is divided into six chapters. The first chapter presents background of the study, problem statement, rationale, aim of the study, objectives and hypotheses. Chapter two covers literature review pertinent to this study. Chapter three details the overview of sorghum industry in South Africa, chapter four focused on the methodology part of the study and clearly highlighted how the objectives have been achieved. The chapter five is the empirical results and discussion of the research findings, lastly chapter six provided the summary, conclusions and recommendations.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter presents the explanations of the different concepts used in this study, as well as the analysis of various supply response models used by previous authors. The review of literature highlights numerous methodologies applied by different authors in estimating the supply response functions.

2.2 Definition of concepts

a) Elasticity

Economic theory defines elasticity as the responsiveness of supply and demand to changes in price. Therefore, elastic product means that any change in price can result in changes in supply or demand, on the other hand inelastic product means that changes in price do not affect to a noticeable degree, the supply or demand. Elasticity can also be referred to as a measure of a variable's sensitivity to a change in another variable (Gujarati & Porter, 2009).

b) Supply

The supply curve of a product is a schedule indicating the quantities producers are willing to supply (produce) at a given price, time and locality assuming that all other factors influencing supply, such as technology or production costs, remain the same *ceteris paribus* (Nicolaas van Wyk, 2011). The law of supply states that: when the price of the commodity is low, quantity supplied will be low. Similarly, when the price of the product is high the supply of the commodity in question will be high (increased), following an increase in the price of the commodity.

c) Error Correction Model (ECM)

The Error Correction Model (ECM) developed by Engle and Granger is a means of reconciling the short-run behaviour of an economic variable with its long-run behaviour (Gujarati & Porter, 2009). The ECM is used to analyse the short-run and long-run dynamics in the model. It has two distinct characteristics: first, an ECM is dynamic in the sense that it involves lags of the dependent and explanatory variables; it thus captures the short-run adjustments to changes of particular adjustments into past disequilibria and contemporaneous changes in the explanatory variables. Second, the ECM is transparent in displaying the co-integrating relationship between or among the variables (Paltasingh & Goyari, 2013). The Error

Correction Term (ECT) expresses the long-run causal effects, while the coefficients of lagged explanatory variables give an indication of short-run adjustments. The coefficient of ECT must be negative and significantly different from zero. Being negative implies that if there is a deviation from the current and long-run levels, there would be an adjustment back to long-run equilibrium in subsequent periods to eliminate the disequilibrium.

d) Yield and Area response functions

According to Belete *et al.* (1995) estimation of supply function can be explained using two different dependent variables, which is quantity supplied and crop land. Additionally, the scholars backed-up their arguments by mentioning that; the reason for which hectarage is used as dependent variable is that farmers can have control over the kinds and quantities of inputs (seeds, fertiliser, labour, land etc.) they employ in production but not over output, hence supply analysis based on area may reflect the actual situation.

Munyati *et al.* (2013) further confirmed that the area cultivated is mostly used as proxy variable for actual output in the supply model. However, actual output is the most preferable. The reason for choosing area cultivated is because it shows the decisions of farmers to plant more of the crop, as farmers decide how many hectares to plant sorghum. This approach is particularly applicable to locations where there is extreme variability of yields due to the unreliability of rainfall, which means that farmers have limited control over actual output. The, area planted is therefore used to indicate farmers' planned output.

Many estimated models use the area cultivated by the crop as the dependent variable. The cultivated area has been favoured over the production since farm production is similarly influenced by climatic conditions that cannot be controlled by the farmers. Similarly, yield is an issue of random variation than the area cultivated because of some factors that are uncontrollable to farmers (Alhaji *et al.* 2014).

According to Rao (1988) many researchers use proxy variables for cases where there is no data on the required variables. Hence, the choice of proxy influences the results obtained. Most time-series studies are for particular crops and use acreage as the proxy for output because acreage is thought to be more subject to the farmer's control than output. If this single input index of output is employed, acreage elasticity provides lower bounds to output elasticity. However, in so far as land area grows independently over time, hence there occurs overestimation of output elasticity if this is not explicitly allowed for.

The idea of yield response to price is further convinced by the earlier discussion in the literature that area function might underestimate actual level of supply response. The reason attributed is that farmers may display their response by adopting better technology of production with no change in the area or by adopting intensive cultivation through using more or better quality of inputs. This will change the output without changing the area, something that is hidden in the acreage function (Mutua, 2015).

The standard procedure is to use area as an indicator of supply due to the reason that area decision is totally under the control of farmers (Mythili, 2006). Moreover, using supply conceals some variations in the area and yield if they move in the opposite directions. It was hypothesised by the study that acreage response underestimates supply response. Thus, farmers respond to price incentives partly through intensive application of other inputs given the same area, which is reflected in yield. Acreage and yield response functions were estimated and the supply response estimates were derived from these two responses. Taking the various arguments and justifications above, this study used both hectarage and output as dependent variables and eventually considered one of these two dependent variables on the basis of the significance of coefficients of the two models.

2.3 Supply response models

a) Error Correction Model (ECM)

ECM is used to analyse the short-run and long-run dynamics in the model (Paltasingh & Goyari, 2013). The validity of error correction specification requires the existence of co-integration between variables concerned. The modelling strategy therefore begins with testing for the existence of a co-integrating vector involving variables of interest. Co-integration requires that the variables concerned be integrated of the same order and that some linear combination of these variables need to be described by a co-integrating regression. This model has been used to estimate agricultural supply response by a number of researchers, including Mutua (2015); McKay *et al.* (1998); Mose *et al.* (2017); Anwarul & Arshad (2010).

$$\Delta Y_t = \alpha \Delta X_t - (Y_{t-1} - \beta X_{t-1}) + v_t \qquad \ldots(1)$$

Where v is a disturbance with mean zero, constant variance, and zero covariance α measures the short-run effect on y of changes in x, while β measures the long-run equilibrium relationship between y and x,

$Y_t = \beta X_t + U_t$ …(2)

($Y_{t-1} - \beta X_{t-1}$) measures 'errors' - divergences from this long-run equilibrium and corresponds to the residuals of a lagged version of (1). X measures the extent of correction of such 'errors' by adjustments in y (Hallam & Zanoli, 1993).

b) Nerlovian Partial Adjustment Model

Nerlovian model states that the area cultivated is a function of expected price, output adjustment, and some exogenous variables. The Nerlovian model is a dynamic model and in this model the supply response is directly estimated by including partial adjustments and expectations formation. The area of the crop planted in the previous year could be included on the basis of Nerlove's Partial adjustment model, which states that the achieved agricultural output by a farmer in any one period is only a fraction of the desired change (Nerlove, 1958).

This means that the adjustment of farmers' crop plans to a change in price is unlikely to take place in full in one year but will probably persist and be distributed over several years. The traditional approach used for estimating aggregate supply response has been criticised on both empirical and theoretical grounds. The Nerlove and Griliches techniques seem unable to give an adequate clear-cut distinction between short-run and long-run elasticity, while the use of OLS may produce spurious results. The ad hoc behavioural assumptions of the Nerlove empirical approach are by no means satisfactory whereas the estimating supply response from the Griliches model is often not feasible given the data requirements (Mckay *et al.* 1998).

$Q^*_t = \alpha + bP^*_t + cZ_t + U_t$ ……(1)

Where, Q^*t is actual output (or hectare planted), P^*t is expected relative prices of the crop and of other competing crops, Zt is a set of supply shifters such as time trend, rainfall, etc. Actual output may differ from the desired level because of the adjustment lags of variable factors. Therefore, it is assumed that actual output would only be a fraction ϕ of the desired output.

$(Q_t - Q_{t-1}) = \phi(Q^*_t - Q_{t-1})$ …..(2)

Where, Q_t is actual output in period t, Q_{t-1} is actual output in period t-1, and P is adjustment coefficients. Its value lies between 0 and 1.

$P^*_t = P^*_{t-1} + \gamma(P_{t-1} - P^*_{t-1})$ ….(3)

Putting the value of P^*_t and Q^*_t from equation 2 and 3, in equation 1, the equation 1 becomes;

$$Q_t = b_0 + b_1P_{t-1} + b_2Q_{t-1} + b_3Z_t \qquad ....(4)$$

c) Linear programming

The idea that linear programming approach is capable of handling complex multi-relationships on farm level exposes it to a lot of econometric errors. These could include autocorrelation, heteroskedasticity, etc. Additionally, the data requirements are extensive, the collection of data at farm level is costly and the development of such models requires extensive time to be developed (Nicolaas van Wyk, 2011). The assumption that farmers maximise their profits may lead to the overestimation of supply that is not always true in practice. Due to the restricted availability of data and the resource-intensive nature of this technique, this approach is not widely used among researchers when supply response studies are conducted.

d) Autoregressive Distributed Lag approach

The Autoregressive Distributed Lag (ARDL) approach to co-integration, developed by Persaran, Shin and Smith in 2001 was used to test for the existence of a non-spurious long-run relationship between economic and non-economic variables (Persaran *et al.* 2001). Unlike other co-integration techniques, the ARDL model does not impose restrictive assumptions that all the variables in the study must be integrated of the same order. This implies that the ARDL approach can be applied regardless of whether the underlying variables are stationary, non-stationary or mutually integrated (Nmadu, 2010). Another difficulty that the ARDL approach poses is the decision regarding the number of endogenous and exogenous variables to be included in the supply model, as well as the time lags applicable to each variable.

e) Co-integration

The co-integration analysis primarily tests the impact matrix to gather information on the long run relationship(s) among variables contained in the Yt vector. If the rank of ıı matrix (r) is equal to zero, the impact matrix is a null vector thereby implying that there is no co-integration at all, since there is no linear combination of Yt that are I(0). In this case, the VAR in first differences is suitable involving no long-run elements. If ıı has a full rank (i.e., r = n), then the vector process of Yt is stationary. This implies that there is no problem of spurious regression and the appropriate modelling strategy is to estimate the traditional VAR in levels. But, in case of 0 < r < n, there exists ‘r’ co-integrating vectors (Paltasingh & Goyari, 2013).

There is a strong case for believing that co-integration analysis could describe the dynamics of supply better than the Nerlovian methodology; indeed, the dynamics of supply is directly observed with cointegration, whereas in the Nerlove model it can only be asserted by recourse to theoretical assumptions which are not explicitly tested. Furthermore, the optimal output is not observable and only the reduced form of the Nerlovian model can be estimated (Mckay *et al.* 1998). Looking at the strength and weaknesses of each and every model discussed above, therefore this study chose Error Correction Model as a better model compared to the other aforementioned analytical techniques.

2.4 Review of past studies

Alemu *et al.* (2003) applied Error Correction Model to study the response of a number of crops. It was ascertained that planned supply is positively affected by own price, while negatively affected by substitute crops and other factors. ECR was employed to devise differences in terms of accuracy, reliability and validity of the two response models namely; Nerlovian and Error Correction Model. Co-integration technique was also used to establish the long-run equilibrium relationship between variables. However, two conditions have to be met. Firstly, individual variables should be integrated of the same order. Second, the linear combination of these variables must be integrated of an order one less than the original variables.

It has been realised that the pricing and non-pricing policy are the major factors at the heart of Zimbabwe’s sorghum activity stagnation in terms of output and these have contributed to the current starvation in the country (Munyati *et al.* 2013). The Nerlovian partial adjustment model was used to determine the responsiveness of sorghum farmers to price and non-price. It was found that sorghum supply is inelastic to own price both in the long-run and short-run. In the long-run, the own price elasticity was found to be 0.51 whilst in the short-run was 0.24. These results mean that agricultural price policy alone cannot guarantee sorghum production growth targets.

A study conducted by Alhaji *et al.* (2014) investigated the two most prominent rice varieties in Sierra Leone namely; Rok and Nerica. Like many other countries, rice crops have to compete with substitute products in the country. The goal of the study was to increase the awareness of the description and assessments of rice acreage response and to offer mechanisms for agricultural policy scrutiny. It was found that both lagged acreages for Rok and Nerica were positive and highly significant, implying that farmers' adjustment rate was very slow. The short-run price elasticity was lower than the long-run, which suggests a long term adjustment of the acreage under the crop.

According to Belete (1995), the competitive crops to summer wheat are maize and sorghum. This study considered three price variables; wheat price, wheat price relative to maize price and wheat price relative to sorghum price. Furthermore, price variables were regressed using simple adaptive expectations model, thus statistical comparisons of the three using t-tests and R-squared revealed that only wheat price was relevant in explaining supply of wheat.

Thus, the competitive crop for this study will be wheat production. In addition, the price of wheat and area planted will play a crucial role in determining the amount to be produced by sorghum farmers. According to Munyati (2013); LaFrance & Burt (1983), wheat flour tends to be an ideal substitute for sorghum flour.

Nerlovian models are built to examine the farmers' output reaction based on price expectations and partial area adjustment and these models have the flexibility to introduce non-price production shift variables into the models. Desired output can be expressed as a function of expected price and supply shifters (Nerlove, 1958).

Gujarati & Porter (2009) stated that the lag order selection is considered an important preliminary step in model building and further conducting a causality analysis. The study will use some commonly used lag order selection criteria to choose the lag order, such as AIC (Akaike Information Criterion), HQIC (Hannan-Quinn Information Criterion), and SIC (Schwartz Information Criterion). Using the "VARselect" in R, the lag length selection under different criterion for individual analyses of climatic indicators and maize prices will be calculated.

Kuan (2008) reported that if a time series is serially uncorrelated, no linear function of the lagged variables can account for the behaviour of the current variable. For a serially independent time series, there is no any relationship between the current and past variables. Diagnostic testing on data series provides information regarding how these data might be modelled. When a model is estimated, diagnostic tests can be applied to evaluate model residuals, which also serve as tests of model adequacy.

Research by Nicolaas van Wyk (2011) showed a significant long-run relationship between the average Namibian mutton producer price and mutton supply. Results revealed that a one per cent increase in the mutton producer price leads to a 1.97 per cent increase in mutton supply. Beef producer price was included as a substitute product to mutton. Seemingly, this showed a significant negative long-run effect towards mutton production, whereas, rainfall showed a meaningful positive long-run contribution to mutton supply. These supply shifters towards mutton production also showed significant short-run elasticity. The Autoregressive Distributed Lag approach to co-integration was used to determine the long-run and short-run supply response elasticity towards economic and climatology factors.

Rao (1988) studied the agricultural supply response and found that empirical estimates of elasticity depend both on the methodology adopted and on country-specific factors relating to technology, economic structure and macro constraints. Supply response to output prices at the aggregate and at the crop levels is considered first. Crop-specific acreage elasticity range between zero and 0.8 in the short-run while long-run elasticity tend to be higher between 0.3 and 1.2. Yield elasticity is smaller and less stable than acreage elasticity. The findings on the short-run and long-run elasticity resemble those of other authors namely; Alhaji *et al.* (2014) and Shoko (2014).

Mythili (2006) modelled the supply response of Indian farmers on pre and post reforms. This study estimated supply response for major crops during pre and post reform periods using Nerlovian adjustment cum the adaptive expectation model. The standard procedure was to use area as an indicator of supply due to the reason that area decision is totally under the control of farmers. Moreover, this study took into consideration the notion that using supply conceals some variations in area and yield if they move in the opposite directions. Furthermore, the study found no significant difference in supply elasticity between pre and post reform periods for a majority of crops. Supply response to price changes is likely to increase with the increasing liberalisation of the agricultural sector. Results confirmed that farmers respond to price incentives equally by more intensive application of non-land inputs.

A study by Ryan (1977) demonstrated the empirical importance of price risk in an aggregate U.S. supply equation for Pinto beans. O.L.S. was used and the empirical results showed that omission of the risk variables seriously biases the estimates of supply elasticity. Furthermore, it was noted that the risk variables greatly improves the statistical fit of the supply equation, are quantitatively important and that a substantial bias occurs if they are neglected.

LaFrance & Burt (1983) documented a modified Nerlovian Partial Adjustment Model of aggregate agricultural supply in the United States. The study examined some alternative specifications from the basic Nerlove model and the consequences to empirical estimates of supply elasticity. The various specifications focused on the way in which stochastic components of a dynamic regression equation were treated, and they had implications for time series estimation of supply response equations for individual farm commodities as well as aggregate indices. Hence, the refinements in specification of partial-adjustment equations for supply response tend to produce higher long-run and lower short-run price elasticity than a straightforward use of the lagged output variable.

A study by Gosalamang (2010) investigated supply response of beef farmers to price changes and non-economic factors. The researcher applied Nerlovian partial adjustment model to ascertain the short-run and long-run elasticity of the supply of beef farmers in Botswana. The results of the study revealed that Botswana beef farmers respond positively to price incentives and time trends (proxy for technology), and negatively to all other variables. Elasticity of supply showed that cattle supply is elastic with respect to variations in producer price and almost unit elastic to changes in cattle inventory. Short-run price elasticity of supply was 1.511 whereas long-run price elasticity is 10.57. This is a clear sign that pricing can be employed as a strategy to enhance beef production in Botswana.

Hallam & Zanoli (1992) applied the error correction model on the supply response of pork meat. The variables included in this study were breeding herd, pig price and feed price. The parameters for these variables in their respective order were; 2.56, 1.69 and 0.70. Hence, the study found the short-run elasticity of 0.16 for pig price and 0.23 for feed price. The coefficient of 0.17 on the error correction term measured adjustment towards long-run relationship between pig prices, feed prices and breeding herd. It was found that the modelling of the short-run dynamics is consistent with any such long-run relationship. The correspondence of error correction model's notion of long-run relationship to statistical concept of co-integration was clearly explored by the researcher.

Paltasingh & Goyari (2013) used the vector error-correction approach to investigate supply response of rice in rainfall agriculture. This model was considered given that it avoids the unrealistic assumption of fixed supply on the basis of static expectations. In this case, the only condition for observing significant differences between short-run and long-run elasticity is the introduction of no-static assumption. Furthermore, it was stated by this author that the studies employing these mechanisms were considered biased, hence in most cases have found low values, sometimes even zero for long-run elasticity. Yield response short-run price elasticity was 0.37 and long-run price elasticity was 0.36. Acreage response short and long - run price elasticity was 0.01 and 0.26 respectively.

Leaver (2003) presented that the computed Jarque-Bera statistic of 0.02 and associated p-value of 0.99 confirms that the residuals are normally distributed. This finding is important because it ensures the validity of the t and F tests. The Durbin-Watson statistic of 1.81 does not allow a decision to be made regarding the presence of auto-correlation among the residuals. Based on these results, the model appears to be adequate in terms of its specification.

Mose *et al.* (2017) investigated aggregate supply response of maize to price incentives and it was estimated that the price elasticity for maize was 0.53 in the short-run and 0.76 in the long-run. The model also estimated that the price elasticity for fertiliser was -1.05 in the short-run and -1.26 in the long-run. This implies that in the short-run, a 10 percent increase in the price of maize would result in a 5.3 percent increase in maize production and 7.6 percent increase in maize production in the long-run. Moreover, when the price of maize decreases, there is a tendency for farmers to reduce the amount of productivity-enhancing inputs and timeliness of maize production activities for the following season is hampered. In certain circumstances, when the price of maize decreases, a farmer is likely to decrease area under maize assuming there are alternatives for the use of the land (enterprise substitution).

Anwarul Huq & Arshad (2010) estimated supply response of potato in Bangladesh and it was found that in the short-run, the relevant real potato price elasticity was 0.45 and was significant at 1% level while in the long-run, the real potato price elasticity was 0.62 which was equally significant at 1% level. Clearly, both coefficients are inelastic and suggest that a 100% increase in the price of potatoes (relative to boro paddy price) results in an increase by 45% in the following year while the same percentage increase would raise the supply of potato by 62% in the long-run. Furthermore, an ECM of -1.1838 was found, which concluded that the coefficient indicates a feedback of about 118.38% of the previous year's disequilibrium from the long-run elasticity of potato price. This implies that the speed with which potato price adjust from the short-run disequilibrium to changes in potato supply in order to attain long-run equilibrium is 118.38% within one year.

Tripathi (2008) studied the supply response of agricultural output and classified it in three agricultural based states namely; high, medium and low. The results indicated that elasticity of technology, irrigation ratio, and annual rainfall were positive for both the short-and long-run period. Regional level analysis showed that the short-run and long-run supply elasticity were insignificant for low and high agriculture based states, whereas it was significant and negative for medium agricultural based states. The author further stated that high R^2 in the long-run regression equation is necessary to minimise the effect of a small sample bias on the parameter estimates of the co-integrating regression, which otherwise may be carried over to the estimates of the error correction model. All selected variables together explained 69 per cent of variation in agricultural output.

2.5 Conclusion

The reviewed literature indicated that most of the studies used Nerlovian methodology found low supply response elasticity, both in the long and short-run. Hence, the kind of methodology applied affected the results obtained by authors. The most robust and elastic results were found through the application of Error Correction Model.

CHAPTER 3: OVERVIEW OF SORGHUM INDUSTRY

3.1 Introduction

This section details the sorghum industry in South Africa. Hence, it highlights the different climatic conditions under which the sorghum grain is grown, the type of farmers producing the crop, consumption of sorghum by livestock and human beings and the sorghum markets within and outside South Africa.

3.2 Executive summary

Grain sorghum is indigenous to Africa, can prosper on marginal land, has a lower water requirement than other grain crops and has been successfully cultivated on smaller hectares in South Africa for a long time by emerging farmers as a subsistence crop (DAFF, 2010). It is presumed that sorghum was introduced in East Africa through the shipping trade route between India and Africa. Shipping trade also took place from India all along the coast of Asia, with the result that sorghum also found its way to China. Sorghum originally reached the USA as a result of the slave trade from West Africa, but later (1874 - 1908) also from North Africa and South Africa (MabeleFuels, 2010).

3.3 Climatic requirements: temperature and rainfall

The climatic requirements for the production of sorghum are divided into temperature, day length and water needs. In terms of temperature, sorghum is a warm-weather crop, which requires high temperatures for good germination and growth. The minimum temperature for germination varies from 7 to 10 ºC. At a temperature of 15 ºC, 80 % of seed germinate within 10 to 12 days (DAFF, 2014). The best time to plant is when there is sufficient water in the soil and the soil temperature is 15 ºC or higher at a depth of 10 cm. Temperature plays an important role in growth and development after germination. A temperature of 27 to 30 ºC is required for optimum growth and development. The temperature can, however be as low as 21 ºC, without a dramatic effect on growth and yield. Exceptionally high temperatures cause a decrease in yield. Flower initiation and the development of flower primordial are delayed with increased day and night temperatures (Jean du Plessis, 2008).

Sorghum is produced in South Africa on a wide range of soils, and under fluctuating rainfall conditions of approximately 400 mm in the drier western parts to about 800 mm in the wetter eastern parts. Temperatures below freezing point are detrimental to sorghum and may kill the plant. At an age of one to three weeks, plants may recover if exposed to a temperature of 5 ºC below the freezing point, but at 7 ºC below freezing, plants usually die (Jean du Plessis, 2008). Plants older than three weeks are less tolerant to low temperatures and may be killed at 0 ºC. Sorghum is a short-day plant, which means that the plant requires short days (long nights) before proceeding to the reproductive stage. The optimum photoperiod, which will induce flower formation, is between 10 and 11 hours (DAFF, 2009).

3.4 Category of farmers and production areas

In South Africa, the farming community is divided into two groups these being the smallholder and commercial farmers with differences in land sizes, production and marketing methods. On average, smallholder farmers farm on 3 ha which they do not own. They consume their products and are net buyers of grain. For these reasons, total sorghum production of smallholder farmers is not known. Average sorghum yield on smallholder farms is estimated based on observation for the SADC countries which is 0,8 t/ha (DAFF, 2010).

In the Limpopo Province, sorghum is grown on at least 25 342 ha, with Sekhukhune 19 033 ha, Waterberg 3 410 ha and Capricorn 2 899 ha as the most important districts. From these data it is estimated that the Limpopo Province produces more than 20 000 tons of sorghum. Sorghum is also produced in other provinces such as Mpumalanga, North West, Gauteng and Free State. Statistics from these provinces are not available. South African commercial farmers, located mostly in the Free State, produce on average 300 000 tons on 150 000 ha. Average production per ha is 2 tons (Wenzel, 2003). Nearly all the harvest is marketed. These differences are of importance when considering or planning the future production, consumption, commercialisation and development of the sorghum industry (DAFF, 2010).

Table 3.1: Major sorghum production areas in South Africa.

Province	**District**	**Town**
Free state	Xhariep	Fauresmith, Jacobsdal, Jagersfontein, Koffiefontein, Petrusburg, Rouxville, Trompsburg, Smithfield, Springfontein, Verwoerd Dam, Zastron, Koffiefontein, Luckhoff, Edenburg
	Motheo	Bloemfontein TLC, Botshabelo, Eastern Free State DC, Excelsior, Kopano, Ladybrand, Maluti, Morojaneng /

		Dewetsdorp, South East Free State, Thaba Nchu TLC & TRC, Wepener, Thaba Nchu
	Lejelweputswa	Allanridge, Boshof, Bothaville, Bultfontein, Dealesville, Goldfields, Ladybrand Tswelopele
Mpumalanga	Gert Sibande	Eastvaal, Badplaas, Carolina Lc & Rc, Ekulindeni, Elukwatini, Empuluzi, Breyten
	Nkangala	Highveld Dc, Delmas Lc & Rc, Kriel Lc & Rc, Ogies, Witbank Lc & Rc, Hendrina, Middelburg Lc & Rc, Belfast
	Ehlanzeni	Lowveld Escarpment Dc, Graskop, Lydenburg Lc & Rc, Sabie, Hazyview, Nelspruit Lc & Rc , White River
Limpopo	Waterberg	Modimolle, Thabazimbi, Lephalale, Mookgopong
	Vhembe	Northern Dc, Musina, Nzhelele/Tshipise, Alldays, Elim/Tshitale/Hlanganani/ Thohoyandou, Louis Trichardt
North West	Ngaka Modiri Malema	Mafikeng, Delareyville, Lichtenburg, Zeerust, Sannieshof, Mmabatho
	Dr Ruth Segomotsi Mompati	Schweizer-Reneke, Vryburg, Christiana, Bloemhof, Reivilo, Taung
	Dr Kenneth Kaunda	Ventersdorp, Klerksdorp, Potchefstroom, Wolmaransstad, Hartbeesfontein
Gauteng	Metsweding	Bronkhorstpruit, Cullinan, Eastern Gauteng, Roodeplaat, Ekangala

Source: DAFF (2010)

3.5 Marketing of sorghum

a) Utilisation of sorghum: livestock feed, human food and beverages

Livestock feed and other animal products

The utilisation of sorghum in the feed market is inconsistent and opportunistic. The average share of sorghum processed for animal feed is 13,5%. Thus, livestock feed is the most important market for surplus sorghum, as it competes effectively with other grain products in terms of price and quality. Sorghum is an important component in poultry feed and good progress has been made in the manufacturing of dog food, pigeon and ostrich food (Sorghum South Africa, 2006). Sorghum can be processed to further improve its feed value and techniques such as grinding, crushing, steaming, steam flaking, popping and extruding have all been used to enhance the grain for feeding. The products are then fed to beef and dairy cattle, laying hens and poultry and pigs, and are also used in pet foods (DAFF, 2010).

Human food and beverages market

The market for food and beverages comprise of sorghum processed for malt, meal and other food such as rice and grits (mostly for brew). The average share of the food market of the total consumption is 86,5%. Between 52% and 62% of total domestic demand is used for malting/brewing (Sihlobo & Kabuya, 2015). Sorghum meal, also known as "Mabele", competes directly with maize meal and is served as a breakfast cereal or as soured porridge sorghum rice, sometimes called "corn rice". This involves the whole sorghum that has had the outer bran layers removed and is served instead of rice (Sorghum South Africa, 2006).

b) Sorghum export and import trends

South Africa's sorghum exports are generally irregular and inconsistent. This lack of consistency can primarily be attributed to uneven surplus levels and increasing production in traditional export markets. Approximately 99% of sorghum is exported by South Africa to the Southern African Development Community. Botswana and Swaziland account for 98% of the South African sorghum exports' share (Sihlobo & Kabuya, 2015). The other key export markets within the continent are Kenya, Uganda and Sudan, which in total account for 0,5% of South Africa's export share. Currently, Botswana's domestic sorghum production is increasing, which might limit its import needs in future. In fact, South Africa's exports share in Botswana has been decreasing from 2010 to 2014, notably by 15% in the year under consideration (2015). A substantial amount of sorghum was exported to the SADC region, while only lower and erratic volumes of grain sorghum were exported to other regions such as the Americas, Asia, Europe and Oceania (DAFF, 2010).

South Africa imports sorghum mainly from the United States of America. However, part of the total sorghum imports are acquired mainly from the SADC region namely, from Mozambique, Zimbabwe and Zambia, although imports from these countries have been fluctuating throughout (DAFF, 2014). Malawi was the largest exporter of sorghum to South Africa in 2013, followed by Mozambique.

Overall, there are 16 African markets ranking among the top 50 sorghum global importers. On average, African markets account for 10% of the global import demand. Sudan and Ethiopia are the largest markets on the continent. However, they each account for just 2% of the global import demand. Outside the continent, Japan, China, Mexico and Colombia are the leading sorghum importing markets, all constituting more than 73% of the global import demand. In particular, Japan and Mexico are the leading importers of sorghum in the world.

They both account for 55% of the world's sorghum imports. The top 20 sorghum import markets account for 95% of the global import demand share (Sihlobo & Kabuya, 2015).

Emerging markets have also been among the fastest growing regions for sorghum imports. The Middle East (25% Asian and Far East markets 36%) showed significant growth between 2009 and 2013. Above all, Europe has shown the most impressive growth, with imports increasing by an annual average of 54% over the same period. Global import demand is also increasing since in the same period, the increase was 17,6% (DAFF, 2015).

c) South African sorghum exit points

The KwaZulu-Natal province generally commanded the greatest share of South Africa's total value of sorghum exports, followed by Gauteng and Western Cape provinces. This indicates that the greatest percentage of sorghum exports are recorded as originating from these three provinces, although they are not the largest producers of the grain sorghum (Sihlobo & Kabuya, 2015). The implication is that most of the grain sorghum is produced in other areas and transported to the aforementioned three provinces, because they are well equipped with suitable infrastructure and are also well located to serve as exportation points. The aforementioned sorghum exit points have sufficient transportation facilities such as an airport and harbour which facilitate movement of agricultural products from Cities to other countries. As such, the availability of the mentioned facilities encourages grain sorghum producers from various areas to export their products to the three mentioned provinces (DAFF, 2014).

3.6 Sorghum prices

Sorghum prices are highly volatile. In a year when local sorghum production exceeds consumption for food and beverage, the sorghum price is determined by the lowest price of competing grains. Currently the sorghum price is discounted against the cheapest of white and yellow maize. When sorghum demand exceeds production, the price for sorghum depends on the import parity price and a premium is paid for malting quality (NAMC, 2007).

3.7 Competitiveness

The value chain for sorghum is marginal in terms of international competitiveness. At a workshop on competitiveness held by the NAMC on 29 June 2005, participants agreed that the basis for competitiveness is sustainable production and a consolidated agricultural industry plan. Costs need to be contained by means of relevant research, training, applied extension, efficient input and infrastructure markets, economies of scale where possible, and efficient use of the value chain. Income needs to be increased by means of product differentiation, new export markets and efficient processing infrastructure. There is a common acceptance of a range of factors constraining performance in the grain industry which also affect competitiveness and profitability in the sorghum industry (NAMC, 2007).

The following factors affect competitiveness and profitability of the industry

- Restricted access to affordable finance,
- lack of access to timely, relevant and accurate market information,
- infrastructure and logistical issues,
- international agricultural policies distorting grain markets,
- surplus production and volatile currencies

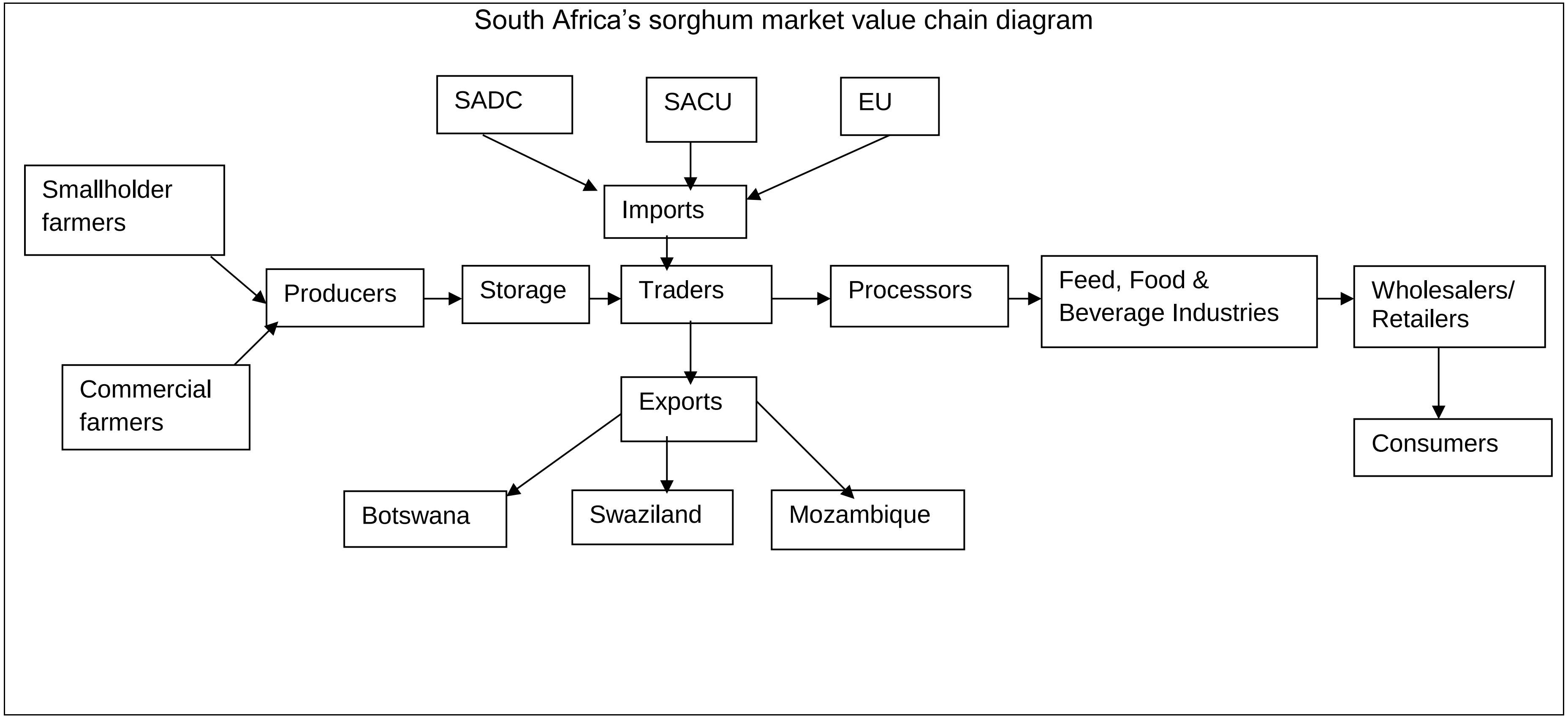

Figure 3.1: Sorghum market value chain

Source: DAFF (2014)

The above diagram depicts a typical sorghum market value chain in South Africa. From left it indicates the category of farmers producing sorghum in South Africa classified as producers. Sorghum is stored for value addition; traders can either buy from domestic producers or receive imports (from SADC, SACU and EU) thereafter, traders can sell to domestic processors or export to countries such as Botswana, Swaziland and Mozambique. However, it must be noted that the countries to which South Africa exports are not limited to those stated above. Meanwhile, the same applies to countries from which it receives imports, for example, South Africa imports sorghum from the United States of America but this is not depicted on the diagram just to limit the scope to essential parts. The processed items would be as follows: Feed for livestock, Human food and beverages, which are sold to either wholesalers or retailers. Lastly, the processed items are sold to final consumers.

3.8 Conclusion

This chapter highlights the overview of sorghum industry and the importance of the crop in South Africa and outside the country. There are numerous countries importing the crop and boosting South Africa economy in terms of gaining foreign exchange and better economic performance. There are five major sorghum producing areas, these being the Free State, Mpumalanga, Limpopo, North West and Gauteng provinces.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

The chapter four of this study covers the research methodology which is divided into three sections. These are the study area, which explain clearly the location where the study was conducted, the data collection broken down into the type of data, the sample size and data source, that is the areas where data was obtained. Lastly, it explains the data analysis, the analytical techniques used in this study.

4.2 Study area

The study area is South Africa and it is located at the Southern tip of the continent of Africa, marked by several distinct ecosystems, and it shares land borders with six neighbouring countries namely, Swaziland, Zimbabwe, Botswana, Namibia, Lesotho and Mozambique. South Africa is divided into nine provinces with different population density in each province, with Gauteng having the highest population. StatsSA (2016) and DAFF (2016) confirmed that the population in South Africa is currently 55 909 million. South Africa covers 1,214,470 square kilometres of land and 4,620 square kilometres of water, making it the twenty-fifth largest nation in the world (South African map and satellite images, 2000).

Figure 4.1: Location of South Africa.

Source: South African map and satellite images (2000)

4.3 Data collection

This study has employed time series data of a period of 19 years spanning from 1998 – 2016. Variables included in this study were: rainfall (mm), technology advancement (trend), sorghum area planted (ha), sorghum total output (ton), sorghum price (rand) and maize price (rand). Data on sorghum, rainfall and maize were obtained from Agricultural Statistics, published by DAFF. These data were verified by the South African Grain Information Service (SAGIS).

The data on sorghum were based on the nine provinces as the crop is produced throughout the country. Maize was incorporated in the study as a substitute product for sorghum. Average annualised data on rainfall, maize producer price; sorghum hectares; sorghum output and sorghum producer price were employed. The nominal producer prices on both sorghum and maize were deflated by the producer price index to remove the effects of inflation.

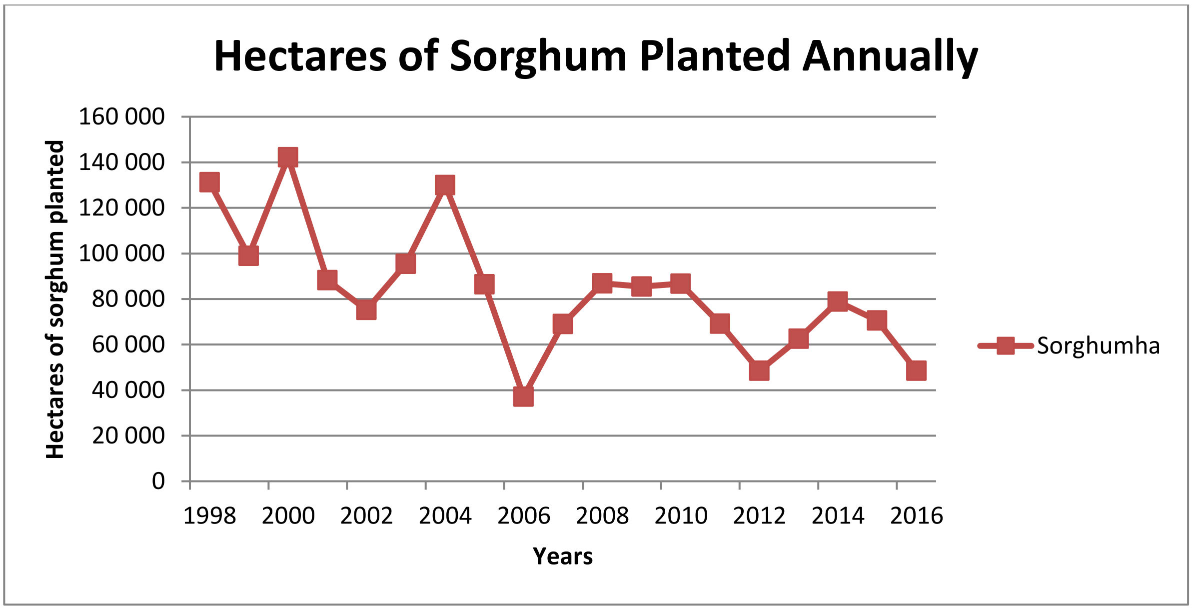

Figure 4.2: Hectares of sorghum planted annually

Data source: DAFF (2017)

Figure 4.2 above depicts the amount of hectares of sorghum produced over the past 19 years in South Africa. The diagram clearly indicates the amount of sorghum planted, thus there is discrepancy in the hectares planted due to variation in factors that affect the production of sorghum. Economic theory states that when the price of the commodity (sorghum) is high the supply of the product in question will increase. Thus, it can be deduced here that when a maximum amount of 142 200ha was realised the price was at its highest, this is in line with the economic theory stated. The opposite is true as the price of sorghum goes down an amount of 37 150ha was planted and recorded to be the lowest in the period under consideration.

The year 2000/2001 was recorded to be flood year and has been marked as one of the prosperous years for farmers as the amount of rainfall was at its pick and a maximum amount of hectares of sorghum were planted (KrugerI & Nxumalo, 2017 and Phakula, 2016).

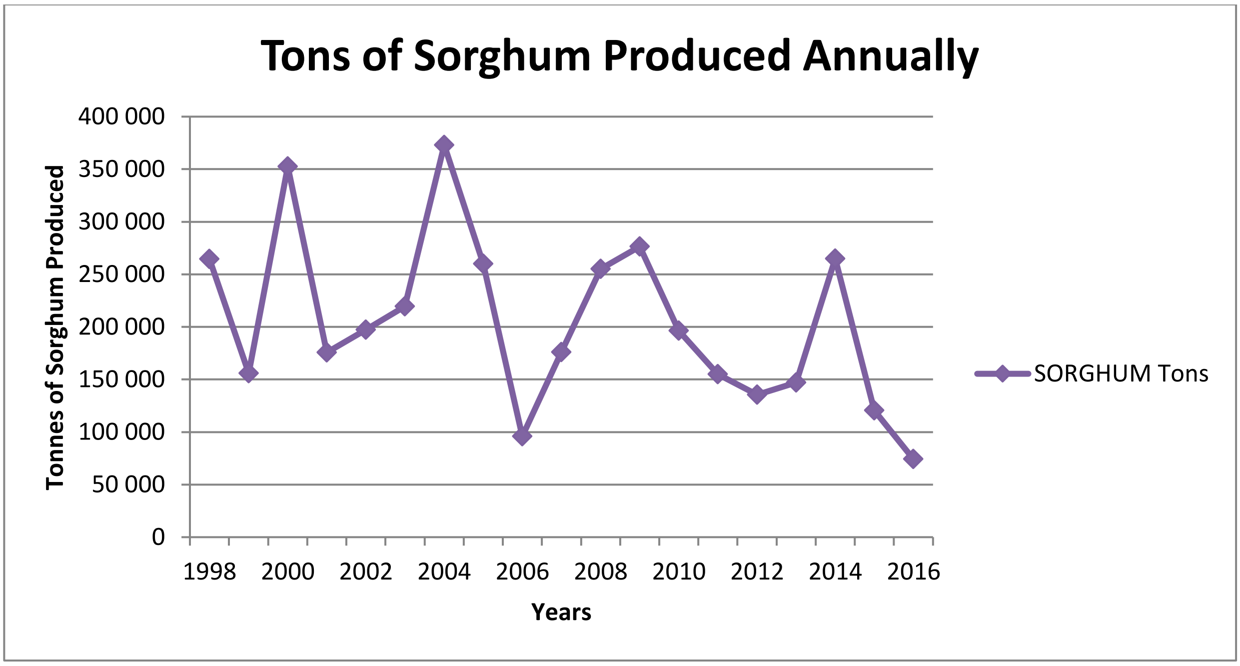

Figure 4.3: Tons of sorghum produced annually

Data source: DAFF (2017)

The above figure presents the tons of sorghum that were produced in the period under consideration. There is a variation in the amounts of sorghum produced from one year to the other and the factors that have influenced this among other things includes; the advancement in technology used by the farmers and amount of rainfall received. The highest tons of sorghum produced were standing at 373 000t in 2004 and this might be caused by enough amount of rainfall (836mm) realised in the previous seasons. On the other hand, the minimum tons of sorghum produced were standing at 74 150t in 2016. This could also have been attributed to the lowest rainfall (average annual rainfall 403mm) received in South Africa in 2015. This low rainfall was further confirmed in reports by the Staff writer (2016) and AgriSA (2016) wherein it was indicated that the year 2015 was declared to be a drought year in South Africa. Hence, this is the reason behind inadequate amounts of tons produced in 2016.

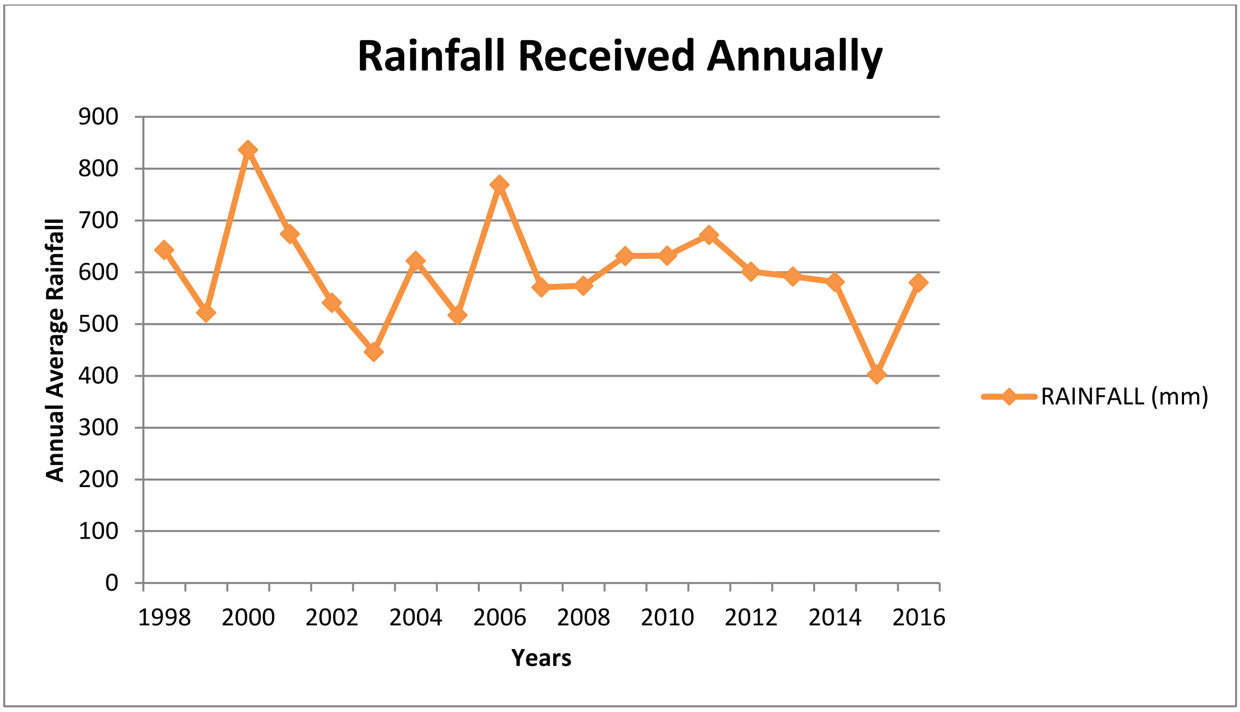

Figure 4.4: Average annual rainfall received

Data source: DAFF (2017)

In agriculture, rainfall is one of the most important factors that directly influence the amount of hectares that farmers plan to plant and ultimately affects the output farmers realise. This is based on the fact that, most of the farmers in South Africa particularly sorghum farmers rely on rainfall for irrigation, which is usually known as rain-fed agriculture. Thus, rainfall remains a major input for agriculture as it influences farmers' decision to increase or decrease land under cultivation.

It can be deduced from the diagram that average annual amount of rainfall has been fluctuating from one year to the other. The highest rainfall was standing at 836mm received in the year 2000, while a minimum amount of 403mm was received in 2015 as it was declared to be drought year (AgriSA, 2016). A minimum amount of rainfall has wide spreading impacts as the prices increase in the market following decreased supply of the commodity in question. Additionally, this lowest average annual rainfall in 2015 was more felt in the subsequent year

2016 as the season of harvest and selling. The price of sorghum per ton was at its highest R3 449.78/t due to low amount of rainfall received in the previous season (2015), as compared to price of sorghum per ton in the year 2000 standing at R520.00/t with the highest average annual rainfall in the period under consideration.

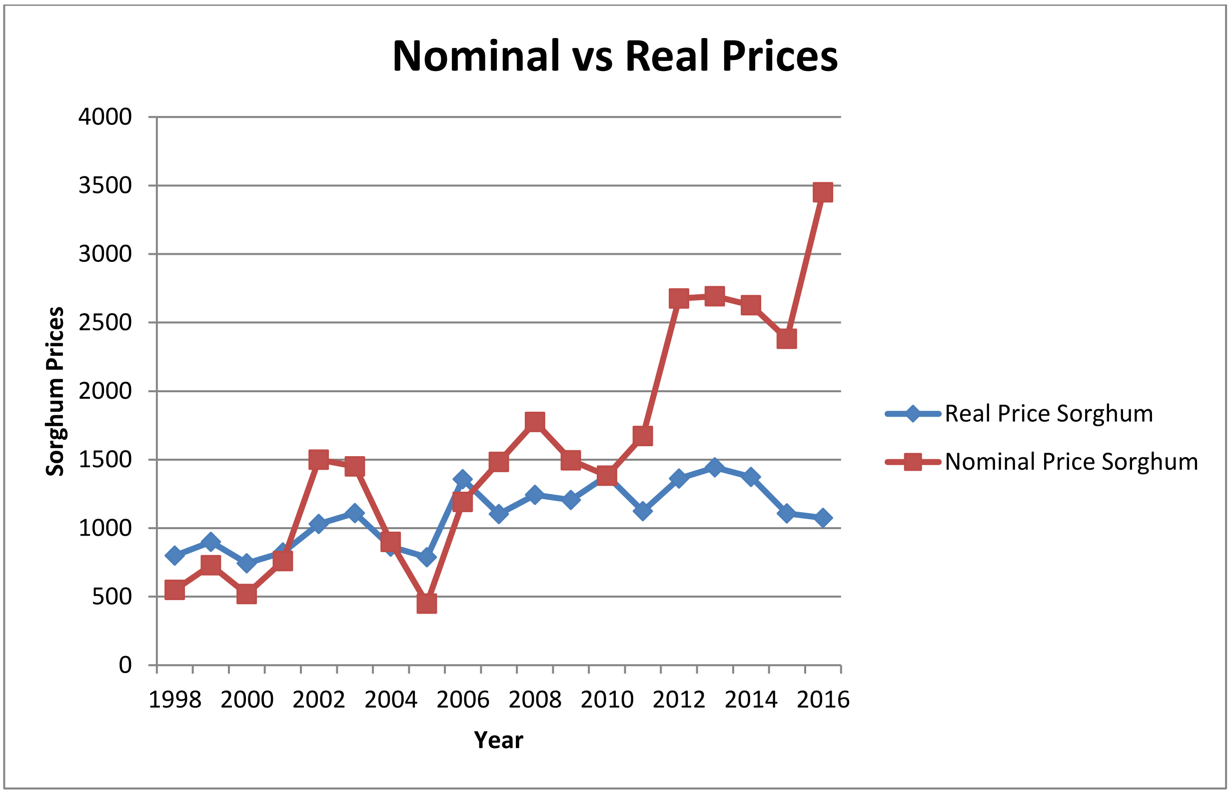

Figure 4.5: Sorghum producers' price per ton

Data source: South African Grain Information Services (SAGIS, 2017)

This figure presents nominal and real producer prices of sorghum. The nominal prices graph indicates increasing producer prices over the period under consideration, while the graph of real prices have shown a slight increase compared to that of nominal prices. The highest real price of sorghum was standing at R1 442.45 per ton, whereas the lowest real price was R743.92 per ton, the difference between the two being R698.53 price per ton. On the other hand, the highest nominal price was standing at R3 449.78 per ton and the lowest nominal price was R450.00 per ton making the difference of R2 999.78. Thus, it is inferred that after removing the effects of inflation the prices have not changed at a greater magnitude.

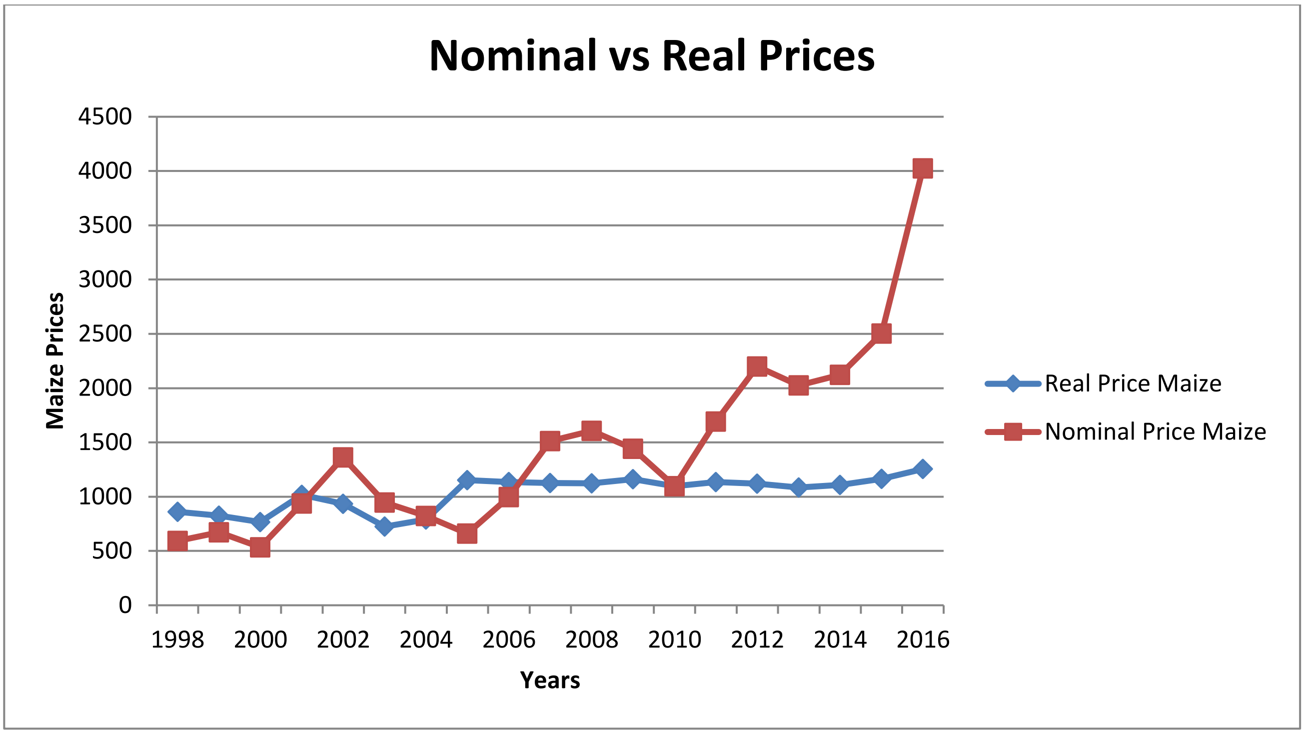

Figure 4.6: Maize producers’ price per ton

Data source: SAGIS (2017)

The above figure depicts nominal and real producer prices of maize as the competing crop of sorghum. The nominal prices graph indicates increasing producer prices over the period under consideration, while the graph of real prices have shown a slight increase compared to that of nominal prices. The highest real price of maize was standing at R1 255.10 per ton, whereas the lowest real price was R724.53 per ton, the difference between the two being R556.57price per ton. On the other hand, the highest nominal price was standing at R4 025.09 per ton and the lowest nominal price was R535.10 per ton making the difference of R3 489.99. The same narration prevails that after removing the effects of inflation the prices have not changed at a greater magnitude.

4.4 Data analysis

4.4.1 Analytical techniques

Error Correction Model (ECM)

ECM was used to analyse the short-run and long-run dynamics in the model (Paltasingh & Goyari, 2013). This model has been used to estimate agricultural supply response by a number of researchers, including Mutua (2015); McKay *et al.* (1998); Mose *et al.* (2017); Anwarul Huq & Arshad (2010) etc.

The Error Correction Model is expressed as follows:

$\Delta Y_t = \alpha \Delta X_t - (Y_{t-1} - \beta X_{t-1}) + v_t$ …(1)

Where v is a disturbance with mean zero, constant variance, and zero covariance α measures the short-run effect on y of changes in x, while β measures the long-run equilibrium relationship between y and x,

$Y_t = \beta X_t + U_t$ …(2)

(Yt-1 – βXt-1) measures 'errors' - divergences from this long-run equilibrium and corresponds to the residuals of a lagged version of (1). X measures the extent of correction of such 'errors' by adjustments in y (Hallam & Zanoli, 1993).

Table 4.1: Description of variables and their measurement

Variables	**Description**	**Unit of measurement**
Dependent variable		
Sorghum supply elasticity	It is the response of the total output to price and non-price factors. This study has two dependent variables namely: area response function and yield response function (Shoko, 2014; Belete, 1995; Nmadu, 2010; etc).	Area/Hectare (hectarage), equivalent to 100 acres (10,000 m^2). Yield (ton/ha)
Independent variables		
Sorghum price	This is the actual producer price of sorghum per ton.	Rand/ton
Sorghum area planted	This represents area of sorghum planted annually.	Hectare
Sorghum tons produced (Yield)	This refers to the actual total output/yield of sorghum produced annually.	Tons
Rainfall	This is average amount of rainfall received annually.	Millimetres (mm)
Maize price	Producer price of maize per ton (substitute product).	Rand/ton
Technology Advancement (time trend as proxy)	Improvement in the knowledge of sorghum farmers, seeds varieties, GMO, extension services and mechanization.	Trend

Source: Author’s study

4.4.2 Diagnostic tests

a) The Augmented Dickey Fuller test

ADF test here consists of estimating the following regression:

$\Delta Yt = \beta 1 + \beta 2t + \delta Yt-1 + \alpha i\_Yt-i + \varepsilon t$

where εt is a pure white noise error term and where $\Delta Yt-1 = (Yt-1 - Yt-2)$, $\Delta Yt-2 = (Yt-2 - Yt-3)$, etc. The number of lagged difference terms to include has been determined empirically using AIC (Akaike Information Criterion), HQIC (Hannan-Quinn Information Criterion), and SBIC (Schwartz Bayesian Information Criterion). The idea is to include enough terms so that the error term is serially uncorrelated (Gujarati & Porter, 2009). Preliminary tests need to be performed before exposing the data series to more advanced data analysis. The unit root and diagnostic tests have to be done in order to ensure that the study does not produce spurious regression results.

A number of researchers used ADF to test stationary of the series, these include but are not limited to (Munyati, 2013; Tripathi, 2008 and Gosalamang, 2012). After running the mentioned regression, one tests for the null hypothesis of the form H_0: $B_1 \geq 0$ versus the alternative hypothesis of H_1: $B_1 < 0$. This is a one sided test. If B_1 is equal or greater than zero, then Y is non-stationary and H_0 is accepted. If the Dickey-Fuller test rejects the null hypothesis, then we can assume that Y is stationary (Gosalamang *et al.* 2012).

b) Serial correlation test

The term autocorrelation is defined as correlation between members of series of observations ordered in time (as in time series data) or space (as in cross-sectional data). In the regression context, the classical linear regression model assumes that such autocorrelation does not exist in the disturbances. The nature of time series data often results in correlated error terms as a result of inertia, the cobweb phenomenon, and data smoothening (Gujarati & Porter, 2009). Thus, With regard to model misspecification, under-specifying the number of lags in a VECM can significantly increase the finite-sample bias in the parameter estimates and lead to serial correlation (Mutua, 2015).

c) Heteroscedasticity

Heteroscedasticity can also arise because of the presence of outliers. An outlying observation, or outlier, is an observation that is much different (either very small or very large) in relation to the observations in the sample. More precisely, an outlier is an observation from a different population to that generating the remaining sample observations. The inclusion or exclusion of such an observation, especially if the sample size is small, can substantially alter the results of regression analysis. Skewness in the distribution of one or more regressors included in the model is another source of heteroskedasticity (Gujarati & Porter, 2009).

d) Stability condition of VECM estimates

The stability of a VECM refers to the ability of the system to revert to the equilibrium after a shock. The stability of linear dynamic systems can be determined from Eigen values. For a K-variable VECM with r co-integrating equations, the stability matrix will have K-r unit Eigen values. For stability, the moduli of the remaining Eigen values should be strictly less than unity (Mutua, 2015). If a VECM has K endogenous variables and r co-integrating vectors, there will be K-r unit moduli in the companion matrix. If any of the remaining moduli computed by vecrank are too close to one, either the co-integrating equations are not stationary or there is another common trend and the rank specified in the vec command is too high. Unfortunately, there is no general distribution theory that allows one to determine whether an estimated root is too close to one (1) for all the cases that commonly arise in practice (StataCorp, 2011).

e) Test for normally distributed disturbances

A normality test estimates the parameters of a VECM. The test vecnorm computes a series of test statistics of the null hypothesis that the disturbances in a VECM are normally distributed for each equation and all equations jointly. Three statistics should be computed: a skewness statistic, a kurtosis statistic, and the Jarque–Bera statistic. The overall null hypothesis is that the disturbance term in that equation has a univariate normal distribution (StataCorp, 2011 and Gujarati & Porter, 2009).

The Jarque–Bera results present test statistics for each equation and for all equations jointly against the null hypothesis of normality. The single-equation and overall Jarque–Bera statistics should be able to reject the null of normality.

The single-equation skewness test statistics are of the null hypotheses that the disturbance term in each equation has zero skewness, which is the skewness of a normally distributed variable. The row marked ALL (in chapter 5) shows the results for a test that the disturbances in all equations jointly have zero skewness. The kurtosis statistics present the null hypothesis that the disturbance terms have kurtosis consistent with normality.

f) Selection order criteria

Akaike Information Criterion (AIC)

AIC criterion is defined as:

$$\ln \text{AIC} = \frac{2k}{n} + \ln \frac{\text{RSS}}{n}$$

where ln AIC = natural log of AIC and 2k/n = penalty factor. In comparing two or more models, the model with the lowest value of AIC is preferred. One advantage of AIC is that it is useful for not only in-sample but also out-of-sample forecasting performance of a regression model. Also, it is useful for both nested and non-nested models. It also has been used to determine the lag length in an AR(p) model (Gujarati & Porter, 2009).

Schwarz's Information Criterion (SIC)

Similar in spirit to the AIC, the SIC criterion is defined as:

$$\ln \text{SIC} = \frac{k}{n} \text{Inn} + \ln \frac{\text{RSS}}{n}$$

where [(k/n) ln n] is the penalty factor. SIC imposes a harsher penalty than AIC. Like AIC, the lower the value of SIC, the better the model. Again, like AIC, SIC can be used to compare in-sample or out-of sample forecasting performance of a model (Gujarati & Porter, 2009).

g) Co-integration test

The Johansen co-integration test is based on the maximum likelihood (ML) estimation and two statistics; trace statistics and maximum Eigen values. If the rank of the matrix is zero, then there is no co-integrating relationship. However, if it is greater than zero, then there are a number of co-integrating relationships equal to the maximum rank (Johansen, 1988).

If a series is integrated, it accumulates past effects. This means that perturbation to the series does not return to any particular mean value. Therefore, an integrated series is non-stationary. The order of integration of such a series is determined by the number of times that it must be differenced before it is actually made stationary. It follows that if two or more series are integrated of the same order then a linear relationship can be estimated (Tripathi, 2008 and Gujarati & Porter, 2009). If co-integration is confirmed, a non-spurious long-run equilibrium relationship exists. When this is combined with ECM, whose variables are I (0), consistent estimates of both long-run and short-run elasticity are evident (Hallam & Zanoli, 1992; Nerlove, 1958 and Alemu, *et al.* 2003).

Table 4.2: Summary of diagnostic tests applied

Test	**Method**
Unit root test	Augmented Dickey Fuller test (ADF)
Serial correlation	Breusch-Godfrey LM test
Heteroscedasticity	Breusch-Pagan/Cook-Weisberg test
Stability test	Ramsey RESET test
Normality test	Jarque–Bera statistic
Selection order criteria	Varsoc test
Co-integration	Johansen co-integration test

Source: Author's study

This table summarises relevant diagnostic tests performed in this study. As presented in the table, the diagnostic tests include unit root, serial correlation, heteroscedasticity, stability, normality, selection order criteria and co-integration. Diagnostic tests must be applied in order to ensure that the study does not produce spurious regression results.

4.5 Conclusion

The figures presented in this chapter are six and explains clearly the price and non-price variables used. The diagnostic tests have been analysed in depth to eliminate the issue of spurious regression results and the Error Correction Model was applied in two dependent variables.

CHAPTER 5: EMPIRICAL RESULTS AND DISCUSSION

5.1 Introduction

This chapter discusses the results of this study and has been achieved through the application of Ordinary Least Squares (OLS) methodology. It is divided into three sections being descriptive statistics, results of diagnostic tests and empirical results. The study has two dependent variables, these being sorghum area allocation and sorghum output produced. Time series data was used, and the model employed was Variance Error Correction Model. Several diagnostic tests were applied to ensure non-spurious regression results.

5.2 Descriptive statistics

The table below indicates the statistical properties of five variables used in the estimation of sorghum supply elasticity. This table presents the mean, standard deviation, maximum and minimum of the series. On average, the yield level for sorghum is 2.45 ton/ha with a standard deviation of 2.91ton/ha. The average real producer price of sorghum is R1 095.63/ton which was higher than the real producer price of maize standing at R1 030.32/ton. The average hectare of sorghum is 83 751 while the average tons of sorghum were standing at 20 5037. The average annual rainfall was 600mm with standard deviation of 100mm per year.

Table 5.1: Statistical properties of the data.

	Sorghum hectares (ha)	**Sorghum tons (tons)**	**Real Price of Sorghum (R/ton)**	**Real Price of Maize (R/ton)**	**Rainfall (mm)**
Mean	83751	205037.8	1095.63	1030.32	600.37
Standard dev.	27920.23	81316.93	227.48	160.51	100.15
Maximum	142200	373000	1442.45	1255.10	836
Minimum	37150	74150	743.92	724.53	403

Note that some figures were rounded off to two decimal places.

Source: Author's study

5.3 Results of diagnostic tests

a) Augmented Dickey-Fuller test (ADF)

A unit root test was carried out using ADF test, which states that the null hypothesis (H_0) should be rejected if the absolute value of the test statistics is greater than the critical values at 1%, 5% and 10% significant levels. Area/hectares of sorghum (sorghumha) and yield/tons of sorghum (sorghumton) were stationary at 10% critical value, while, technology advancement (tech) and average annual rainfall (rainfall) were stationary at 1% critical value. However, two variables namely: real producer price of sorghum (realsorprice) and real producer price of maize (realmaizeprice) were not stationary. The series was stationary at first difference I (1) integration. Indeed, the null hypothesis that the series is not stationary was rejected, thus the alternative hypothesis was accepted since the series has a unit root.

Table 5.2: Unit root test using ADF test.

Variables	**ADF test statistics**	**10% Critical Value**	**Lag length**	**p-value**	**Decision**
LnSorghumha	2.700	2.630	0	0.0740	Stationary
LnSorghumton	2.914	2.630	0	0.0437	Stationary
LnTech	27.798	2.630	0	0.0000	Stationary
LnRealsorprice	2.412	2.630	0	0.1384	Non-stationary
LnRealmaizeprice	1.714	2.630	0	0.4240	Non-stationary
LnRainfall	4.287	2.630	0	0.0005	Stationary

Critical values were 3.750, 3.000 and 2.630 with significant level of 1%, 5% and 10% respectively.

Source: Author's study

Table 5.3: Results of unit root test after first difference.

Variables	**ADF test statistics**	**10% Critical Value**	**Lag length**	**p-value**	**Decision**
LnRealsorprice	4.246	2.630	1	0.0006	Stationary
LnRealmaizeprice	2.978	2.630	1	0.0370	Stationary

Critical values after differencing of the data remained the same at 3.750, 3.000 and 2.630 with significant level of 1%, 5% and 10% respectively.

Source: Author's study.

Tables 5.2 and 5.3 above depicts results obtained from testing stationary of the series as indicated. Four variables were stationary namely; sorghumha, sorghumton, tech and rainfall, while two variables, realsorprice and realmaizeprice had to be differenced in order to be stationary. Overall, this means that the null hypothesis (H_0) was rejected.

b) Serial correlation test

The data were tested for serial correlation using Breusch-Godfrey LM test and H_0: that the data serially correlated was rejected, meaning that there is no serial correlation.

Table 5.4: Lagrange-multiplier (LM) test for autocorrelation.

Lag	**Chi^2**	**df**	**Prob> chi^2**
1	2.4770	4	0.64876
2	5.4470	4	0.24443

H_0: no autocorrelation at lag order

Source: Author’s study

Table 5.4 above demarcates autocorrelation results using Breusch-Godfrey LM test and it is clear that there is no autocorrelation found among the variables included in the VECM. If the *p*-value for any of the lag levels is less than 0.1 then the H_0 is rejected at the respective significance level and the conclusion is that the disturbance terms are uncorrelated. Thus, this test finds no evidence of model misspecification (StataCorp, 2011).

c) Heteroscedasticity

A test for heteroskedasticity was employed using Szroeter's test and Breusch-Pagan/Cook-Weisberg test. The H_0: that the variance of the error term is not constant was rejected, hence the series is homoscedasticity.

Homoscedasticity is given by the following equation:

E(Ui2) = σ^2 i = 1,2,…,n

Table 5.5: Breusch-Pagan / Cook-Weisberg test for Heteroscedasticity.

chi^2(6)	**Prob > chi^2**
3.19	0.7850

H_0: Constant variance

Source: Author’s study

The heteroscedasticity states that the error term be constant such that the homoscedasticity is reached. Hence, the H_0 that the variance is not constant was rejected.

Table 5.6: Szroeter's test for homoscedasticity.

Variable	chi^2	df	p-value
LnSorghumha	0.23	1	0.6293
LnSorghumton	0.20	1	0.6556
LnTech	0.02	1	0.9025
LnRealsorprice	0.02	1	0.9439
LnRealmaizeprice	0.14	1	0.7127
LnRainfall	1.47	1	0.2252

H_0: variance constant

Ha: variance monotonic in variable

Source: Author's study

Table 5.5 and 5.6 are interlinked, hence homoscedasticity solves the problem of inconstant error term. Thus table 5.6 is a more desired table.

d) Stability condition of VECM estimates

The stability of the model has also been tested using Ramsey RESET test. The H_0: that the model has omitted variables was rejected and accepted the H_a: that there is no omitted variable. This test was undertaken to check the stability condition of the VECM estimates.

Table 5.7: Eigenvalue stability condition.

Eigen Value		Modulus
0.3592958	+ 1.037711i	1.09815
0.3592958	- 1.037711i	1.09815
1		1
-0.0253561		0.025356

The VECM specification imposes a (1) unit modulus.

Source: Author's study

Following the results on the stability condition of the VECM estimates, it was deduced that the stability condition was met in that there was a unit (1) modulus and the table footer confirms that indeed the specified VECM imposes one unit modulus on the companion matrix. Therefore, it was concluded that the estimates obtained from the VECM in this study was stable. This implies that the respective ECM terms are able to bring back the system to equilibrium after a shock (Johansen, 1988 and StataCorp, 2011).

e) Test for normally distributed disturbances

A Vecnorm test was employed to test for normality after estimating the parameters of a VECM. The test vecnorm computes a series of test statistics of the null hypothesis that the disturbances in a VECM are normally distributed for each equation and all equations jointly. Three statistics were computed: a skewness statistic, a kurtosis statistic, and the Jarque–Bera statistic. The overall null hypothesis is that the disturbance term in that equation has a univariate normal distribution (StataCorp, 2011 and Gujarati & Porter, 2009).

Table 5.8: Test for normality Jarque-Bera test.

Equation	chi2	df	Prob > chi2
D_LnSorghumha	0.240	2	0.88676
D_LnSorghumton	0.559	2	0.75614
ALL	0.799	4	0.93853

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_LnSorghumha	-.18738	0.099	1	0.75245
D_LnSorghumton	-.37737	0.403	1	0.52529
ALL		0.503	2	0.77764

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_LnSorghumha	3.446	0.141	1	0.70742
D_LnSorghumton	2.5314	0.156	1	0.69329
ALL		0.296	2	0.86225

Source: Author's study

The Jarque–Bera results present test statistics for each equation and for all equations jointly against the null hypothesis of normality. In this instance, the single-equation and overall Jarque–Bera statistics do reject the null of normality.
The single-equation skewness test statistics are of the null hypotheses that the disturbance term in each equation has zero skewness, which is the skewness of a normally distributed variable. The row marked ALL shows the results for a test that the disturbances in all equations jointly have zero skewness. The skewness results shown above do suggest normality.

The kurtosis statistics presented in the table test the null hypothesis that the disturbance terms have kurtosis consistent with normality. The results in this instance do reject the null hypothesis (StataCorp, 2011 and Johansen, 1988).

f) Selection order criteria

Table 5.9: Determination of optimal lag.

lag	**Log likelihood (LL)**	**Likelihood ratio (LR)**	**P-value**	**Final prediction error (FPE)**	**(Akaike Information Criterion (AIC)**	**(Hannan and Quinn information criterion) (HQIC)**	**(Schwarz' Bayesian information criterion) (SBIC)**
0	8.83742	-	-	0.004221	0.155011	0.149983	0.627044
1	10.0206	2.3663	0.669	0.006815	0.530588	0.523548	1.19143
2	20.6276	30.685*	0.000	0.003505*	-1.54775*	-1.56082*	-0.320459*
3	22.2656	3.276	0.513	0.00744	-0.035407	-0.046469	1.00307
4	37.6081	21.214	0.000	0.004462	-0.350343	-0.359394	0.499317

The asterisks(*) indicates the optimal lag selection for the various selection criterion

Source: Author’s study

The varsoc test was applied to determine the optimal number of lagged values of the explanatory variables to be included in the model. The test generates log-likelihood, likelihood ratios and values for three lag selection criteria: AIC, the HQIC and the SBIC. These three selection criteria suggested the inclusion of two lagged values per variable. Therefore, ECM was specified using two lagged values per explanatory variable as well as for the lagged dependent variable.

g) Co-integration

The Johansen co-integration test was used to test the time series data for co-integration. The Johansen co-integration test is based on the maximum likelihood (ML) estimation and two statistics; trace statistics and maximum Eigen values.

Table 5.10: Johansen Co-integration test.

Maximum rank	**Eigen value**	**Trace statistics**	**1% critical value**
0	-	29.8343	20.04
1	0.77939	4.1410*	6.65
2	0.21619	-	-

The asterisk (*) indicates the point at which the null-hypothesis will be rejected; where the critical value exceed trace statistics.

Source: Author’s study

At a maximum rank of zero r=0 the trace statistics (29.8343) is greater than the critical value (20.04), thus the null hypothesis of no co-integrating equations was rejected. However, when r=1 the trace statistics (4.1410) is lower than the critical value (6.65), hence the null hypothesis that there is at least one co-integrating equation could not be rejected. The conclusion was that there is at least one co-integrating equation among the series. Therefore, ECM was specified with the inclusion of one co-integrating equation.

Table 5.11: Log-likelihood test for goodness of fit (sorghum area/hectares planted).

Source	SS	df	MS
Model	1.88533727	5	0.377067454
Residual	0.246061499	13	0.018927808
Total	2.13139877	18	0.118411043

Number of obs = 19
F(5, 13) = 19.92
Prob > F = 0.0000
R-squared = 0.8846
Adj R-squared = 0.8402
Root MSE = 0.13758

LnSorghumha	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnSorghumton	0.4989881	0.0925121	5.39	0.000	0.2991279	0.6988483
LnTech	17.96136	22.56552	0.80	0.440	-30.78849	66.7112
LnRealsorpr~e	-0.586228	0.2195652	-2.67	0.019	-1.06057	-0.1118864
LnRealmaize~e	-0.6193366	0.3195333	-1.94	0.075	-1.309646	0.0709732
LnRainfall	-0.1449771	0.205932	-0.70	0.494	-.5898661	0.2999118
_cons	-122.0618	169.8251	-0.72	0.485	-488.9466	244.8229

Source: Author’s study

Table 5.12: Log-likelihood test for goodness of fit (sorghum output/yield)

Source	SS	df	MS	
Model	2.55372099	5	5.510744198	Number of obs = 19
Residual	0.683030862	13	0.052540836	F(5, 13) = 9.72
				Prob > F = 0.0005
				R-squared = 0.7890
				Adj R-squared = 0.7078
Total	3.23675185	18	0.179819547	Root MSE = 0.22922

LnSorghumton	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnSorghumha	1.385118	0.2568001	5.39	0.000	0.8303354	1.939901
LnTech	-25.69454	37.83614	-0.68	0.509	-107.4345	56.04547
LnRealsorpr~e	0.7161464	0.4095742	1.75	0.104	-0.1686849	1.600978
LnRealmaize~e	0.5251744	0.5866066	0.90	0.387	-0.7421121	1.792461
LnRainfall	0.2943297	0.3399154	0.87	0.402	-0.4400129	1.028672
_cons	181.403	284.0902	0.64	0.534	-432.3365	795.1426

Source: Author's study

To test for the goodness of fit of the model a log-likelihood ratio was computed. Following Gujarati & Porter (2009); Mutua (2015) and StataCorp (2011) Where: LLR is the Log-likelihood ratio, LLFur is the log-likelihood function for the model with all the variables while LLFr is the log-likelihood for the restricted regression that includes only the constant. LLFur is equivalent to the residual sum of squares (RSS) while LLFr is equivalent to the total sum of squares (TSS) in a linear regression model.

5.4 Empirical results

Table 5.13: Model one VECM results area/hectarage response function.

Variable	**Coefficient**	**Test Statistic (z)**
Short-run supply elasticity		
$LnSorghumha_{t-1}$	-0.17	-0.27
$LnSorghumton_{t-1}$	0.77***	1.60
$LTech_{t-1}$	8.4***	1.76
$LnRealsorprice_{t-1}$	0.99***	1.62
$LnRealmaizeprice_{t-1}$	-0.49***	-1.84
$LnRainfall_{t-1}$	0.89***	-1.72
Constant	13.15	0.39
Error correction term	-1.55***	1.78
Long-run supply elasticity		
LnSorghumha	1	-
LnSorghumton	0.85*	-15.55
LnTech	3.78*	2.11
LnRealsorprice	1.74*	8.76
LnRealmaizeprice	-1.15*	1.81
LnRainfall	1.69*	-5.90
Constant	-161.85	-
Adj. R^2	= 0.76	
Log likelihood	= 0.97	
P>chi^2	= 0.0005	

*** Significant at 10% ** Significant at 5% * Significant at 1%

Source: Author's study

a) Model one: Area response function

LnRealsorprice

The short-run indicates that the single lagged real price of sorghum (own price) was statistically significant at 10% and has positively influenced the area under sorghum production. This simply means that a one-rand (R1.00) increase in the price of sorghum will result in an increase in the area of sorghum planted by 0.99 hectares in the subsequent period. The coefficient of the price of sorghum was less than unity, this means that own price was inelastic in the short-run. This inelastic price explains that when own price increase, hence, the area under sorghum production is likely to increase in the subsequent period. However, that increase in hectares is relatively lower than the price change.

The long-run own price was statistically significant at 1% with a coefficient (1.74) greater than unity. The price of sorghum has positively influenced the area under sorghum production with elastic supply. This implies that area allocation is more responsive to price incentives in the long than short-run. Hence, a unit increase in own price in the long-run will increase the area of sorghum planted by 1.74 hectares. Moreover, both null-hypotheses were rejected and the conclusion is that own price was significant, responsive, elastic and has positively influenced the area response function. Similar results were found by the following authors: Mutua (2015); Townsend & Thirtle (n.d.) and Shoko (2014).

LnRealmaizeprice

The short-run indicates that real price of maize (as a competing crop) was statistically significant at 10% with a coefficient of -0.49. This means that the price of the competing crop has negative influence on the area under sorghum production. Furthermore, this implies that when the price of maize increase by one-rand (R1.00), the area under sorghum production will reduce by 0.49 hectares, following an increase in the price of the competing crop as farmers reallocate resources towards the more rewarding crop (maize). The price of maize is inelastic in the short-run, indicating that when the price increases, the planned area of sorghum production is likely to decrease in the subsequent period. Hence, the area under sorghum production responds slightly to changes in maize price in the short-run.

Long-run price elasticity of maize was statistically significant at 1% with a coefficient of -1.15 and carrying the expected negative sign. The price of maize was elastic in the long-run indicating that an increase in the price of maize would have a negative influence in the planned area under sorghum production in the subsequent year. The long-run magnitude is greater than the short-run implying that sorghum production is better responsive to maize price changes in the long than in the short-run. Thus, the study rejected both null-hypotheses and concluded that maize price was significant, responsive and elastic.

These results are in line with Anwarul Huq & Arshad (2010) and Munyati *et al.* (2013) wherein it was found that the sorghum sector is highly sensitive to changes in the maize prices. This happens due to the fact that, maize and sorghum are substitutes and they compete for land, thus an increase in the price of maize will lead to farmers switching to the production of maize. Before farmers grow a particular crop they look at the opportunity cost of growing that crop. The cross price elasticity of sorghum was -0.93, which means that for every increase in the price of maize by 10%, the acreage of sorghum will reduce by 9.3%.

LnSorghumton

The short-run yield was statistically significant at 10% with a coefficient of 0.77. This is less than unity and it represents inelastic supply of sorghum output. The positive sign of yield was expected as sorghum output per hectare was increasing, producers tend to increase area under sorghum production.

The long-run yield was statistically significant at 1%. The long-run elasticity showed an increase with a coefficient of 0.85 tons per hectare indicating an improvement in the tons per hectare in the long than the short-run. Hence, better yield will infer more profit and reallocation of more land towards production of sorghum. Furthermore, the null-hypotheses that lagged tons of sorghum do not have an influence on the planned area under sorghum production were rejected.

LnTech

In the short-run the technology advancement of the sorghum supply elasticity was statistically significant at 10% and has positively influenced the area under sorghum production with a high coefficient of 8.4. This implies that improvement in the knowledge of farmers, level of fertilizers, herbicides, seeds variety, mechanisation, extension advisory and change of policies have a great influence on the hectares of sorghum planted. Technological improvement will lead to 8.4 hectares planted in the subsequent period.

The long-run technological improvement was statistically significant at 1% with a magnitude of 3.78 and it was elastic, however this was lower than the short-run elasticity. This means that in the short-run, technological improvement is more responsive than in the long-run. This was not expected as the state of technology usually has an impact in the long than short-run. The null-hypotheses were also rejected as the technological change proved to have significantly influenced the sorghum area planted. Mutua (2015) found a very low magnitude of coefficient (0.008) of technological change and concluded that there was a very minimal technological change in the sugarcane sub-sector over the study period. The technological change however seems to have affected the supply response of sugarcane farmers in

Mumias negatively. This was further reported by Tripathi (2008) with a coefficient of 0.10, thereby confirming that time trend plays a major role in defining the agricultural output.

LnRainfall

The short-run average annual rainfall received was statistically significant at 10% with a coefficient of 0.89 and positively influenced the area under sorghum production. The positive sign was expected as rainfall tends to have a positive relationship with crop production. The average annual rainfall was inelastic implying that an increase in rainfall by one per cent would result in 0.89 per cent increase in the area of sorghum planted in the next season. In the long-run the average annual rainfall was significant at 1% and it was elastic with a coefficient of 1.69 implying that the area under sorghum production is more responsive when the country has received enough rainfall. Thus, the null-hypothesis that average annual rainfall does not influence the area under sorghum production was rejected. Tripathi (2008) explained that the coefficient (0.29) of annual rainfall was statistically significant at one per cent level and influenced agricultural output, thus these results were compatible with this study and those of other researchers such as Shoko (2014) and Alhaji *et al.* (2014).

The error correction term, which measures the speed of adjustment to long-run equilibrium was statistically significant with the expected negative sign indicating that the model is able to revert to equilibrium after an economic shock. The coefficient of error correction term was -1.55 implying that area response function was able to recover from short-run disequilibrium and revert to its long-run mean within one time period (one year). In comparing the author's results, Tripathi (2008) found an ECM of -0.48 and concluded that 0.48 of the deviation of the agricultural output from its long run equilibrium level is corrected each year. Furthermore, this was confirmed by Mose *et al.* (2017), who stated that the ECM shows that both the price of maize and fertiliser have an impact on the long-run relationship on the maize supply response as expected. However, when the price of maize decreases, there is a tendency for farmers to reduce the amount of productivity-enhancing inputs and timeliness of maize production activities for the following season.

The coefficient of determination (adjusted R^2) presents supply model's goodness of fit. The magnitude of 0.76 describes that the regressor variables explain about 76% of the variation in the area response function. A log-likelihood ratio closer to one implies a better fit showing that the model fits the data well (Gujarati & Porter, 2009). In this instance, the log likelihood ratio was 0.97.

Table 5.14: Model two VECM results yield/output response function.

Variable	**Coefficient**	**Test Statistic (z)**
Short-run supply elasticity		
$LnSorghumton_{t-1}$	0.10	0.14
$LnSorghumha_{t-1}$	0.14	0.14
$LnTech_{t-1}$	4.8***	1.85
$LnRealsorprice_{t-1}$	0.66	0.69
$LnRealmaizeprice_{t-1}$	0.66	0.41
$LnRainfall_{t-1}$	0.26	0.41
Constant	-18. 22	-0.35
Error correction term	-1.30	-1.38
Long-run supply elasticity		
LnSorghumton	1	-
LnSorghumha	-1.17*	-18.34
LnTech	0.31	0.01
LnRealsorprice	-2.06*	-9.49
LnRealmaizeprice	-0.16	-1.03
LnRainfall	0.80*	7.07
Constant	148.95	-
Adj. R^2	= 0.70	
Log likelihood	= 0.32	
P>chi^2	= 0.0081	

*** Significant at 10%   ** Significant at 5%   * Significant at 1%

Source: Author's study

b) Model two: Output response function.

LnRealsorprice

The short-run single lagged real price of sorghum was statistically insignificant but has a positive relationship with sorghum output. The indication here is that a one-rand (R1.00) increase in the price of sorghum will lead to an increase in sorghum output by 0.66 tons in the subsequent period. The coefficient of the price of sorghum was less than unity, meaning that own price was inelastic in the short-run. Furthermore, this inelastic price explains that when own price increases, sorghum output is likely to increase in the subsequent period, following an increase in own price. However, that increase in output is relatively lower than the price change.

The long-run own price was statistically significant at 1% with a coefficient (-2.06) greater than unity. This coefficient -2.06 implies that a one-rand (R1.00) increase in own price in the long-run will decrease sorghum output by 2.06 tons in the subsequent period. Hence, this was not expected, since the economic theory states that there is a positive relationship between the price of the commodity and the product in question. Own price has elastic supply, implying that an increase in price is likely to decrease sorghum output in the long-run at a greater magnitude. Moreover, this means that yield respond negatively to own price. Thus, the null-hypotheses were rejected as own price was significant and negatively influenced the yield supply function. Surprisingly, Munyati *et al.* (2013) reported different findings wherein the long-run own price elasticity was found to be 0.51 whilst in the short run it was 0.24. These results mean that agricultural price policy alone cannot guarantee sorghum production growth targets.

LnRealmaizeprice

In the short-run, the real price of maize (as a competing crop) was statistically insignificant with a coefficient of 0.66, however this sign was not expected. The meaning here is that maize price has a positive influence on yield/sorghum output. Furthermore, this implies that when the price of maize increases by one-rand (R1.00) sorghum output will increase by 0.66 tons. Hence, this does not conform to the law of supply stated above. Under normal circumstances, farmers would not reallocate their resources when the price of the commodity in question is rewarding. The price of maize is inelastic in the short-run, indicating that when the price increases the sorghum output is likely to increase in the subsequent period. Thus, sorghum output is not responsive to maize price in the short-run.

The long-run price elasticity of maize was statistically not significant with a coefficient -0.16, however it carried an expected sign. The price of maize is inelastic both in the short and long-run indicating that an increase in the price of maize would not have a significant influence on the sorghum output produced. In addition, the short-run magnitude is greater than the long-run. The negative sign of maize price means that a one-rand (R1.00) increase in the price of maize would reduce sorghum output by 0.16 tons. Thus, we cannot reject the second null-hypothesis that the price of maize is not elastic in both short and long-run elasticity terms.

lnSorghumha

In the short-run the lagged area of sorghum planted was statistically not significant, however, has positively influenced sorghum output. The coefficient was 0.14 implying that a unit increase in the area under sorghum production would increase sorghum output by 0.14 tons in the subsequent season. The elasticity of area allocation is inelastic, meaning that when the area under sorghum production increases in the short-run, output will increase but at a lower rate, though that increase in hectarage is lower than increase in yield.

The long-run area allocation was significant at 1% with a coefficient of -1.17, implying that the supply is elastic in the long than short-run. This elastic supply means that increase in the area under sorghum production by one per cent would result in a decrease in sorghum output by 1.17 tons. Therefore, the null-hypotheses that the area of sorghum planted does not have influence on sorghum output were rejected and it was concluded that the area allocation was significant and elastic. These results are compatible with Rao (1988) where it was estimated that crop-specific acreage elasticity range between zero and 0.8 in the short-run while long-run elasticity tend to be higher between 0.3 and 1.2. Yield elasticity is smaller and less stable than acreage elasticity. Again, these findings on the short-run and long-run elasticity resemble those of other authors namely Alhaji *et al.* (2014) and Shoko (2014).

LnTech

The short-run technology advancement of the sorghum supply elasticity was statistically significant at 10% and has positively influenced sorghum output with a very high coefficient of 4.8. This implied that improvement in agricultural policies, mechanisation, fertilizers, herbicides, seeds variety, extension advisory, etc; have a great influence on sorghum output. This technological improvement will result in 4.8 sorghum tons produced in the subsequent period, hence, it was elastic in the short-run.

The long-run magnitude of technological improvement was 0.31 hence this was inelastic. Moreover, it was lower than the short-run elasticity. Surprisingly, in the short-run technological improvement is more responsive than in the long-run. However, this was not expected as sorghum output tends to improve with time and experience gained by farmers in the long than in the short-run. Hence, the null-hypotheses were rejected as technology advancement proved to have significantly influenced the sorghum output and was elastic in the short-run. Contrary to this, Mutua (2015) found a very low magnitude of coefficient (0.008) of technological change and concluded that there was a very minimal technological change in the sugarcane sub-sector over the study period. The technological change however seems to have affected the supply response of sugarcane farmers in Mumias negatively. However, Tripathi (2008) found the coefficient of the technological change to be 0.10 and concluded that the time trend plays a major role in defining the agricultural output.

LnRainfall

In the short-run the average annual rainfall received was statistically insignificant with a positive sign of the coefficient. This positive sign was expected as rainfall tends to have positive relationship with production. The average annual rainfall was inelastic with coefficient of 0.26, and this implies that an increase in rainfall by one per cent would result in 0.26 per cent increase in sorghum output in the next season.

In the long-run the average annual rainfall was significant at 1% but inelastic, with a coefficient of 0.80, however the magnitude has increased in the long-run although it is not elastic. Thus, the null-hypotheses that average annual rainfall does not have an influence on sorghum output were rejected and it was concluded that rainfall was significant in the long-run. Tripathi (2008) explained that the coefficient (0.29) of annual rainfall was statistically significant at one per cent level and influenced agricultural output, thus these results were compatible with this study and those of other researchers such as Shoko (2014).

The error correction term, which measures the speed of adjustment to long-run equilibrium was statistically insignificant with an expected negative sign indicating that the model was able to revert to the equilibrium after an economic shock. The coefficient of error correction term was -1.30 implying that the yield response function was able to recover from the short-run disequilibrium and revert to its long-run mean within one time period (one year). Anwarul Huq & Arshad (2010) found the ECM of -1.1838 and concluded that the coefficient indicates a feedback of about 118.38% of the previous year's disequilibrium from the long-run elasticity of potato price. This implies that the speed with which potato price adjusts from the short-run disequilibrium to changes in potato supply in order to attain long-run equilibrium is 118.38% within one year. These findings were compatible with those of Tripathi (2008).

The coefficient of determination (adjusted R^2) presents supply model's goodness of fit. The magnitude of 0.70 describes that the regressor variables explain about 70% of the variation in the yield response function. A log-likelihood ratio closer to one implies a better fit showing that the model fits the data well (Gujarati & Porter, 2009). In this instance the log likelihood ratio was 0.32.

c) Comparison of the two models

Assessment of the two models were scrutinised, wherein the models were judged based on the significance of the coefficients, log likelihood, $P>Chi^2$ and the goodness of fit of the models. It has been ascertained that model one; LnSorghumha (area/hectares planted) is more preferred than model two LnSorghumton (yield/sorghum output), since sorghum production has shown to be more responsive on the area than the yield function. Thus, it was concluded that the area response function was found to be a robust model. This occurred because acreage is thought to be more subject to the farmer's control than output and implies that farmers have control over the area decisions.

Mythili (2006) supported the above idea by stating that the standard procedure was to use area as an indicator of supply due to the reason that area decision is totally under the control of the farmers. Therefore, variations in the price of sorghum have significantly explained adjustment of the area under sorghum cultivation. Rao (1988) ascertained that yield elasticity is smaller and less stable than acreage elasticity. These findings on the short-run and long-run elasticity resemble those of other authors namely Alhaji *et al.* (2014) and Shoko (2014).

5.5 Conclusion

The results obtained by this study conform with those obtained by other researchers. The ECM methodology provides robust results as it was highlighted in the literature review, hence, this study is in-line with other studies.

CHAPTER 6: SUMMARY, CONCLUSIONS AND POLICY RECOMMENDATIONS

6.1 Summary

The focus of this study was to examine how sorghum production respond to own price (sorghum price), price of the competing crop (Maize), hectares of sorghum planted, sorghum output, rainfall received and technological change. The objectives of this study were to estimate elasticity of sorghum production to changes in price and non-price factors, as well as estimating the short-run and long-run sorghum price elasticity.

Time series data were obtained from DAFF through Abstracts of Agricultural Statistics and verified by the South African Grain Information Services (SAGIS). Data were processed through STATA and VECM was employed to address the aforementioned objectives. Technological change was included in the analysis to capture the effects of advancement in the level of technology. Estimates of parameters of yield and area response functions were obtained through application of Ordinary Least Square (OLS) procedure. A number of diagnostic tests were applied; these include unit root test using ADF test, serial correlation, heteroscedasticity, stability test, normality test, selection order criteria, co-integration and log likelihood test.

In the area response function (model one) own price has significantly and positively influenced the area under sorghum production both in the short and long-run. Maize price (as a competing crop) negatively influenced the area under sorghum as expected, the coefficient of yield was positive, however inelastic both in the short and long-run. Technological advancement has significantly affected the area under sorghum production with a very high coefficient in the short and long-run, average annual rainfall influenced sorghum production positively, however, it was inelastic in the short-run. The null hypotheses were rejected and concluded that all variables in model one were significant, responsive, elastic and have positively influenced the area response function with the exception of maize price. Therefore, the sorghum area allocation in South Africa is more sensitive to changes in price and non-price incentive.

While on the other hand there is a yield response function (model two), surprisingly own price (sorghum price) was insignificant and had negatively influenced sorghum output; the same happened to maize price wherein it was insignificant with different signs of coefficient in the short and long-run. The short-run hectares influenced yield positively, however the long-run coefficient was negative. Technological advancement was significant with elastic short-run and inelastic long-run elasticity. The average annual rainfall was inelastic in the short and long-run; however positively influenced the yield. The formulated null hypotheses cannot be rejected as most of variables in this model were insignificant, not responsive and inelastic. Therefore, it was concluded that sorghum output in South Africa is less sensitive to changes in price and non-price incentives.

Overall, this study examined sorghum supply elasticity using two dependent variables; sorghum area planted and sorghum output as model one and two respectively. This study found that model one (area response function) was a robust model, while model two (yield response function) was not robust and hence not adopted. Thus, sorghum production showed better response to the area than yield function. Price elasticity of maize had negative influence on sorghum area allocation in South Africa. Area under sorghum was sensitive to own producer price. This means that an increase in the price of sorghum resulted in more area allocated to the crop by farmers.

The error correction term for area response was -1.55 and -1.30 for yield response and both were greater than unity, which indicated that farmers were able to adjust their production and revert to the long term equilibrium in one time period after an economic shock. Therefore, the study rejects the null-hypotheses and concludes that area allocation was elastic and more responsive to changes in price and non-price factors.

6.2 Conclusions

All variables fitted in model one (area response function) carrying expected signs and were significant at 10% in the short-run and 1% in the long-run. Area allocation was highly responsive to technological change and own price, however, the price elasticity of maize had negative influence on sorghum area allocation in South Africa. In the short-run, only technological change was elastic, however, in the long-run all variables were elastic except for sorghum output. Therefore, it was concluded that sorghum producers were slightly flexible in their area allocation decisions in the short-run, nevertheless, in the long-run they were more flexible when it comes to allocating more land to sorghum production. The implication is that sorghum producers needed enough time to adjust land allocation in response to changes in price and non-price factors.

All variables have significantly influenced area response function and most of them were elastic in the long-run. Hence, the changes in price and non-price factors have induced elastic supply response. The conclusion is that, the area allocation was highly responsive to factors included in this study. The formulated null hypotheses were rejected and it was concluded that all variables in model one were significant, responsive, elastic and positively influenced the area response function with the exception of maize price. Therefore, sorghum area allocation in South Africa is more sensitive to changes in price and non-price factors.

Own price was inelastic in the short-run and the implication was that decisions by farmers to change production following price increase was minimal. Therefore, the long-run own price was greater than unity (elastic price) and it was concluded that sorghum farmers need enough time before they alter the area under cultivation following own price increase. Overall, the study inferred that an increase in the price of sorghum results in an increased area under sorghum production.

The cross price elasticity of maize negatively influenced the sorghum area allocation. This was as expected since an increase in the price of maize resulted in a reduction in the area under sorghum production. The conclusion is that farmers move from the production of sorghum to the production of maize following an increase in the price of maize (as a competing crop). This is in-line with economic theory where an increase in the producer price of the commodity in question results in a shift of supply towards more rewarding products. This particular finding is very critical because an increase in the price of maize will encourage more farmers to plant the crop, meanwhile reducing food insecurity and poverty issues in the country.

Average annual rainfall was significant and with an expected positive sign. This indicated that rainfall contributes positively towards land allocation to grain sorghum in South Africa. This is because most of the smallholder farmers practice rain-fed agriculture, hence failure of rainfall would affect the supply of sorghum negatively. Moreover, this is also applicable to farmers producing on irrigated land as underground water will be affected if there is no rain. The yield of sorghum was statistically significant and with an expected positive sign, however inelastic both in the short-run and long-run. Hence, it was concluded that farmers were willing to increase the area under sorghum production as long as ton/ha were increasing.

On the other hand, there was model two (yield response function) which presented that own price was statistically insignificant but had a positive sign. This insignificance made it difficult to tell whether own price had influenced the yield. Furthermore, the yield was not dependent on the price of sorghum (increase or decrease in price does not influence the yield) but on other variables not specified in this study. The negative sign meant that increase in the price of sorghum results in the reduction of the yield. Hence, it was concluded that this is not compatible with economic theory (the law of supply) which states that price increase will cause an increase in the supply of the commodity in question.

The price of the competing crop (maize) was also statistically insignificant with an unexpected positive sign. Surprisingly, the long-run maize price had expected negative sign. The insignificance here also made it difficult to provide a concrete interpretation of the coefficient. Under normal circumstances as envisaged in model one; it could be expected that the sign of maize price be negative. Thus, both the short-run and long-run maize price elasticity were inelastic. Sorghum hectares were statistically significant only in the long-run, however with an unexpected negative sign, which meant that increasing the area under sorghum production by one hectare, would decrease the yield. Therefore, it was concluded that yield is not explained by adjustment in maize price and hectares, rather on other factors not specified in this study.

The technological change was statistically significant only in the short-run with an expected positive sign. Surprisingly, it became insignificant in the long-run and was not expected. The conclusion was that, sorghum output was more responsive to improvement in new seeds varieties, machineries, extension services and knowledge (experience gained over the years) in the short than long-run. Thus, this contradicts with what was stated in the area response function, where it was postulated that sorghum farmers are more responsive to technological change in the long than short-run. Average annual rainfall was statistically significant in the long-run with an expected positive sign, indicating that rainfall is as important as own price in explaining the yield response in South Africa.

Model two had only one variable (technological change) significant at 10% in the short-run and three variables significant at 1% in the long-run (sorghum hectares, own price and rainfall). However, with these few variables being statistically significant, model two was not robust and hence not adopted. Nevertheless, the yield was highly responsive to technological change in the short-run. The formulated null hypotheses cannot be rejected as most of the variables in this model were insignificant, not responsive and inelastic. Thus, it was concluded that sorghum output in South Africa is less sensitive to changes in price and non-price factors. Furthermore, it was concluded that model one is robust, as sorghum production has shown better response to area than yield response. This was backed up by a closer look at other statistical properties such as the significance of the coefficients, goodness of fit of each model and error correction term.

6.3 Policy Recommendations

The findings of this study inferred the following recommendations.

This study found out that own price positively influenced the area allocated to sorghum cultivation. Since the producer price of sorghum inferred increase in the area under sorghum grain. Therefore, input subsidies become critical and will play a massive role in improving the farm incomes, thereby enhancing profitability of sorghum farmers. Increase in the area under sorghum production will assist in improving food security and alleviation of poverty in South Africa and the world at large. Given that approximately 99% of sorghum is exported by South Africa to the (SADC) Southern African Development Community, hence, this study recommends that the government of South Africa should try by all means to keep the currency as strong as possible for the benefit of domestic sorghum producers.

The negative influence of the price of the competing crop (maize) postulates that when the price of maize increases the area under sorghum reduces, hence government should put in place strategies that encourage sorghum production at the cost of maize when it is necessary to do so. In addition, the government of South Africa could also put maize hectarage restriction as well as increase tax per ton of maize produced to discourage switching of farmers from sorghum to maize, because this will cause shortages of sorghum as the price has fallen. Furthermore, this will assist in keeping both maize and sorghum producer prices stable *ceteris paribus*.

The magnitude of technological change was found to be very high and this implied that investment of sorghum farmers in skills development, utilisation of improved varieties, provision of extension services will go a long way in addressing the current sorghum shortages. Hence, the government of South Africa should invest in the education of sorghum farmers through symposium, wherein the following discussions are addressed: the adoption of new and improved seed varieties, better marketing strategies, infrastructure and so forth. Furthermore, the government should assign extension officers to all sorghum producers to enhance production and information dissemination.

Average annual rainfall has positively influenced sorghum area response function and thus enough rainfall is necessary for increased sorghum production in the South Africa. Drought was experienced in 2015 and this has resulted in the reduction in agricultural output including sorghum. Hence, mitigation strategies such as utilisation of drought resistant seeds, mulching, testing of moisture before irrigating the land in order to save water, use of hydroponics systems, the use of drip and sprinkler irrigation instead of flood irrigation will go a long way in addressing the effects of drought. Due to the issue of climate change, farmers need guidance to change commencement of planting because rainfall is no longer received as expected, compared to the past decades. Hence, farmers need to change with climate as early planting results in dying of crops due to failure or late rainfall, consequences of which include increasing production costs in the farm. Information on rainfall predictions should be made available to farmers to guide their planting decisions.

The yield has positively influenced the sorghum area response function and it was inferred that as ton/ha increases sorghum farmers tend to increase the area allocated to sorghum production, assuming that tons per hectares will improve. Therefore, the study recommends that amongst other methods to enhance sorghum output, producers could use improved varieties or hybrids, as this action would result in allocation of more land to sorghum production, following price change.

6.4 Recommendations for further studies

After having found that the price of maize has significantly affected the supply of sorghum, therefore the profitability study for both maize and sorghum must be conducted to find out which crop is more rewarding. This could assist to back up the findings of this study.

This study further suggests that a comprehensive investigation around input use intensification as opposed to area increase under sorghum production be undertaken. This will outline input use efficiency in sorghum industry.

As yield was not influenced by increase in own price, therefore a study on factors enhancing yield of sorghum crop need to be investigated. This is vital because yield response function was not well explained by factors included in this study; hence, there is a need to model a study in this context.

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APPENDICES

A1: Augmented Dickey Fuller tests

. dfuller lnSorghumha

Dickey-Fuller test for unit root Number of obs = 18

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.700	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0740

. dfuller lnSorghumton

Dickey-Fuller test for unit root Number of obs = 18

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.914	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0437

. dfuller lnTech

Dickey-Fuller test for unit root Number of obs = 18

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-27.798	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller lnRealsorprice

Dickey-Fuller test for unit root Number of obs = 18

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.412	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.1384

. dfuller lnRealmaizeprice

Dickey-Fuller test for unit root Number of obs = 18

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.714	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.4240

. **dfuller lnRainfall**

Dickey-Fuller test for unit root Number of obs = 18

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.287	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0005

Differencing Prices

dfuller lnRealsorprice, lag(1)

Augmented Dickey-Fuller test for unit root Number of obs = 17

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.246	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0006

dfuller lnRealmaizeprice, lag(1)

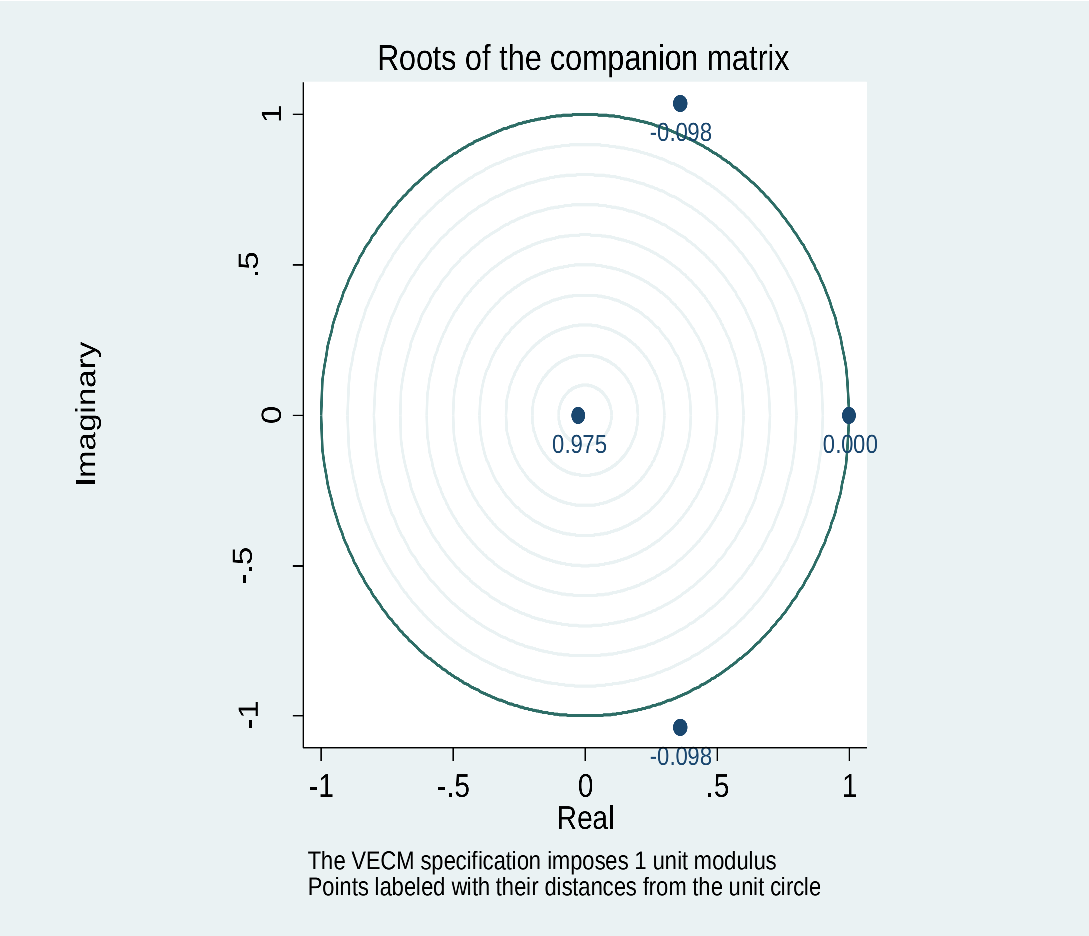
Augmented Dickey-Fuller test for unit root Number of obs = 17

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.978	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0370

A2: Stability test.

Eigenvalues of companion matrix graph



This graph visually represents the eigenvalues of the companion matrix and their associated moduli and plots the eigenvalues of the companion matrix with the real component on the x axis and the imaginary component on the y axis.

A3: QUESTIONNAIRE

YEAR OF PRODUCTION	SORGHUM AREA/ HECTARES	SORGHUM YIELD/ TONS	SORGHUM NORMINAL PRICE PER TON	REAL PRICE SORGHUM	WHITE MAIZE NORMINAL PRICE PER TON	REAL PRICE MAIZE	RAIN (MM)	PPI MAIZE & SORGHUM
1998								
1999								
2000								
2001								
2002								
2003								
2004								
2005								
2006								
2007								
2008								
2009								
2010								
2011								
2012								
2013								
2014								
2015								
2016								