Maize Output Supply Response to Climate Change in Kenya: An Econometric Analysis

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Abstract

Sufficient production of maize in Kenya is synonymous to food security and a source of income. Majority of the households in the country grow maize as the main staple food and forms the diet of over 85 percent of the population. Climate change potentially compromises maize production as 98 percent of agriculture is rainfed, threatening food security and rural livelihoods. This study sought to understand the effects of the changing temperature and rainfall patterns in Kenya on maize output. The study adopted Autoregressive distributed lag econometric modeling approach using data for the period between 1970 and 2014. The findings shows mixed response of maize output to rainfall and temperature changes depending on the period, with temperature variability having negative effects. In absence of climate change adaptation and mitigation, Kenya will become more food insecure. There is need to formulate all-inclusive policies paramount in building adaptation and mitigation mechanisms.

Keywords: Maize Output Supply, Temperature Variability, Rainfall Variability and Climate Change, Climate Variability

1. Introduction

Agriculture sector in Kenya is earmarked as a key sector to contribute towards a sustained economic growth and poverty alleviation according to the national development plan Kenya Vision 2030. The sector contributes nearly 30 percent of Kenya's Gross Domestic Product (GDP), employs over 40 percent of total population, while over 80 percent of rural people depend on agriculture for their livelihood. Indirectly the sector contributes nearly 27 percent of GDP through linkages with manufacturing, distribution and other service related sectors. Imperatively, the sector forms a strong base for food security, employment creation, income generation and thus central to the country's development strategy (Republic of Kenya, 2005; 2015).

According to Kenya Climate Smart Agriculture Strategy-2017-2026, rain fed agriculture accounts for approximately 98 percent of agricultural activities in Kenya. This makes the sector highly vulnerable to climate change, explained as "change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer "(Intergovernmental Panel on Climate Change (IPCC), 2014: 120). Changing climate is manifested through increasing temperatures, droughts, floods and changing rainfall patterns.

The performance of the agricultural sector in Kenya mainly depends on crop production, which is largely dependent on climate conditions. Crop farming in Kenya has limited diversification and maize serves as the main staple and a major source of livelihood and thus key to food security and income generation (UNDP, 2002; Alila &Otieno, 2006; Stern, 2007). However, maize output level has been fluctuating making its production fall below consumption in most years. Further, the growth rate in maize output has been marginal, averaging about two percent which is lower than the population growth rate which averages 3.5 percent (Republic of Kenya, 2015; FAOa, 2016). It is indisputable that there is need for a sustainable increase in maize output to adequately support the livelihoods of the growing population in Kenya. Although, economic incentives are provided to farmers to improve crop production, climate change is likely to undermine these efforts, threatening the livelihood of over 85 percent of Kenyan population. So far studies analyzing maize output supply in Kenya have not in depth considered the effects of climate change (Mose et al., 2007; Olwande et al., 2009; Onono et al., 2013), yet it is expected to influence realization of supply through its influence on farmers crop choices and land allocation (Blanc, 2011). To bridge the gap, this study seeks to empirically, determine the effects of climate variability and change on maize output supply. Anchored on empirical analysis and a detailed review of literature, this study sought to first ascertain the effects of climate change on maize output supply while controlling for economic incentives and thereof draw policy implications.

1.1 Climate Change in Kenya

Climate change is expected to increase with global warming with the average temperatures expected to increase by between 1.4° Celsius (C) and 6.4° C by 2100. This is above threshold limit of 3oC, beyond which it becomes impracticable to avoid dangerous interference with the global climatic system (World Trade Organization (WTO) &United Nations Environment Programme (UNEP), 2009). Countries near the equator like

Kenya, many of which are developing, are likely to experience unbearable heat 1.5 times more than the global level, more frequent droughts and ruined crops, exacerbating the hunger crisis (Food and Agriculture Organization (FAO), 2012; WTO & UNEP, 2009).

Kenya has experienced patterns of climate variability, with El Nino and La Nina episodes being most severe (Stockholm Environmental Institute (SEI), 2009). As well, temperatures are expected to increase by about 4oC and variability in rainfall will rise up to 20 percent by 2030. From the 1960s, Kenya has experienced increasing temperatures at an average rate of 0.21°C per decade with trends in both minimum and maximum temperatures depicting a general warming over time. Annual highest rainfall events show a falling trend for the 24 hour intense rainfall and long rains from 1960 to 2014. See Figure 1 and 2 for the year to year variability of temperature and rainfall in maize growing areas in Kenya.

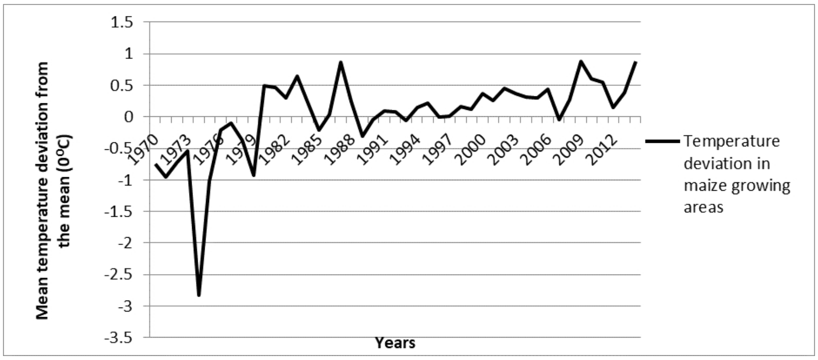

Figure 1: Annual Mean Temperature Variations in Maize Growing Areas in Kenya (1970-2014)

Source: Data from Kenya Meteorological Department

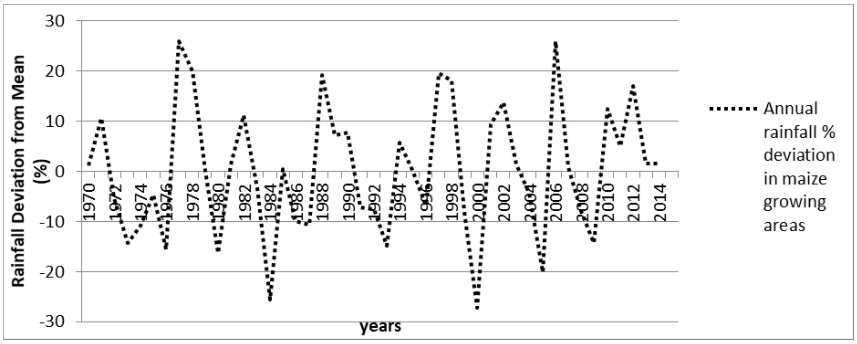

Figure 2: Annual Rainfall Deviations (%) From the Mean in Maize Growing Areas in Kenya (1970-2014).

Source: Data from Kenya Meteorological Department

Temperature and rainfall variations in maize growing areas are computed using data recorded in various weather stations, in areas where there is high potential for maize farming. These stations include: Kitale, Nyahururu, Nyeri, Thika, Narok, Nakuru, Kabete, Machakos, Kakamega, Meru, Embu, Kisii, Kericho and Eldoret. The year to year variation of average temperature for the period 1970 to 2014 shows a slight increase in temperature with fluctuations of up to minus 2.8ºC and plus 1ºC. The deviation of rainfall amount from the mean annual rainfall for the period between 1970 and 2014 show drought and flood conditions in the crop growing regions. The fluctuations depict occurrence of extreme weather events that have been witnessed in Kenya. For instance, severe droughts occurred in 1971/73, 1983/84, 1991/92, 2004-2006, and 2008-2010. As well, flooding occurred in 1997/98 and 2002, which is closely linked to El Nino events with a severe frost occurring in 2012 (Rarieya *et al.*, 2009; KIPPRA, 2013).

Projections of mean rainfall indicate increases in annual rainfall in Kenya at -3 to +49mm per month for the months of October to December (OND) and larger proportional changes in January and February (JF) at -7 to +89% by 2030. The unpredictability of Kenya's rainfall and the tendency for it to fall heavily during short periods is likely to cause problems by increasing the occurrences of heavy rainfall periods and flooding. As well, temperature increase is expected to exacerbate the drought conditions (Osbahr& Viner, 2006; McSweeney, 2010). These changes are likely to affect the optimal conditions required at each stage of crop growth and development and consequently affect the quantity and quality of harvested crops (Stern, 2007). This is likely to place more burden on rural livelihoods who depend on economic activities that are inextricably linked to climate (FAO, 2016b).

1.2 Maize Production in Kenya

In Kenya, Small scale maize (*Zea Mays*) production accounts for 75 percent with different hybrid varieties being recommended for different agro ecological zones (National Farmers Information Service (NAFIS), 2015). Enhancement of maize production is critical as a shortage in maize supply is, largely, synonymous with food insecurity (Owuor, 2010). The cereal grain forms the diet of over 85 percent of the population, accounts for 68 percent of daily per capita cereal consumption, 35 percent of total dietary energy consumption and 32 percent of protein consumption (FAO, 2008; Mohajan, 2014). Hence, Kenya's national food security has a strong relation to production of sufficient quantities of maize to meet an increasing domestic demand arising from a growing population. In addition, maize accounts for more than 20 percent of total agricultural production and 25 percent of agricultural employment (FAO, 2008; Schroeder *et al.*, 2013)

In Kenya, maize farming is spread all over the country from 0- 2200 meters above sea level (masl), facilitated by hybrids and composites developed for different ecological zones by the national maize breeding program (National Farmers Information Service (NAFIS), 2015).The crop performs best in well drained and well aerated loam soils with a pH of 5.5 -7 and is intolerant to water logging. Low production is recorded in very high and low altitudes with optimum temperatures for good yield ranging between 18 to 30^{o}C. Cold conditions lengthen the maturity periods with high temperatures reducing production. Maize grows well with 600-900 mm of rainfall, which should be well distributed throughout the growing period. Rainfall is most critical at flowering and silking stage. Drought at the flowering stage obstructs pollination and considerably reduces yield. Towards harvesting dry conditions are necessary to support drying of the grain (Schroeder *et al.*, 2013). Bergamaschi et al., (2004) notes that maize plants are sensitive to water deficit during a critical stage from flowering to the start of grain filling period. At this stage, there is high water requirement in terms of high evapotranspiration and high physiological sensitivity as number of ears per plant and number of kernels per ear is determined.

In the face of the need to increase quantity and quality of maize produced, there is evidence of stagnation. This has led to an increasing gap between production and consumption besides increasing frequency of supply shortages. See Figure 3 for trends in maize production and consumption and the supply surpluses/ shortages in Kenya for the for the period 1970 to 2014

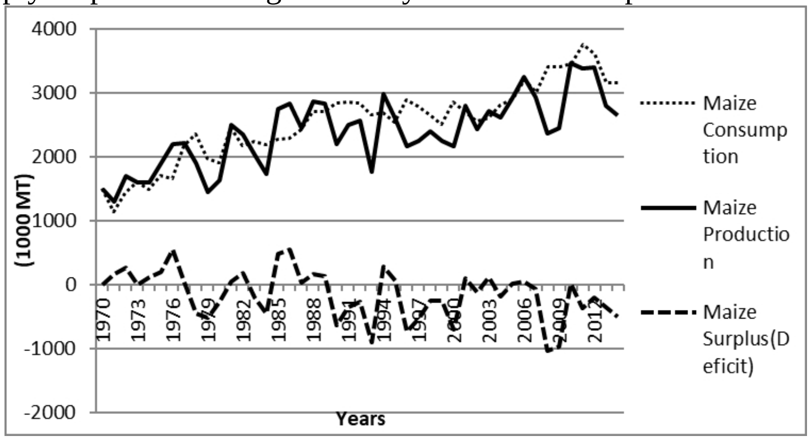

Figure 3. Maize Production and Consumption Trends in Kenya (1970-2014)
Source: Republic of Kenya. Economic survey (various issues).

The trend shows wide fluctuation in maize production over the years resulting to a supply shortage since 1989 save for 1994, 2001 and 2003 where production was above consumption. During this period the average annual maize production stood at 2.3 million tonnes compared to an average annual consumption of 2.6 million tonnes in the same period (FAOa, 2016). Equally, the production of rice and wheat, the main substitutes for maize, has been below the demand with the country only being able to produce 40 percent of its wheat requirements and 34 percent of the national rice consumption requirement (Republic of Kenya, 2003; 2005; 2009; 2011; 2015; Gitau *et al.,* 2011). Moreover, maize production growth averages two percent which is lower than population growth which averages 3.5 percent. For self sufficiency, maize production needs to grow by over 4 percent. Kenya remains a net food importer with about 40 percent of its population being food insecure which triggers diversion of development resources for food procurement (Mutimba *et al.,* 2010; FAOa, 2016).

2. Methodology

2.1 Theoretical Model

This study adopted a quantitative research design and employed production theory in developing theoretical framework and to specify empirical model.

2.1.1 Household Utility Maximization Model

The foremost assumption is that a farmer is a rational economic agent, the household head and largely influences the household's decision making as a family unit. For a household that consumes three goods, a farm produced good (X_a), a market purchased good (X_m) and leisure (X_l). The objective of the household is to maximize utility derived from consumption of the three goods subject to an income constraint where the expenditure on the market purchased good is equal to the sum of net income from the marketed surplus of the farm produced good and income derived from other sources other than from the farm or labor supply. The income constraint in turn depends on production of the staple. Thus, the household chooses the levels of consumption for each of the three goods that will maximize utility and as well make production decisions on the farm produced good, given that X_a is a share of the farm produced good Q_a, with the surplus being marketed as a source of income (Singh *et al.,* 1986).

Notably, the production of the farm produced good is influenced by various factors that include: production inputs such as labor and fertilizer and agro-climatic factors. Thus, the household production technology for the staple can be specified as:

$$Q\_a = \mathrm{Q}\ (\mathrm{L}, \mathrm{V}, \mathrm{A}, \mathrm{K}, \mathrm{W}) \tag{1}$$

Where L is the labor input, V is variable input such as fertilizer, A is the household's fixed quantity of land; K is its fixed stock of capital and W represent agro-climatic conditions such as temperature and precipitation.

Accordingly, the objective of the household can be stated as:

$$\text{Maximizing } \mathrm{U} = \mathrm{U}\ (\mathrm{X_a}, \mathrm{X_m}, \mathrm{X_l}) \tag{2}$$

Subject to an income constraint specified as

$$\mathrm{P_m}\,\mathrm{X_m} + \mathrm{P_a X_a} + \mathrm{P_l X_l} = \mathrm{P_l}\,\mathrm{T} + (\,\mathrm{P_a Q_a}(\mathrm{L}, \mathrm{V}, \mathrm{A}, \mathrm{K}, \mathrm{W}) - \mathrm{P_l L} - \mathrm{P_v V}\,) + \mathrm{E} \tag{3}$$

Where P_m is the price of the market-purchased commodity; P_a is the price of the agricultural staple; P_L is the market wage; P_V is the variable input's market price; T is the total stock of household time, E is any non labor, nonfarm income and other variables are as previously defined.

Let Y denote total income as:

$$\mathrm{Y} = \mathrm{P_l}\,\mathrm{T} + (\,\mathrm{P_a Q_a(L, V, A, K, W)} - \mathrm{P_l L} - \mathrm{P_v V}\,) + \mathrm{E} \tag{4}$$

Therefore, the household maximization problem may be expressed in a Lagrangian function as:

$$Z = \mathrm{U}\,(\mathrm{X_a, X_m, X_l}) + \lambda(\mathrm{Y} - \mathrm{P_m\,X_m} - \mathrm{P_a X_a} - \mathrm{P_l X_l}) \tag{5}$$

Setting up the partial derivatives of (5) with respect to L,V, X_a, X_m ,X_l and λ to zero, yields the following first-order conditions necessary for maximization problem:

$$\frac{\partial Z}{\partial L} = P_a \frac{\partial \mathrm{Q_a(L, V, A, K, W)}}{\partial L} - P_l = 0 \tag{6}$$

$$\frac{\partial Z}{\partial V} = P_a \frac{\partial Q_a \mathrm{(L, V, A, K, W)}}{\partial V} - P_V = 0 \tag{7}$$

$$\frac{\partial Z}{\partial \mathrm{X_a}} = U_{\mathrm{X_a}}(\mathrm{X_a, X_m, X_l}) - \lambda\,\mathrm{P_a} = 0 \tag{8}$$

$$\frac{\partial Z}{\partial \mathrm{X_m}} = U_{\mathrm{X_m}}(\mathrm{X_a, X_m, X_l}) - \lambda\,\mathrm{P_m} = 0 \tag{9}$$

$$\frac{\partial Z}{\partial \mathrm{X_l}} = U_{\mathrm{X_l}}(\mathrm{X_a, X_m, X_l}) - \lambda\,\mathrm{P_l} = 0 \tag{10}$$

$$\frac{\partial Z}{\partial \lambda} = \mathrm{Y} - \mathrm{P_m\,X_m} - \mathrm{P_a X_a} - \mathrm{P_l X_l} = 0 \tag{11}$$

Since the functional forms are not specified, the standard profit maximizing conditions given in (6) and (7), can be written in general as:

$$F(\mathrm{P_a, P_m, P_v,\ P_l}, L, V, A, K, W) = 0 \tag{12}$$

Using the implicit function theorem (Chiang, 1984), from (11) the input demand for labor and capital can be written generally as:

$$V = f(\mathrm{P_a, P_m, P_l, P_v}, L, V, A, K, W) \tag{13}$$

$$L = f(\mathrm{P_a, P_m, P_l, P_v}, L, V, A, K, W) \tag{14}$$

Once the profits are maximized, its value can be substituted into the constraint equation to yield:

$$\mathrm{Y^*} = \mathrm{P_m\,X_m} + \mathrm{P_a X_a} + \mathrm{P_l X_l} \tag{15}$$

Where Y^* denotes total income for a profit maximizing household. Having optimized on profit, the household maximizes utility subject to the total income. The solution to (4), (5) and (15) can implicitly be written as:

$$F(\mathrm{X_a, X_m, X_l, P_a, P_m, P_v,\ P_l}, Y^*) = 0 \tag{16}$$

Again, using the implicit function theorem (Chiang, 1984), from (16) the input demand for farm produced good can generally be wrtten as:

$$X_a = f(\mathrm{P_a, P_m, P_l, P_v}, Y^*) \tag{17}$$

Equation (17) shows that the demand for farm produced good is affected by price of outputs, prices of variable inputs and total income. The presence of profits in Y^* further shows that farm technology, quantities of fixed inputs and agro-climatic conditions affect the demand for the farm produced good (Singh *et al.*, 1986).

If the farmer is a price taker in all markets, for all commodities which he both consume and produces; the farmers' solution gives an output supply dependent on output prices $(P_i, i = 1, \dots, n)$, variable input prices $(P_v, v = 1, \dots, V)$, production technology, quasi fixed inputs of land and capital $(A_j, j = 1, \dots, J)$ and agro-climatic conditions (W). The output supply function for crop i can therefore be expressed as:

$$Q_i = f\left(\mathrm{P_i}, \mathrm{P_v}, \mathrm{A_j}, \mathrm{W}\right) \tag{18}$$

An increase in output prices with fixed input raises the profits serving as an incentive to farmers to produce more. Conversely, an increase in prices of inputs raises the cost of production serving as a disincentive to increase production (Singh *et al.*, 1986).

According to Key et al. (2000) transaction costs raise the total cost of production. Fixed transaction costs include: the search for market, negotiations, bargaining and screening of buyers of the produce and sellers of inputs while variable transaction costs include transportation costs and time taken to transport products to the market and inputs from the market. The fixed transaction costs are lump sum while the variable transaction costs increase the per unit cost of accessing the market which raise the price effectively paid for inputs and lowers the price effectively received for output. Consequently, this creates a price band within which households find it unprofitable to supply output or buy inputs. Thus, net prices can be expressed as:

$$P^*{}_i = P_i - t^s(Z_{it}^s) \tag{19}$$

$$P^*{}_{vi} = \mathrm{P}_{vi} - t^b\left(Z_{it}^b\right) \tag{20}$$

Where $P^*{}_i$ is net output price received; $P^*{}_{vi}$ is the net input prices paid; P_i is the output market price, P_{vi} is the input market price; t^s is the transaction cost associated with marketing output and $t^b$are transaction cost associated with purchase and use of inputs. Z is a vector of all factors that influence transaction costs such as rural infrastructure and macroeconomic conditions. Incorporating (19) and (20) into (18) yields:

$$Q_i = f\left(\mathrm{P_i}^*, \mathrm{P_v}^*, \mathrm{A_j}, \mathrm{W}\right) \tag{21}$$

Equation (21) implies that factors influencing transaction costs influences output supply.

Following the utility maximization theory, (21) is augmented to account for factors considered important in explaining output supply. Manmingi (1997) argued that, in addition to price of input and price of output, supply function can be extended to include other factors that do influence the farmers' production decisions. These factors can be classified under four categories namely: rural infrastructure, human capital, technology and agro-climatic conditions. Among the climatic factors, temperature and rainfall amount and distribution are expected to be the most influential in explaining supply response. These two climatic measures are observable by farmers and likely to influence decisions to grow a certain crop and the area to allocate it as demonstrated in (1) and (17). Climate forecast and timing are critical in informing farming decisions such as planting and harvesting. As well, seasonal climate forecasts provide a chance to reduce vulnerability of crop production to climate variations by helping farmers make informed cropping decisions(Smit and Skinner, 2002; Hansen, 2002). In Kenya as revealed by Recha et al., (2008) majority of farmers do not base their decisions based on climate forecasts but on perceived change in climate over the previous years and what they perceive as expected future weather conditions (Blanc, 2011).

To encourage maize production the Kenyan government provides funds for infrastructure development, subsidizes fertilizers, funds research and provides a market for output through National Cereals and Produce Board. Thus output price, input prices, expenditure on rural infrastructure services, market availability and agro-climatic conditions more specifically temperature and precipitation can be considered to be important factors influencing maize supply. Incorporating these factors in (21) yields:

$$Q_i = f(\mathrm{P_i}^*, \mathrm{P_v}^*, \mathrm{W}, \mathrm{G}) \tag{22}$$

Where variables are as defined earlier and G is a vector that includes: area under crop, expenditure on rural infrastructure services, purchase of output in the case of maize and fixed inputs$(\mathrm{A_j})$.

2.2 Output Supply Model

Maize farmers in Kenya cultivate maize for subsistence and income generation by selling the surpluses. Majority of Farmers in Kenya are small holders and assume the dual character of being producers and consumers at the same time.

Following the utility maximization problem (22) may be generalized to specify the output supply model for a particular crop (j) given as:

$$Q_j = \alpha j e_T + P_j\beta_j + W_j\theta_j + G_j\pi_j + \varepsilon_j \tag{23}$$

Where: Q_j is a (Tx1) vector of observations on maize crop (j); P_j is a (TxK) matrix of observations on all prices of output and input prices; W_j is a (TxH) matrix of agro-climatic variables specific to maize growing areas and season; $G_j$is a (TxM) matrix of other factors influencing output supply; α is the unknown intercept; e_T is a column vector of I's with dimension T ; β_j, θ_j and π_j are vectors of unknown coefficients corresponding to P_j , $W_j$and G_j

respectively; ε_j is the stochastic error with zero mean and constant variance, uncorrelated with the explanatory variables and its previous realizations.

The farmers are assumed to be forward looking, seek to maximize crop production in a dynamic situation, and take into consideration their past experiences in making production decisions in the future. The farmer's behaviour has been taken into consideration in earlier literature, such as the work of Nerlove (1958) which included partial adjustment and price expectations in modeling agricultural supply. However, the Nerlove model is not capable of providing a distinction between short run and long run elasticities, when both partial adjustment and price expectations are included and thus restrictions have to be made. Consequently, the Nerlove model assumes a fixed target supply based on stationary expectations and thus it is not able to capture the full dynamics of supply (Thiele, 2003). The shortcomings of the Nerlove model can be addressed through the use of ARDL in modeling output supply, where lags of dependent and explanatory variables are included in the model. The lagged values enables the model to capture the full dynamics of output supply as it takes into consideration, the role of observed variables in influencing farmers decision (Muchapondwa, 2008; Ogazi, 2009).

Therefore, the model in (23) can be modified to include the lags of the dependent and explanatory variables in the form of an ARDL model, specified as:

$$Q_{jt} = \alpha_{j0} + \sum_{i=1}^{P} \delta_{ji} Q_{jt-i} + \sum_{k=1}^{K}\sum_{i=0}^{P} \beta_{jki}\, P_{jkt-i} + \sum_{h=1}^{H}\sum_{i=0}^{P} \theta_{jhi}\, W_{jht-i} + \sum_{m=1}^{M}\sum_{i=0}^{P} \pi_{jmi}\, G_{jmt-i} + \varepsilon_j \qquad (24)$$

This can be rewritten as,

$$Q_{jt} - \sum_{i=1}^{P} \delta_{ji} Q_{jt-i} = \alpha_{j0} + \sum_{k=1}^{K}\sum_{i=0}^{P} \beta_{jki}\, P_{jkt-i} + \sum_{h=1}^{H}\sum_{i=0}^{P} \theta_{jhi}\, W_{jht-i} + \sum_{m=1}^{M}\sum_{i=0}^{P} \pi_{jmi}\, G_{jmt-i} + \varepsilon_j \qquad (25)$$

By employing a lag operator and dropping the subscript j for ease of illustration, the corresponding equation in lag polynomial is

$$A(L)Q_t = \alpha_0 + \sum_{k=1}^{K} \beta_k\,(L)P_{kt} + \sum_{h=1}^{H} \theta_h\,(L)W_{ht} + \sum_{m=1}^{M} \pi_m\,(L)G_{mt} + \varepsilon_t \qquad (26)$$

Where:

$$A(L) = 1 - \sum_{i=1}^{P} \delta_i \mathrm{L}^{\mathrm{i}} \ , \ \beta_k(L) = \sum_{\mathrm{i}=0}^{\mathrm{P}} \beta_{ki} \mathrm{L}^{\mathrm{i}}, \ \ \theta_h(L) = \sum_{h=0}^{H} \theta_{hi} \mathrm{L}^{\mathrm{i}}$$

and $\pi_m(L) = \sum_{m=0}^{M} \pi_{mi} \mathrm{L}^{\mathrm{i}}$

The distributed lag form of the model that defines long run relationship is given as:

$$Q_{jt} = \frac{\alpha_0}{A(L)} + \frac{\sum_{\mathrm{k}=1}^{\mathrm{K}} \beta_k (L)}{A(L)} P_{kt} + \frac{\sum_{h=1}^{H} \theta_h (L)}{A(L)} W_{ht} + \frac{\sum_{m=1}^{M} \pi_m (L)}{A(L)} G_{mt} + \varepsilon_t \qquad (27)$$

Where: $A(L) \neq 0$

The number of lags is determined using Akaike Information criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQ).

2.3 Data Type and Source

The study used annual time series data for the period between 1970 and 2014. The data was obtained from government publications, Kenya Meteorological Department, World Bank, IMF and FAOSTAT database. Weather variables used in maize model were computed using data from the following weather stations in maize growing areas.

2.4 Definition and Measurement of Variables

Maize output is the quantity maize harvested measured in tonnes for a given year; price of output is the average market price for maize in a given year in Kenya shillings per kg; price of fertilizer is the price of fertilizer measured in growth terms by the difference between input price index for the given period and that in the previous year; wage rate is the average wage in agricultural sector measured by the minimum wage for rural farm worker in Kenya shillings; price of seed is the price of certified maize seed measured in growth terms by the difference between input price index for the given period and that in the previous year; land use is the area under crop production measured by the number of hectares; government spending on infrastructure is the amount of money allocated by the government for development in transport system for a given fiscal year measured in Kenya shillings and maize sales to marketing boards is the quantity of maize in metric tonnes delivered to marketing boards in a year. Climatic variables are measured using data recorded in the periods JF, March to May (MAM), June to September (JJAS) and OND in a given year for selected weather stations in maize growing areas. Temperature is mean temperature in degree celsius; rainfall is the amount of rainfall measured in millimeters, rainfall variability is intra rainfall variability measured by the coefficient of variation of rainfall in a given year. Temperature variability is year to year variability of mean temperature measured by the squared annual temperature deviation from the long term mean.

2.5 Data Analysis

The ARDL maize output model was estimated by least squares method. An ARDL model is consistently estimated by Ordinary Least Squares (OLS) if the error term has a zero mean, constant variance and uncorrelated with the explanatory variables and its previous realizations. Thus prior to model estimation, series were subjected to various tests to confirm these properties to guarantee results that are efficient and consistent. The model was estimated in a semi log linear form to derive elasticities with respect to control variables and semi elasticities with respect to the climatic variables. Preceding the estimation of the model an optimal lag length of order 2 was determined based on the AIC, SIC and HQ criteria.

2.5.1 Unit root tests, Cointegration and Diagnostic tests

The major reason for conducting unit root tests was to establish the order of integration, crucial for setting up the econometric models from which implications are made. Since most of the economic data are non-stationary, OLS regression based on such data is likely to give spurious results. Use of least squares method in model estimation requires that all assumptions of the model hold, as well as various properties of data used, for it to yield estimates that are efficient and consistent. Thus, each of the series used in the study was tested for presence of a unit root based on Augmented Dickey Fuller (ADF), Phillips and Perron (PP) and Kwiatkowski Phillips, Schmidt and Shin's (KPSS) tests. KPSS is a confirmatory test because ADF and PP statistics have limitations of lower tests power and successive or persistent unit roots respectively. The ADF and PP tested the null hypothesis of unit root against the alternative hypothesis of no unit root. If the computed test statistic was found greater than the critical value at 5 percent level of significance then the null hypothesis was not rejected. If null hypothesis could not be rejected, then the time series variable contained a unit root and hence non stationary, otherwise it was stationary. If its first difference is then tested and found stationary, the series was concluded to be an I(1) (Green, 2008; Gujarati, 2004; Dickey and Fuller, 1979). To confirm the results KPSS was employed to eliminate a possible low power against stationary near unit root processes which occurs in the ADF and PP tests. KPSS tests a null hypothesis of stationarity of a series around either mean or a linear trend and the alternative hypothesis that assumes that a series is non-stationary due to presence of a unit root. If the computed test statistic was found less than the critical value then the null hypothesis was not rejected. (Kwiatkowski, Schmidt &Shin 1992; Green, 2008).

The unit root test results, indicate the following variables were stationary: rainfall variability, temperature variability, log maize sale to marketing boards, log development expenditure on roads, transport and communication, log agricultural wage rate, mean temperature in maize growing areas; rainfall amount and squared terms for rainfall and temperature. Conversely, the following variables were found to be integrated of order 1: log maize output; log area of maize production; log price of maize; log price of maize seed; log price of fertilizer. The regression of non-stationary series on other series may possibly produce spurious regression. However, there is a possibility that the regression can be meaningful if the variables are cointegrated (Ssekuma, 2011). Hence, there is need to carry out cointegration tests on the integrated variables.

The test for cointegration involved running a regression of log maize output on climate and other control variables. Residual series were obtained from the estimated equation and tested for the presence of unit root. The null hypothesis of existence of a unit root, which implies there is no cointegration, was rejected at 5 percent level of significance for the estimated residuals. The results show that linear combination of the variables was stationary. The results vindicate existence of a long run relationship among variables.

To ensure that estimates obtained were unbiased and consistent, diagnostic tests were undertaken. The tests included: the normality test using Jarque- Bera statistics, Breuch-Godfrey Lagrange Multiplier test for serial autocorrelation, Lagrange Multiplier test for autoregressive conditional heteroskedasticity (ARCH), Ramsey RESET test for specification error. The P values associated with the computed test statistics were greater than 0.05 and estimates were considered to be unbiased and consistent. To determine parameter constancy, recursive estimations were performed on each of the crop response equations. Recursive coefficient tests, CUSUM tests, CUSUM residual squares test, one step forecast test and N steep forecast tests were performed. In all the cases, the plots did not diverge significantly from the zero line and the residuals lie within the standard error band signifying stability in the parameters of the equation.

3. Results And Discussion

The coefficient estimates and their corresponding standard errors and long run coefficient estimates are shown in Table 1 and Table 2 respectively.

Table 1: Output Response Equation Coefficient Estimates

Dependent Variable: Log maize output		
Explanatory variables	**Coefficients**	**Standard Error**
First lag of log crop output	0.0769	(0.1269)
Second lag of log crop output	-0.4131***	(0.1211)
Log price of output	-0.1528	(0.0846)
First lag log price of output	0.2627***	(0.0952)
Rainfall variability	-0.0999	(0.3176)
Temperature variability	-0.0348**	(0.0158)
Mean temperature (Jan- Feb)	0.1271	(0.0777)
Mean temperature(June-Sept)	-0.3034***	(0.0940)
Mean temperature (March-May)	-0.0890	(0.0860)
Mean temperature (Oct-Dec)	0.2706***	(0.0838)
Rainfall (Jan-Feb)	0.0002	(0.0003)
Rainfall (June -Sept)	0.0014***	(0.0004)
Rainfall (March-May)	3.75E-05	(0.0002)
Rainfall (Oct-Nov)	0.00048**	(0.00018)
Log Spending on roads transport and communication	0.0301	(0.0276)
Log Price of fertilizer	-0.0628	(0.0883)
Log Agricultural Wage	-0.2399**	(0.0885)
Log Area under crop	0.1195**	(0.0479)
Log Price of maize seed	0.0119	(0.0612)
Log Sales to marketing board	-0.0274	(0.0706)
First Lag of Sales to marketing board	0.1595*	(0.0789)
Constant	18.5486***	(2.7747)
R-squared	0.90	
Adjusted R-squared	0.81	
F-statistic	9.38	
Prob(F-statistic)	0.00	

*****, **,* significant at 1%, 5% and 10% respectively;**

Source: Author computation

Table 2: Elasticity and Semi Elasticity Estimates of Maize Output with Respect to Climate Variables and other Control Variables

Dependent Variable: Log maize output	
Explanatory variables	**Coefficients**
Log Price of output	0.082
Temperature variability	-0.03
Mean temperature(June-Sept)	-0.23
Mean temperature (Oct-Dec)	0.20
Rainfall (June-September)	0.002
Rainfall(Oct-Dec)	0.003
Log Agricultural wage	-0.18
Log Area under crop	0.09
log sales to marketing board	0.10

Source: Author computation

The long run coefficient for an independent variable X_i was derived according to the ratio of sum of coefficients of explanatory variable X_i from lag zero to lag 2 to the value of the polynomial associated to the dependent variable. The adjusted R^2 value imply that 81 percent of variations in maize output respectively are explained by climate variables and specified control variables.

The findings show that the coefficient estimates of rainfall amount in the month of June to September and October to December are positive sign and significant at one percent and 5 percent level respectively. The coefficient of rainfall variability and the coefficient of rainfall in the months of January and February and March to May periods are insignificant. The positive sign of the coefficient estimate shows that an increase in rainfall leads to an increase in maize production in both the main crop season and the short rains season. Further, the study findings show that the amount of rainfall in January and February, which is the pre-season before the main growing season, marked by onset of long rains in March, does not influence the level of maize output. This findings contrast those of Kawuma (2011) which showed that the preseason rainfall coefficient had a positive and significant influence on crop production in Ethiopia.

Semi elasticity estimates show that an increase in rainfall amount by 100 mm increases maize output by 0.2 percent during the months of June to September while an increase in rainfall by 100 mm increases maize output by 0.3 percent during the short rains season between October and December. Overall rainfall has a positive effect on maize supply. These results indicate that when rainfall amount is not limiting in the months of June to September, production of the main crop planted at the onset of long rains increases. This is in line with the observation that maize requires rainfall to be well distributed throughout the growing period and especially during flowering and silking stages which corresponds to these period. As well, the results imply that additional rains during the main growing season and during the short rain season maize growing season raise maize production and thus may in turn serve as an incentive to farmers expand maize production through allocation of more land to crop and better farm management.

In addition, occurrence of short rains presents an opportunity to boost maize production in medium and low altitude areas that support two growing seasons. During this period of three months, the short rain varieties go through vegetative and reproductive stages that require adequate rainfall. This concurs with Seifu, (2004) observation that greatest decline in maize output is caused by water deficient during the flowering period and yield formation periods. However, water deficient during ripening period has little effect on grain yield. The findings are consistent with those of Oseni (2011) that a reduction in mean annual rainfall in the planting season has a negative impact on maize production and those of Eregha et al., (2014) and Issahaku and Maharjan (2014) that rainfall has a positive impact on the production of maize.

The coefficient of mean temperature in June to September period is negative and significant, while the coefficient of mean temperature in October to December season is positive and significant. The coefficients of mean temperature in other periods were insignificant. Semi elasticity estimates for maize production with respect to mean temperature in June to September period shows that when mean temperature increases by 1^0 C maize output reduces by 0.23 percent. Mean temperature increases by 1^0 C in the short rains period, between October and December raises output by 0.20 percent. Notably, June to September period coincides with critical flowering and silking stages for the late maturity hybrid variety planted in the major planting season at the onset of long rains. These stages are highly sensitive to water deficit and an increase in temperature when moisture content is limiting obstructs pollination adversely affecting the output level (Bergamaschi *et al.*, 2004). The positive effect of temperature on maize output in the short rain season indicates that when moisture content is not limiting an increase in temperature boost maize production. Overall, temperature has a negative net effect on maize output supply.

Temperature variability coefficient estimate is negative and significant. As temperature variability increases by one standard deviation from the mean, maize production reduces by 0.03percent. The expected rise in temperature in the next decades could end up straining maize production that will further exacerbate food insecurity. The findings are consistent with those made by Nyairo (2011). On the other hand, Akpalu *et al.*, (2008) and Bhandari, (2013) found that changes in temperature had a positive effect on maize crop. Issahaku and Maharjan (2014) observed no relationship between maize yields.

The coefficient of second lag of maize output is significant showing a partial adjustment of output in each period towards equilibrium values. The coefficient of the first lag of price of maize is positive and significant. This is in line with the theory that output supply positively responds to price changes. As price increases, farmers are encouraged to increase production. Elasticity estimate shows that when price increases by 10 percent maize output increases by 0.8 percent. This inelastic finding is consistent with literature on crop supply responses in Africa. Notably the response is lower than in Mbithi (2000), Olwande et al., (2009) Mose et al., (2007) and Onono *et al.*, (2013).

The coefficient of area under maize production is positive and significant. Moreover, the elasticity value of 0.09 shows that a 10 percent increase in acreage is expected to increase maize production by 0.9 percent. The coefficient estimate of price of fertilizer is statistically insignificant in influencing maize output supply. This result is consistent with other studies that blame low application of fertilizers due to escalation of farm gate prices of fertilizer as a cause of low production (Nyoro, 2002; Kibaara & Kivoi, 2012; Olwande, 2012; Onono, 2013).

The coefficient of agricultural wage is negative and significant. The negative sign implies that high wages leads to a decline in maize output. Increase in wages translate to higher cost of production which hinder proper management of maize crop translating to decline in production. Increased labour costs therefore inhibit expansion of maize production. The estimated elasticity of -0.18 shows that a 10 percent increase in agricultural wage reduces maize output by 1.8 percent. The inelastic response can be attributed to the fact that over 70 percent of agricultural output is under small scale, which largely makes use of family labor (Olwande, 2012). Together with capital, hired labour is a critical input in maize production.

Estimated coefficients of spending on roads, transport and communication and its first lag are insignificant. The coefficient estimate of first lag of maize sales to marketing board has a positive sign and is weakly significant. This indicates that maize output increases with the capacity of National Cereals and Produce Board to absorb farmer‘s production. This happens with an inelastic response, with a 10 percent increase in sales to marketing boards raising maize output by approximately one percent. The finding imply that there could be institutional rigidities and transport bottlenecks that hinder delivery of produce by small holder farmers to National Cereals and Produce Board.

4. Conclusion

Maize production in Kenya is adversely affected by climate change. Erratic rainfall patterns and temperature variability exposes farmers to climate risk leading to lower production. Thus they are likely to prefer growing other crops or choose alternative income generating activities. In absence of adaptation and mitigation mechanisms Kenya risks being more food insecure. Thus, there is need for a wide-ranging policy paramount in building adaptation and mitigation mechanisms that will elevate the potential of rain fed agriculture. Further, the government needs to champion integration of climate change policy with land use policy in order to assign particular areas for definite purposes to facilitate proper planning of land use. For instance, there is need to shield high agricultural potential areas which are being converted into nonagricultural, real estate development. Lastly, since timing of rainfall considerably affects crop output, provision of timely information on expected climatic changes is critical in improving awareness and for rapid consideration for adaptation. This calls for Kenya Meteorological department and Ministry of Agriculture to commit more resources in creating awareness and enhancing capacity in use of climate information.

References:

1. Akpalu, W., Hassan, R. M., & Ringler, C. (2008). Climate variability and maize yield in South
2. Africa. Environment and Production Technology Division. IFPRI Paper, 843.
3. Alila, P. O., &Atieno, R. (2006). Agricultural policy in Kenya: issues and processes. In Future Agricultures, A paper for the Future Agricultures Consortium workshop, Institute of Development Studies (20-22). Brighton: Institute of Development Studies.
4. Bergamaschi, H., Dalmago, G. A., Bergonci, J. I., Bianchi, C. A. M., Müller, A. G., Comiran, F.,& Heckler, B. M. M. (2004). Water supply in the critical period of maize and the grain production. Pesquisa Agropecuária Brasileira, 39(9), 831-839.
5. Bhandari, G. (2013). Effect of precipitation and temperature variation on the yield of major cereals in Dadeldhura district of far western development region, Nepal. International Journal of Plant, Animal and Environmental Sciences (IJPAES), India, 3(01), 247-256.
6. Blanc, É. (2011). The impact of climate change on crop production in Sub-Saharan Africa (Doctoral dissertation). University of Otago, Dunedin.
7. Chiang, A. C. (1984). Fundamental methods of mathematical economics. New York. MC Graw –Hill, inc.
8. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.
9. Eregha, P. B., Babatolu, J. S., & Akinnubi, R. T. (2014). Climate change and crop production in Nigeria: An Error Correction Modelling approach.International Journal of Energy Economics and Policy, 4(2), 297-311.
10. Food and Agriculture Organization. (2008).The state of food and agriculture. Biofuels: prospects,risks and opportunities. Rome: FAO.
11. Food and Agriculture Organization. (2012). FAO statistical year book 2012. ROME: FAO.
12. Food and Agriculture Organization (2016a). FAOSTAT data: Accessed on July 01, 2016, from faostat.fao.org/
13. Food and Agriculture Organization. (2016b).The state of food and agriculture: climate change ,agriculture and food security. ROME: FAO.
14. Greene, W. (2008). Econometric Analysis. New Jersey: Pearson Prentice-Hall.
15. Gujarati, D. (2004). Basic Econometrics. New York: McGraw Hill.

16. Intergovernmental Panel on Climate Change, (2014): Annex II: Glossary [Mach, K.J., S. Planton and C. von Stechow (eds.)]. In: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland.
17. Hansen, J. W. (2002). Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. Agricultural Systems 74(3): 309-330.
18. Issahaku, Z. A., & Maharjan, K. L. (2014). Climate change impact on revenue of major food crops in Ghana: Structural Ricardian cross-sectional analysis. In Communities and Livelihood Strategies in Developing Countries (pp. 13-32). Springer, Tokyo.
19. Kawuma, C. (2011). Rainfall variation due to climate change: an intertemporal investigation into its impact on subsistence crop net revenue (master's thesis). Norwegian University of life sciences, Oslo.
20. KIPPRA. (2013). Kenya economic report 2013. Nairobi: KIPPRA.
21. Key, N., Sadoulet, E. and de Janvry, A. (2000)Transaction costs and agricultural household supply response. American Journal of Agricultural Economics, 82(2), 245 - 259.
22. Kibaara, B., & Kavoi, M. (2012). Application of stochastic frontier approach model to assess technical efficiency in Kenya’s maize production. Journal of Agriculture, Science and Technology, 14(1).
23. Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root. Journal of Econometrics, 54(1), 159-178.
24. Mbithi, L. (2000). Effects of agricultural policy on maize production in Kenya (Doctoral thesis),University of Ghent, Ghent.
25. McSweeney, C., Lizcano, G., New, M., & Lu, X. (2010). The UNDP Climate Change Country Profiles: Improving the accessibility of observed and projected climate information for studies of climate change in developing countries. Bulletin of the American Meteorological Society, 91(2), 157-166.
26. Mohajan, H. K. (2014). Food and nutrition scenario of Kenya. American Journal of Food and Nutrition, 2(2), 28-38.
27. Mose, L. O., Burger, K., & Kuvyenhoven, A. (2007). Aggregate supply response to price incentives: the case of smallholder maize production in Kenya. In African Crop Science Conference Proceedings, 8, 1271-1275.

28. Muchapondwa, E. (2009). Supply response of Zimbabwean agriculture. African journal of agriculture and resource economics. African Association of Agricultural Economists, 3(1), 28-42.
29. Mutimba, S. (2010). Climate change vulnerability and adaptation preparedness in Kenya. Nairobi: Heinrich Böll Foundation
30. National Farmers Information Service. (2015). Maize. Retrieved on January 01, 2015, from http://www.nafis.go.ke/agriculture/maize/
31. Nerlove, M. (1958). The dynamics of supply: Estimation of farmers' response to Price. Baltimore:Johns Hopkins.
32. Nyairo, M. (2011). Impact of agricultural market liberalization food security in developing countries: a comparative study of Kenya and Zambia (Doctoral dissertation). University of Helsinki, Helsinki.
33. Nyoro, J. K. (2002). Kenya's competitiveness in domestic maize production: Implications for food security. Nairobi: Tegemeo Institute, Egerton University.
34. Ogazi, G. C. (2009). Rice output supply response to the changes in real prices in Nigeria: An Autoregressive Distributed Lagged Model Approach. Journal of Sustainable Development in Africa, 11(4),83-100.
35. Olwande,J,M. &Nguyo, W. (2009). Supply responsiveness of maize farmers in kenya: a farm- level analysis. A paper prepared for presentation at International Association of Agricultural Economist'2009 conference, Beijing, China.
36. Onono, P.A., Wawire, N.W.H. & Ombuki, C. (2013), "The response of maize production in Kenya to economic incentives", International Journal of Development and Sustainability, 2(2)
37. Osbahr, H & Viner, D. (2006). Linking climate change adaptation and disaster risk management for sustainable poverty reduction. Kenya country study. A study carried out for the Vulnerability and Adaptation Resource Group (VARG) with support from the European Commission. Mexico City.
38. Oseni, T. O., & Masarirambi, M. T. (2011). Effect of climate change on maize (Zea mays) production and food security in Swaziland. change, 2, 3.
39. Owuor, B (2010). The Maize Subsector in Kenya: Mending the Granary. Nairobi: Heinrich Böll Foundation.
40. Rarieya, M., & Fortun, K. (2010). Food security and seasonal climate information: Kenyan challenges. Sustainability Science, 5(1), 99-114.
41. Recha, C. W., Shisanya, C. A., Makokha, G. L. & Krnuthia, R. N. (2008). Perception and Use of Climate Forecast Information Amongst Smallholder Farmers in Semi-Arid Kenya. Asian Journal of Applied Sciences, 1(2): 123-135.

42. Republic of Kenya. (2003). Economic survey. Nairobi: Goverment printer.
43. Republic of Kenya. (2005). Economic survey. Nairobi: Goverment printer.
44. Republic of Kenya. (2009). Economic survey. Nairobi: Goverment printer.
45. Republic of Kenya. (2011). Economic survey. Nairobi: Government printer
46. Republic of Kenya. (2015). Economic survey. Nairobi: Goverment printer.
47. Schroeder, C., Onyango, T. K. O., Nar, R. B., Jick, N. A., Parzies, H. K., &Gemenet, D. C. (2013).Potentials of hybrid maize varieties for small-holder farmers in Kenya: a review based on Swot analysis. African Journal of Food, Agriculture, Nutrition and Development, 13(2), 7562-7586
48. Seifu, A. (2004). Rainfall variation and its effect on crop production in Ethiopia (Doctoral dissertation). Addis Ababa University, Addis Ababa. Retrieved from http://hdl.handle.net/123456789/4341
49. Singh, I., Squire, L. & Strauss, J. (1986). Agricultural household models: Extensions and applications. Baltimore: Johns Hopkins University Press.
50. Smit, B. & Skinner, M. W. (2002). Adaptation options in agriculture to climate change: A typology. Mitigation and Adaptation Strategies for Global Change 7, 85-114.
51. Ssekuma, R. (2011). A study of cointegrating models with applications (master's thesis). University of South Africa, Pretoria.
52. Stern, N. (2007). The economics of climate change: The Stern Review. Cambridge and NewYork, NY: Cambridge University Press.
53. Stockholm Environmental Institute. (2009). The economics of climate change in Kenya: Project report. Oxford: Stockholm Environmental Institute.
54. Thiele, R. (2003). Price incentives, non-price factors and agricultural production in Sub-Saharan
55. Africa: A cointegration analysis. African Development Review 15(2), 425-438.
56. UNDP, (2002). Kenya Human Development Report. UNDP: Nairobi
57. World Trade Organization & United Nations Environmental Programme. (2009). Trade and climate change. WTO Publications. Geneva: WTO.