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Effects of Climate Change on the Long-run Crops' Yields in Nigeria

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ABSTRACT

The study investigated the impact of climate change on yields of leading food crops in Nigeria and assessed the transmission channels of climate shocks to welfare. Long-run causality test, Markov-switching regression and Structural Vector Autoregressive (SVAR) model were used. Long-run causality between climate change and crop yields was not rejected. A rise in temperature by 1% reduces crop yields by -0.12% in the regime of high yield while 1% increase in rainfall increases yields by 0.21% and 0.26%, respectively in high and low yield period. Shocks to welfare is traceable to climate change via crop yields and food prices effect.

Keywords: *Nigeria; Climate change; Long-run crop yields; Short-run crop yields; Rainfall; Temperature.*

JEL Classification: *Q1, Q54*

1 Introduction

Increasing temperature and declining rainfall are part of the globally acknowledged impacts of climate change. The situation in Nigeria reflects this reality. For instance, the available data from the *FAOSTAT*[1] shows that average monthly temperature changes have been increasing and positive, year-on-year, especially between 2010 and 2017. Specifically, average annual temperature of about 26.5 (^{0}C) in 1961 has risen consistently to record about 28.0 (^{0}C) in 2017. There are variations across months. While Januaries and Decembers have shown little increase in temperature between 1961 and 2018, other months especially March/April and June/July (which are wet season and dry season planting periods, respectively) have shown significant rise in temperature within the same period. Also, rainfall in Nigeria has dropped by 81mm (equivalent to about 0.29% reduction) annually and the pattern has continued (Akpodiogaga and Odjugo, 2010). There are variations across Nigeria's ecological zones but over 20% of the land scape has experienced reduction in rainfall in Nigeria (Ogungbenro and Morakinyo, 2014). The forecasts of precipitation and temperature of Nigeria by World Bank's *Climate Change Knowledge Portal*[2] shows an inconsistent and rising trend, respectively, between 2020 and 2039.

Increasing temperature and declining rainfall are closely associated with drought and have several implications for crops yields and food production. While excessive temperature reduces plants survival, grain number and the duration of grain-filling period (Hatfield and Prueger 2015), erratic rainfall pattern could alter farm outputs in Nigeria given that its agriculture is still significantly rain-fed (see High et al. 1973). In the Sub-Saharan Africa (SSA), rain-fed agriculture accounts for more than 95 percent of the cropland (Wani et al, 2009). This renders many SSA countries (including Nigeria) vulnerable to the adverse effects of climate change with implications on reducing farm outputs. This may further discourage the rural farmers leading to rural labour exit, which undermine the development of rural regions in the country.

Improving food production is critical to Nigeria's future economic survival. That is, economic sustainability requires food production to keep pace with expected population growth. Specifically, the United Nations projected that the population of Nigeria will reach about 398 million people by the end of the year 2050. Related to the forecast of the Census Bureau of the United States, the expected Nigeria's population is 402 million by the same year. With these population forecasts, Nigeria will become the third most populated country in the world. Given the current population of about half of the 2050 forecast population figure, Nigeria currently demonstrates significant food production deficit. For instance, the available data from *FAOSTAT* shows that Nigeria has recorded significant trade deficit in major cereals such as wheat and rice. This shows that domestic production is yet to meet up with domestic demand and this is the reason for high food import bills. Nigeria's food import bills recorded \$7.33 billion and \$5.01 billion in 2017 and 2016, respectively (World Bank's *World Development Indicators Online Database*). This shows that food import bills represent 36.0% and 26.7% of 2017 and 2016 national budget, respectively. Comparison of Nigeria's food import bills as a percentage of merchandise imports with other selected leading SSA African countries shows that Nigeria has the highest in Africa after Senegal and Cote d'Ivoire (see Table 1). Nigeria's average food import bills is higher than SSA's average by about 3.8% in the last one decade. However, Nigeria's food production trajectory is the lowest despite that it has the highest population in Africa. Nigeria's food production is less than SSA's average by 8.6 points.

Table 1.

Food imports and Food Production in Africa, 2009-2018

Countries	Food imports (% of merchandise imports)	Food production index (2004-2006 = 100)
Nigeria	16.4	110.2
Kenya	13.4	120.7
South Africa	6.7	117.8
Ghana	16.0	133.4
Senegal	23.5	131.3
Cote d'Ivoire	20.0	117.4
Tanzania	9.0	146.6
SSA	12.6	118.8

Source: World Bank (Online Database)

[1] Food and Agricultural Organization of the United Nations Statistical Database

[2] http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_download&menu=futureGCM

Overall, there is a strong link among climate change, crop yields and poverty (Hertel and Rosch, 2010; Hertel, Burke, and Lobell, 2010; Kar and Das, 2015). On the supply side, food supply is dependent on climate change factors while the huge proportion of Nigeria's labour force (36.5%)[3] are engaged in the sector. Also, the sector serves as source of important raw inputs for agro-processing firms. Hence, food production economic activities have potentials for tackling poverty in Nigeria. On the demand side, adequate food production implies access to cheaper food varieties by the households. Thus, food secured households are left with more income to purchase other non-food items. Therefore, efforts at addressing poverty through agriculture in Nigeria must take into account the climate change factors.

Given the above, this study investigates the impact of climate change (measured by precipitation and temperature changes) on the yields of selected 10 major food crops[4] in Nigeria between 1961 and 2017. The specific objectives are to:

i. estimate the effect of climate change on the long-run yields of the selected important food crops, and
ii. estimate welfare shocks of climate change to Nigerians via its effects on crops yields.

Existing studies such as High, Oguntoyinbo, and Richards (1973); Adams (1989); Parry et al. (2004); Cai, Wang and Laurent (2009); and Moore, Baldos and Hertel (2017) have addressed related objectives. While Nigeria is not the research focus of many of these studies, their analysis of climate change effect from economic perspective is weak. Specifically, the cross-countries study like Parry et al. (2004) investigated the effects of climate change on global food production under special report on climate change scenarios and socio-economic factors. The study found that the crop yields (including wheat, rice, maize and soybean) elucidate complex regional patterns of projected CO_2 effects. Increase in global temperatures exhibits the greatest future decreases both regionally and globally in yields, with a variation in yields change between developed and developing countries. The selected crops are the top 10 food crops grown by over 70% of Nigerian farmers (FAO online database and Olakojo, 2016). Hence, addressing the objectives of this study gives an in-depth insight into climate change adaptation in Nigeria and it is of importance to policymakers on prioritizing actions and developing a robust, integrated approach for greater resilience to climate change risks.

2 Stylized facts on Climate Change and Food Production in Nigeria

In this section, climate change and yields of selected crops as well as other economic realities in Nigeria are examined in order to develop a set of stylized facts on the implications of climate change on the yields of selected crops.

2.1 Rainfall in Nigeria

The rainfall trend shows a gradual declining trend between 1960 and 2016 by examining the trend line in Figure (1). It indicates that the rainfall reduces on the average of 0.62% annually within this period. This value is higher than 0.29% annual reduction indicated by Akpodiogaga and Odjugo (2010) for the period between 1960-2005. The continued decline in rainfall suggests that Nigeria's agriculture cannot continue to be rain-fed. There is a need to have adequate irrigation programmes in place while the existing ones are strengthened.

[3]FAO (2018), Small Family Farms Country Factsheet (http://www.fao.org/3/I9930EN/i9930en.pdf)

[4] The selected food crops are Cassava, Maize, Sorghum (Guinea Corn), Cowpea (Beans), Yam, Millet, Groundnut, Rice, Okra, and Taro (Cocoyam). According to Olakojo (2016), 77.19% of Nigerian farmers grown these crops.

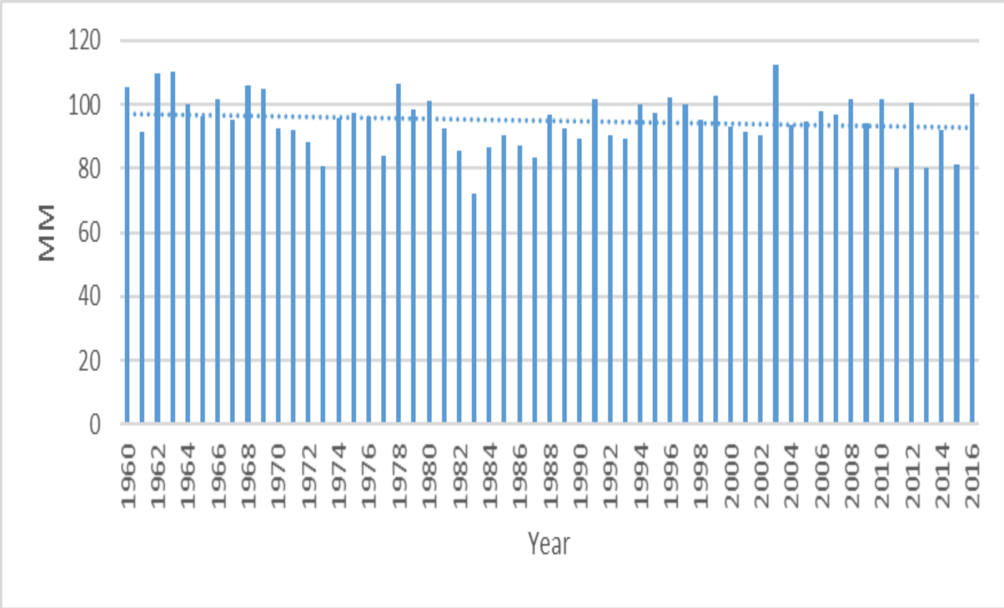

Figure 1. Average Yearly Rainfall (MM), 1960-2016.
Source: Climate Knowledge Portal (https://climateknowledgeportal.worldbank.org/download-data)

Rainfall trend is not only showing a marginal declining trend, there is also an evidence to support high level of variability and inconsistency in Nigeria. This increases the level of uncertainly and risks in crop farming outcomes. Meanwhile, monthly rainfall distribution in Nigeria is bell-shaped with lowest rainfall in January, December, February and March while highest rainfall is experienced in the month of August, July, September and June (Figure A1). Of importance in the rainfall distribution in Nigeria is the month of April. This is the time farmers plant most food crops in anticipation of the onset of the raining season. However, April shows significant decline in rainfall within the period under investigation. For instance, April rainfall of 106.139 MM in 1960 reduced, with a lot of variability, to 64.881 MM in 2016 (Figure A2).

2.2 Temperature Trend in Nigeria

The average air temperature in Nigeria is about 27.0^{0}C between 1960 and 2016. However, temperature has been on a significant rising trend within the same period (Figure 2). The mean temperature of about 26.8^{0}C in 1960 recorded 27.8^{0}C in 2016. This represents about 3.7% increase. This is an evidence of global warming. Also, monthly temperature distribution shows that planting season in March, April and May have the highest temperature in the year (Figure A3). Hence, if the temperature trend continues unabated, farm yields may be negatively affected and may put Nigeria at a high risk of food crisis. The rainfall and temperature trends in Figures 1 and 2 are clear evidence of reality of climate change in Nigeria.

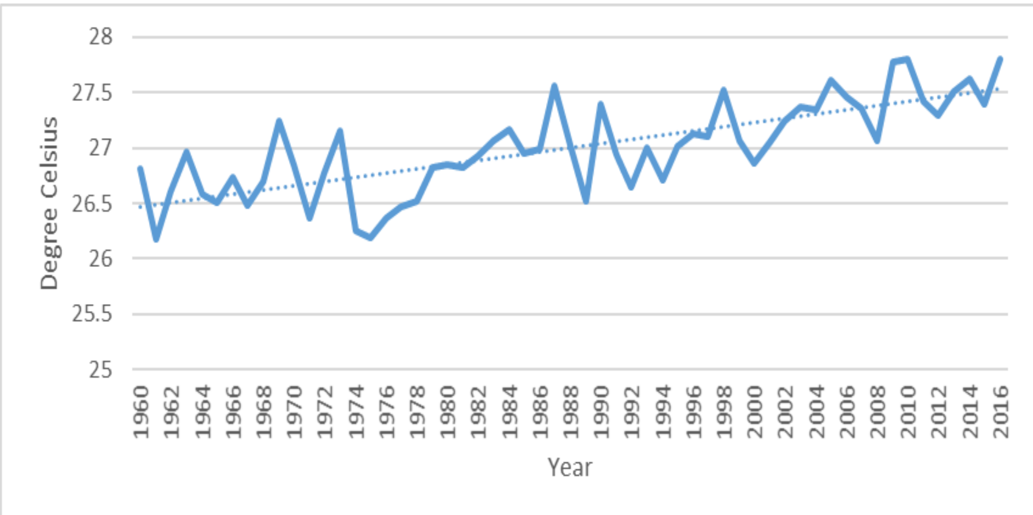

Figure 2. Average Temperature (^{0}C) in Nigeria, 1960 – 2016.
Source: Climate Knowledge Portal (https://climateknowledgeportal.worldbank.org/download-data)

2.3 Structure and Composition of Nigeria's Food System

The leading commodities, grown by over 70% of Nigerian farmers (see Olakojo 2016), are presented in Figure 3. Among these crops, the yields of cassava, yam and cocoyam are the highest indicating that these crops are vital to the economy of Nigeria. The country is the world's largest producer of cassava[5] and yam, accounting for over 70–76% of the world's production[6]. In terms of actual production, these three food crops are also the leading. Average yields of the selected crops show an increasing trend until 2010 when it nosedived in 2011 and recording below 1961 yields in 2013 (Figure 4). Given that the nation accounts for a significant proportion of the world's production of some of the sampled crops, the decline noticed in the recent times may have undesired implications on global supply chain of their derivatives such as human carbohydrate sources, animal feeds, dry extraction of industrial starch, glue or adhesives and modified starch in pharmaceutical in the case of cassava and yam.

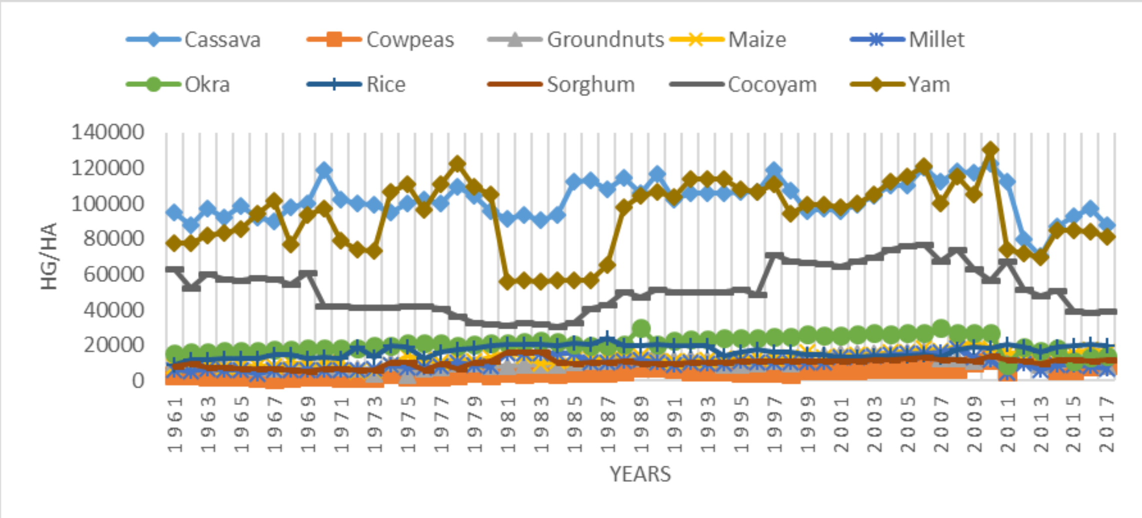

Figure 3. Ten Major Crops Yields (hectogramme (100 grammes) per hectare)
Source: Food and Agricultural Organization of the United Nations, Statistical Database (FAOSTAT)

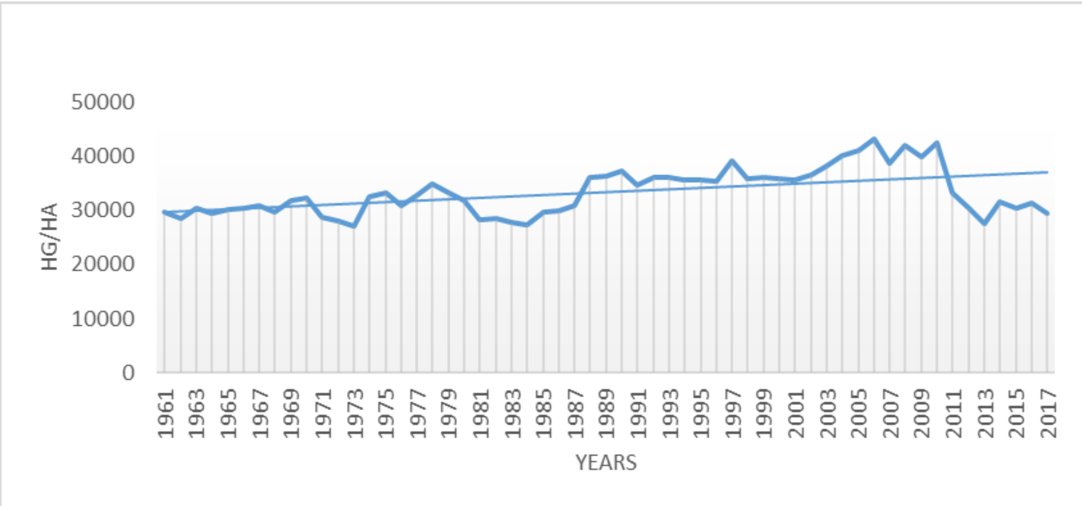

Figure 4. Average yield of the selected 10 crops
Source: Food and Agricultural Organization of the United Nations, Statistical Database (FAOSTAT)

Overall, the average production of the selected crops also shows an increasing trend between 1961 and 2017 (Figure 5). While growth in selected crop yields averages 0.24% between 1961 and 2017, their production averages 3.8% within the same time. This is also shown in their trends (Figure 4 and 5) and is an indication of efficiency loss. That is, the increase in production can be attributed to increase in cultivated areas and not necessarily due to improvement in yields per hectare. In this case, more farm land and labour are employed for less farm outputs. More farm land and labour employment implies

[5] https://en.wikipedia.org/wiki/Cassava_production_in_Nigeria
[6] https://en.wikipedia.org/wiki/Yam_production_in_Nigeria

higher rewards for these factors which will eventually lead to increase in farm commodity prices or loss in profits, depending on price elasticity of demand of a crop. This could explain the ever rising trend of food prices in Figure 7.

Also, while the trend in the production of the major crops over time is desirable (figure 5), comparing food production with population growth clearly indicate there are hunger periods in the land. In the recent time, between 2007 and 2017, there were 6 episodes of hunger when population growth is above food production growth (Figure 6). This means that the ratio of hunger to plenty is about half in a decade. Other prolonged hunger periods were between 1975 and 1979 as well as between 1999 and 2001. What this implies is that increase in food production has not been enough to cater for population growth and the demand for food in Nigeria. This reflects in Nigeria's rising food import bills[7] and consumer prices (Figure 7). The co-movement between food consumer prices and all items consumer prices is extremely high as noticed in Figure 8. This implies that the rising food prices fuel general inflation in Nigeria whereby food account for at least 50 percent and up to 70–80 percent of Nigeria's household budget (FAO 2009)[8]. Hence, the higher share of food in the household budget implies that rising food prices will generate increasing general inflation.

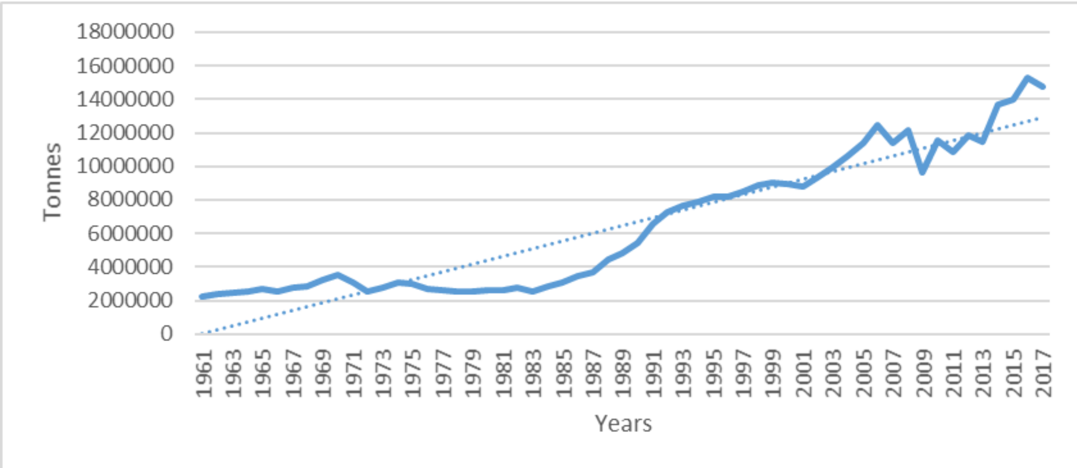

Figure 5. Average production (tonnes) of the Selected Crops
Source: Food and Agricultural Organization of the United Nations, Statistical Database (FAOSTAT)

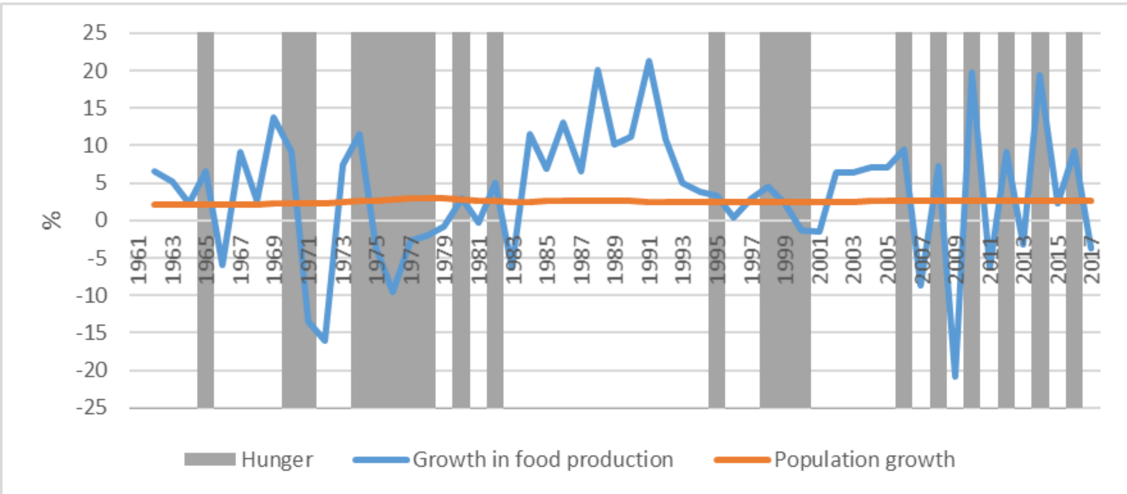

Figure 6. Nigeria's Population and Food Production growth (%)
Source: Computed from the FAOSTAT and World Bank's World Development Indicators

Also, there is a high correlation between episodes of hunger (Figure 6) and food import bills. The prolonged hunger periods between 1976 and 1980, 1997 and 2002, and the recent time between 2008 and 2017 are associated with high import bills.

[7] World Bank's World Development Indicators (Online database)
[8] http://www.fao.org/tempref/docrep/fao/012/i0854e/i0854e01.pdf

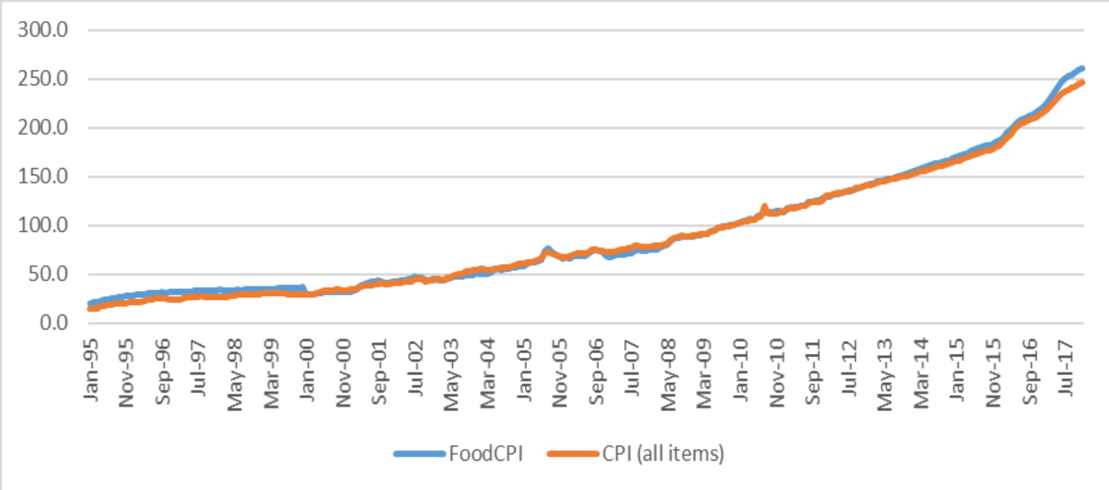

Figure 7. Consumer prices in Nigeria
Source: Central Bank of Nigeria' *Statistical Bulletin*, 2017

In sum, there is a significant food deficit in Nigeria. Hence, climate change conditions that directly or indirectly reduces food production may engender unsustainable development because the nation's economy is linked to rain-fed agriculture-climate-sensitive economic activities. This makes examining the effect of temperature and rainfall on yields of major food crops inevitable.

3 Literature Review

Climate Change is a global phenomenon and is marked with increased intensity and frequency of storms, drought and flooding, altered hydrological cycles and precipitation variance, and these have implications for future food availability (Food and Agricultural Organization 2007). However, its impact is spatially heterogeneous with risk generally believed to be more acute in developing countries considering the region's limited human, institutional and financial capacity (United Nations Framework Convention on Climate Change 2007). Food and Agricultural Organization (2004) estimated 25% loss of cereals, 37% loss of root and tubers and 53% loss of fruits in developing world as a result of factors ranging from weather conditions, production practices to harvesting, handling and processing. It is projected that crop yield in Africa may fall by 10-20% by 2050 or even up to 50% due to climate change (Jones and Thornton, 2009). This is because the continent is predominantly rain-fed and it is also characterised with frequent heat stress, drought and flooding events.

Food costs are directly affected by changes in commodity supply. If climate change affects the capacity to supply crops, decline in supply will lead to a rise in price, *ceteris paribus*. Higher prices reduce consumption levels and adversely affect consumer welfare. The effect of climate change on prices depends on demand dynamics through changes in incomes, population, and the prices of related commodities. Prices may be heavily influenced by changes in global food supplies, especially in many developing countries with limited control on world international prices of agricultural commodities. Hence, assessments of the effects of climate change on prices of agricultural commodities need to reflect changes in world supplies of these commodities. In certain instances, the negative effects on consumers due to higher prices may be partially or totally offset by producers' gains from higher prices, but in general, total welfare tends to decline when supply is reduced (Adams et al. 1998). The changes in prices lead to changes in the economic welfare of food crops to producers and consumers. One of the measures of economic welfare is the dynamic of economic surplus– a monetary measure of producer and consumer welfare (surpluses) under different prices situations. The welfare can also be measured directly in changes in gross domestic product (GDP) or other macroeconomic indicators that measure levels of economic activity (Adams et al. 1998). For instance, in the estimates of Adams et al. (1998), a 5^0C increase in temperature, 0% precipitation increase and 530 ppm (parts per million) CO_2 level will result in a welfare reduction of approximately \$2 billion; for modest warming of 1.5^0C and 2.5^0C, the study reports \$10 billion and \$16 billion gains in welfare, respectively.

Drought has economic effects such as income losses, loss to industries that are directly dependent on agricultural production, decreased land prices, unemployment from drought-related declines in production, strain on financial institutions, reduction of economic development, fewer agricultural producers (due to bankruptcies and need for new occupations), and rural population loss (National Disaster Management Centre 2010). Wheaton et al. (2008) evaluated drought impacts on agriculture by comparing production values during the 2001–2002 Canadian drought. The study found that crop production value losses were in the range of \$1.7 to \$2.4 billion. Horridge, Madden, and Wittwer (2005) used an agricultural production function approach to estimate the impacts of the 2002–2003 Australian drought. The study found a significant aggregate effects of drought on agriculture and on the national economy up to 20% and a 1.6% reduction in Gross Domestic Product, despite the relatively small role of the sector in Australia. More recently, Howitt et al. (2014) estimated the economic impact of drought in California on the state's agricultural sector using an economic optimization model of crop choice that includes regional water availability constraints. The net water shortage results in significant losses in crops of \$2 billion as well as additional groundwater pumping costs of \$1.3 billion and lost jobs of about 43,000.

Also, drought has a major impact on animal production as it directly and/or indirectly affects their productivity, hence reducing the production potentials of animal production sector. The link is straightforward. Drought stops plant growth and forage quality. Since livestock are very selective and prioritise highest quality forage, declining forage quality affect their development. This, by extension, reduces livestock quality and prices leading to reduction in farmers' profits, especially in Nigeria and other African countries where livestock is significantly free range and open grazing. To buttress this, the results of Leister, Paarlberg and Lee (2015) for the United States showed that short-term drought increases crop and forage prices which are in tandem with decreased live cattle prices resulting in drought-induced beef cattle herd liquidation.

Cai, Wang, and Laurent (2009) investigated the effect of climate change on crop yield from a soil water balance perspective in Central Illinois using regional-scale climate models, local-scale climate variability, emissions scenarios, and crop growth models to forecast the possible range of climate change effects on rain-fed corn yield in central Illinois in 2055. The results show that the expected rain-fed corn yield in 2055 is likely to decline by 23%–34%, and the probability that the yield decline may not reach 50% of the potential yield ranges from 32% to 70% if no adaptation measures are instituted. Hatfield and Prueger (2015) assessed temperature effects on plant growth in a controlled environment study. The study found that the major impact of warmer temperatures was during the reproductive stage of crop development and in all cases grain yield in maize was significantly reduced by as much as 80-90% from a normal temperature regime.

Parry et al. (2014) analysed the global consequences of reduction in crop yields and risk of hunger due to socio-economic and climate issues using climate change scenarios developed from the HadCM3 global climate model under the Intergovernmental Panel on Climate Change Special Report on Emissions Scenarios (SRES) A1FI, A2, B1, and B2. The results showed that crop yields (including wheat, rice, maize and soybean) elucidate complex regional patterns of projected CO_2 effects. Increase in global temperatures was found to exhibit the greatest future decrease both regionally and globally in yields, with variations in yields in both developed and developing countries. Moore, Baldos, and Hertel (2017) used a data-base of yield impact studies compiled for the Intergovernmental Panel on Climate Change Fifth Assessment Report to systematically compare results from process-based and empirical studies. The study found little evidence for differences in the yield response to warming, when the differences in representation of CO_2 fertilization between the two methods were controlled for. The study found a very limited potential for on-farm adaptation to reduce yield impacts. Also, using the Global Trade Analysis Project's (GTAP) global economic model to estimate welfare consequences of yield changes, the study found negligible welfare changes for warming of 1^0C–2^0C if CO_2 fertilization is included. The results also showed a substantial probability of large declines in welfare for warming of 2^0C–3^0C, including the CO_2 fertilization effect.

In Africa, related studies such as Maddison, Manley, and Kurukulasuriya (2007) used Ricardian approach to examine how farmers in 11 countries in Africa have adapted to existing climatic conditions and estimated the effects of predicted changes in climate while accounting for farmers' adaptation. The study confirms that African agriculture is particularly vulnerable to climate change. With perfect adaptation, regional climate change by 2050 is predicted to entail production losses of 19.9% for Burkina Faso and 30.5% for Niger. By contrast, countries such as Ethiopia and South Africa are hardly affected, suffering productivity losses of only 1.3% and 3%, respectively.

Knox et al (2012) did a comparative analysis of projected impacts of climate change on the yield of eight major crops in Africa and South Asia using a systematic review and meta-analysis of data in 52 original publications from an initial screen of 1144 studies. The projected mean change in yield of all crops is −8% by the 2050s in both regions. Across Africa, the study found the mean yield changes of −17% (wheat), −5% (maize), −15% (sorghum) and −10% (millet) and across South Asia of −16% (maize) and −11% (sorghum). No mean change in the yield was detected for rice. Further, Adhikari, Nejadhashemi and Woznick (2015) reviewed the impacts of climate change on fourteen strategic crops for eight SSA countries. Climate change is made a proxy with an increase in median temperature by 1.4–5.5^{0}C and median precipitation by −2% to 20% by the end of the 21st century. The study showed that the impact of climate change on crop yields in the region is largely negative, with wheat as the most vulnerable crop for which up to 72% of the current yield is projected to decline. For crops such as maize, rice and soybean, up to 45% yield reductions are expected by the end of this century, while millet and sorghum, as well as root crops, such as sweet potato, potato and cassava are more resilient to climate change for which projected impacts on yields are <20%.

Besides, Ochieng, Kirim, and Mathenge (2016) estimated the effect of climate variability and change on revenue from all crops, maize and tea using a household fixed effects estimator. The study found that climate variability and change affects agricultural production but effects differ across crops. Temperature has a negative effect on maize revenues but a positive one on tea, while rainfall has a negative effect on tea. The study concluded that temperature has a greater impact on crop production than rainfall. The United State Agency International Development (USAID, 2017) for Niger Republic also indicated that an increase in temperature of more than 2^{0}C could decrease yields of millet and sorghum by 15–25%. In small hold farms of southern Niger, sorghum could become nonviable by 2030 and finger millet nonviable by 2050 with incidence of increased temperature. From the above, it is obvious that related studies on Africa did not assess the welfare effect of climate change and the sampling excludes Nigeria. While relevant literature shows that there is variability in rainfall and temperature on Nigeria (Nwaiwu 2013; Nwajiuba and Onyeneke 2010; and Odjugo 2010), the assessment of the impact of climate change on food crops as estimated in this study is significantly lacking. Hence, this study fills this empirical literature gap.

4 Theoretical Framework and Methodology

4.1 Theoretical Framework

The study extends the crop production function to include climate change factors. This is because the focus is on yield per hectare of land. That is, climate change may not be an input in crop production but important in determining crop yields. Hence, the variant crop yield function takes the form:

$$Q(t) = K(t)^{\alpha} C(t)^{\beta} T(t)^{\gamma} A(t)^{\delta} [L(t)]^{1-\alpha-\beta-\gamma-\delta} \quad (1)$$

$$\alpha > 0, \quad \beta > 0, \quad \gamma > 0, \quad \delta > 0; \quad \alpha + \beta + \gamma + \delta < 1$$

Where Q(t) is the yield of crops in year t, K(t) is farm machinery employed, C(t) is climate condition (temperature and rainfall) at time t, T(t) is land used in producing crops, A(t) is the farming knowledge or technology possessed by the farmers, L(t) is the farm labour employed.

Dynamics of variables

That is, the rate at which new farm machinery will be added is a function of the proportion of current crop yields saved for such purpose and the rate at which the existing farm machinery depreciates. This is given as:

$$K\dot{(t)} = sQ(t) - \theta K(t) \quad (2)$$

Note that $K\dot{(t)} = K(t) - K(t-1)$.

Dividing (2) through by K(t) gives:

$$\frac{K\dot{(t)}}{K(t)} = s\frac{Q(t)}{K(t)} - \theta \quad (3)$$

Hence, the growth rate of farm machinery must be equal to the average products of farm machinery (that is, crop yields per farm machinery) less the rate of deprecation of existing farm machinery in the long run. This link is that farm machinery is inevitable for long run crop yields.

Given the current realities of climate change such as rising temperature and declining rainfall and its negative consequences, the dynamics of climate change is:

$$C(\dot{t}) = -aC(t), \quad a > 0 \tag{4}$$

The rate at which climate change happens is a. Equation (4) implies that the current climatic condition will be worse than the previous. The stylized facts previously considered provided the justification of this.

The measure of geographical land on earth does not change over time but the amount of land available for farming does. Hence, the change in farm land is given as:

$$T(\dot{t}) = bT(t), \quad b > 0 \tag{5}$$

That is, if the current land available for farming increases, change in farming land will be positive. The rate at which arable land is being expanded is b.

Whereas the change in farm labour and farming skills or technology possessed by farmers are in the form:

$$L(\dot{t}) = nL(t) \tag{6}$$

$$A(\dot{t}) = g_A A(t) \tag{7}$$

Equation (6) and (7) show that if the current farm labour and current set of farming skills and technology that farmers possess increase, change in farm labour and farming skills will be positive. n and g are the rates at which farm workers are employed and in which new farming skills are being acquired, respectively.

Linearizing equation (1) gives:

$$InQ(t) = \alpha InK(t) + \beta InC(t) + \gamma InT(t) + \delta InA(t) + 1 - \alpha - \beta - \gamma InL(t) \tag{8}$$

Differentiating (8) with respect to time gives:

$$\frac{Q(t)}{Q(t)} = \alpha\frac{K(t)}{K(t)} + \beta\frac{C(t)}{C(t)} + \gamma\frac{T(t)}{T(t)} + \delta\frac{A(t)}{A(t)} + (1 - \alpha - \beta - \gamma)\frac{L(t)}{L(t)} \tag{9}$$

Equation (9) implies that the growth rate of yield per hectare is a function of growth rate of all other inputs. Hence, substituting the expressions from equation (3) to (7) into (9) yields:

$$g_Q(t) = \alpha\left(s\frac{Q(t)}{K(t)} - \theta\right) - \beta a + \gamma b + \delta g_A + (1 - \alpha - \beta - \gamma)n \tag{10}$$

That is,

$$g_Q(t) = \alpha g_k(t) - \beta a + \gamma b + \delta g_A + (1 - \alpha - \beta - \gamma)n \tag{11}$$

Where $g_k(t)$ is the growth rate of farm machinery and equipment.

The long-run equilibrium requires the growth rate of yield per hectare ($g_Q(t)$), farm machinery (g_k), farm labour (n) and arable land (b) to grow at a constant and equal rate. This is because for long-run equilibrium to be stable both farm machinery, farm labour and farm land must be growing at equal rate, while the assumption of constant returns to scale implies that crop yields are also growing at that rate.

Hence, given that $g_Q(t) = g_k(t) = b = n$ in the long run implies that:

$$g_Q^* = \frac{-\beta a + \delta g_A}{1-\alpha-\gamma-(1-\alpha-\beta-\gamma)} = \frac{-\beta a + \delta g_A}{1-(1-\beta)} \quad (12)$$

Equation (12) shows that long-run growth in crops yields can only come about by changes in climate change elements as well as growth in skills and knowledge of farming. While unfavourable climate change reduces long-run crop yields, farming knowledge and skills increase long-run crops yields.

4.2 Methodology and Empirical Strategies

The equation to be estimated for the empirical analysis, following the outcome in equation (12), is specified as follows:

$$\Delta Y_{it} = \alpha_0 + \alpha_1 \Delta R_t + \alpha_2 \Delta T_t + \epsilon_{it} \quad (13)$$

Where Y_{it} is the log of yield of crop i. Since there is no reliable data on farming skills and knowledge spanning over a long time, it is excluded from the estimation. R_t is the log of rainfall in period t, T is the log of temperature in period t, and ϵ is stochastic error term. The sizes and signs of coefficients of intensities of climate change are expected to vary with crops. In terms of estimations, the variables are first tested for unit root to determine their stationarity properties after which co-integration utilizing Johansen cointegration test. The latter is to check for the existence of the long-run relationship among the variables. Further, short and long-run causality[9] are estimated before estimating the Markov Switch model for each crop sampled. This model is adequate to decompose the different effects of climate change on crop yields in different states of low and high yields. That is, since climate change indicators affect crop yields in different ways, it is important to capture these dynamics. For instance, a relatively high rainfall may be good for low yield periods but bad for high yield period.

The general structure of the long-run bi-variate Granger causality can be expressed as:

$$\Delta X_t = \alpha_t + \beta_t ect_{t-1} + \sum_{j=1}^{n} \gamma_t \Delta X_{t-j} + \sum_{j=1}^{n} \delta_t \Delta Y_{t-j} + \mu_{xt} \quad (14)$$

$$\Delta Y_t = \alpha_t + \beta_t ect_{t-1} + \sum_{j=1}^{n} \gamma_t \Delta Y_{t-j} + \sum_{j=1}^{n} \delta_t \Delta X_{t-j} + \mu_{yt} \quad (15)$$

Where ect_{t-1} is the one period lag of error correction terms saved from estimations of climate change on each crop at level utilizing ordinary least squares (OLS).

The specification of Markov-switching, that allows for more general Autoregressive (K) dynamic structures with switching intercept, is specified as:

$$g_t = \alpha + \beta S_t + \gamma_k \sum_{t=1}^{k} g_{t-1} + \varepsilon_t \quad (16)$$

Where g_t is the log of each crop yield which involves two Autoregressive (AR (1)) specifications:

$$g_t = \begin{cases} \alpha_0 + \gamma g_{t-1} + \varepsilon_t, S_t = 0 \\ \alpha_0 + \gamma g_{t-1} + \varepsilon_t, S_t = 1 \end{cases} \quad (17)$$

s_t = 0, 1 are the Markovian state variables with the transition matrix:

$$P = \begin{bmatrix} p(S_t = 0)/S_{t-1} = 0 & p(S_t = 1)/S_{t-1} = 0 \\ p(S_t = 0)/S_{t-1} = 1 & p(S_t = 1)/S_{t-1} = 1 \end{bmatrix} \quad (18)$$

[9] The short-run causal relationship is based on the F-test and the long-run causal relationship are based on the one year lagged error correction term. That is, ect(-1). Hence, the long-run causality is regarded as Vector Error Correction Granger causality (see Al-mulali, Tang and Ozturk, 2015).

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \tag{19}$$

and ε_t are random variables with mean zero and variance δ_ε^2 .

The two possible states in equation (18 and 19) imply the transition from the state of low yield in the past period to the state of low yield in the current period (P_{00}); transition from the state of low yield in the past (current) period to the state of high yield in the current period (P_{01}); transition from the state of high yield in the past period to the state of low yield in the current period (P_{10}); and the transition from the state of high yield in the past period to the state of high yield in the current (P_{11}).

Climate Change Transmission Channels

The assessment of the transmission channels of climate shocks to welfare change is based on the standard demand and supply principles. Climate change is expected to have a reducing effect on food crops yields leading to food deficit (a situation in which food supply falls short of demand). Since excess demand is associated with higher prices, food deficit is expected to lead to increase in food prices. A higher food price, with income remaining fixed, will have two effects: income effects, which implies lower welfare as households are forced to consume less food and substitution effects coming from consuming same amount of food by consuming less of other goods. The climate change transmission channel is estimated with structural vector autoregressive (SVAR) model. The SVAR model imposed restrictions based on the stated economic relationship as:

$$Z_\epsilon^I = (RGDPPC_t, FP_t, CY_t, C_t,) \tag{20}$$

Where Z_ϵ^I is the restriction, C_t is the impulse of climate change variables, CY_t is the impulse of food crop yields– average yields of the 10 sampled food crops, FP_t is the impulse of food prices (proxy with consumer price index[10]), and $RGDPPC_t$ is the impulse of per capita real GDP– a measure of living standard[11] (constant 2010 US$). Hence, the link between the reduced-form errors and the structural disturbance given the imposed restrictions based on equation (20) is given as follows:

$$\begin{bmatrix} \epsilon_t^{RGDPPC} \\ \epsilon_t^{FP} \\ \epsilon_t^{CY} \\ \epsilon_t^{C} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \begin{bmatrix} \mu_t^{RGDPPC} \\ \mu_t^{FP} \\ \mu_t^{CY} \\ \mu_t^{C} \end{bmatrix} \tag{21}$$

The implication of the ordering in Equation (21) is that C_t is assumed not to respond to any variable in the model. Thus, C_t is purely exogenous. CY_t respond only directly to C_t. FP_t respond to C_t and CY_t, while $RGDPPC_t$ respond to all other variables in the model.

The optimal lag length tests are based on the standard Akaike Information Criterion, Schwarz Information Criterion, Hannan–Quinn Information Criterion and the Final Predictor Error.

5 Results and Discussion

The variables considered are significantly normally distributed, except cowpeas and CPI, given the value of Jarque-Bera statistics (Table 2). This implies that the skewness is minimal. However, different normality characteristics results may be obtained when different periods are considered. Between 1961 and 2017, the average yield of the 10 sampled food crops is about 6.3 million hectogramme per hectare with cassava being the highest followed by yam.

Also, different unit root tests (Augmented Dickey–Fuller test, Phillips-Perron, and unit root test with breakpoint) were considered with results compared. All the tests significantly agreed on the stationarity properties of the series. All the series, except cassava yields and rainfall, exhibit unit root (Table 2). This implies that they random walk and less predictable without necessary transformation. Of importance is

[10] The use of consumer price index is due to inadequate data on food CPI for the period covered by the study. The use of CPI is justified based on the previously established stylised facts on the high correlation between food CPI and all commodities CPI in Nigeria.

[11] Per capita GDP is a better indicator of the change or trend in a nation's living standards over time, since it adjusts for population differences over time.

the climate change variables: rainfall and temperature. The unit root tests show that, at level, rainfall is predictable while temperature is not. When a break in the data is considered, the series show a break point at different dates (Table 2). This justifies the use of Markov switching regression which is suitable when time series are characterised with dynamic patterns and non-linearity (Olakojo, 2020).

The Long-Run Effects of Climate Change on Crop Yields

The short-run and long-run causality presented in A1 to A10 reject the short run causality between climate change and the yields of the crops considered. However, long-run causality cannot be rejected. While cassava shows bidirectional long-run causality, other sampled food crop yields show unidirectional long-run causality running from each of them to their long-run error correction terms. The outcome shows that the impact of climate change on the yields of the sampled crops may not manifest in the short-run but will definitely do in the long-run.

The Markov switching estimates for each crop shows an insignificant mean (except for cassava) but a significant variance shift for all the sampled crops including the average crop yields given the test of equality across states in Table 3. This implies that there have been significant shifts in the sampled crop yields between high and low yields over time and climate change has been a significant factor in the shift. In the regime of low cassava yield, 1% increase in rainfall and temperature reduces cassava yield by 1.4% and 2.5%, respectively. However, rising rainfall increases cassava yield by 0.2% in the period of high yield regime. This implies that high rainfall is less beneficial to the yields of cassava because rising rainfall improves cassava yields less proportionally even in the period of high yield unlike what was observed in the period of low yield. In the case of cocoyam, 1% increase in temperature and rainfall improves the yields by 0.2% and 1.5%, respectively during the low yields regime while 1% increase in rainfall increases cowpeas yields by 1.1% in high yield regime.

Increasing temperature enhances the low yields of groundnuts. In the case of maize, rising rainfall is required to increase yields in both low and high yield periods while increasing temperature is necessary to improve yields in the high yield periods. For millet, okra and yam, high rainfall improves yields in high yield seasons. Significant effects of climate change on rice and sorghum could not be established at any of the yields regime.

The expected duration of being in a state of high yield regime compared to low yield regime is high for cassava, cocoyam, cowpeas, maize, and rice while the opposite is the case for groundnuts, millet, okra, yam and sorghum. This means that there is potential for high yield periods in the first five categories of crop and relatively low yield periods in the later categories of crop. These are also established by the respective transition probabilities. Overall, the expected duration of low crop yield episodes is more than high crops yield episodes in the ratio of 14.7 to 1. This is pointing to the food shortage in the Nigerian agricultural space. Climate change contributes to these significantly. While temperature rise reduces average yields by 0.1% in high yield episodes, increase in rainfall increases average yields by 0.3% and 0.2% for low and high yield episodes, respectively. This shows that temperature has a greater impact on crop yields than rainfall. This corroborates Ochieng, Kirim and Mathenge (2016).

Table 2.
Description of Variables

	Cassava	Cocoyam	Cowpeas	CPI	Groundnuts	Maize	Millet	Okra	Rainf	RGDPPC	Rice	Sorghum	Temp	Yam	Yieldsav
Mean	102049.6	51942.11	5111.446	30.1	10957.21	12854.41	10098.21	21333.34	94.8	1718.27	16761.13	10322.77	27.0	92898.23	6347919
Maximum	122155	76868	14783	183.9	17199	21961	18483	29962	112.2	2563.092	23893	16332	27.8	130109	15282422
Minimum	70323	30441	1398	0.1	3230	5731	4299	8735	72.1	1145.826	8926	5241	26.2	56284	2210400
Jarque-Bera	0.8	2.6	30.4	33.7	0.1	0.5	2.6	0.9	0.8	5.2	2.8	0.2	1.2	3.1	5.6
Probability	0.7	0.3	0.0	0.0	0.9	0.8	0.3	0.6	0.7	0.1	0.2	0.9	0.5	0.2	0.1
Sum	5714779	2908758	286241	1683	613604	719847	565500	1194667	5310.0	96223.11	938623	578075	1512.2	5202301	355000000
Observations	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56

Source: Authors' Computation

Table 3.
Unit Root Tests

	Augmented Dickey–Fuller test (ADF)				**Unit root test with breakpoint**				
	Level		**First difference**		**Level**		**First difference**		
	Intercept	intercept with trend	Intercept	Intercept with trend	Intercept	intercept with trend	Intercept	Intercept with trend	
Series	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Remarks
CASSAVA	0.005	0.029	0.000	0.000	0.014 (2010)	0.000 (2011)	0.000 (2012)	0.000 (2012)	I(0)
COCOYAM	0.463	0.733	0.000	0.000	0.900 (1984)	0.964 (1987)	0.000 (1997)	0.000 (1984)	I(1)
COWPEAS	0.761	0.001	0.000	0.000	0.228 (1980)	0.000 (1977)	0.000 (2013)	0.000 (2013)	I(1)
CPI	0.954	0.316	0.002	0.012	0.768 (1987)	0.000 (1991)	0.0000 (1995)	0.000 (1995)	I(1)
GROUNDNUTS	0.339	0.119	0.000	0.000	0.000 (1975)	0.000 (1975)	0.000 (1977)	0.000 (1977)	I(1)
MAIZE	0.145	0.002	0.000	0.000	0.266 (1974)	0.019 (1988)	0.000 (1975)	0.000 (1975)	I(1)
MILLET	0.282	0.695	0.000	0.000	0.147 (1976)	0.045 (2010)	0.000 (2011)	0.000 (2011)	I(1)
OKRA	0.325	0.860	0.000	0.000	0.033 (2014)	0.000 (2010)	0.000 (2011)	0.000 (2011)	I(1)
RAINF	0.000	0.000	0.000	0.000	0.000 (1983)	0.000 (1983)	0.000 (2003)	0.000 (2003)	I(0)
RGDPPC	0.401	0.921	0.001	0.003	0.807 (2005)	0.374 (1980)	0.027 (1999)	0.000 (1980)	I(1)
RICE	0.126	0.373	0.000	0.000	0.140 (1977)	0.000 (1993)	0.000 (1976)	0.000 (1976)	I(1)
SORGHUM	0.071	0.025	0.000	0.000	0.000 (1978)	0.000 (1978)	0.000 (1984)	0.000 (1984)	I(1)
TEMP	0.783	0.000	0.000	0.000	0.918 (1994)	0.000 (1975)	0.000 (2008)	0.0000 (2008)	I(1)
YAM	0.059	0.199	0.000	0.001	0.015 (1994)	0.033 (1995)	0.000 (1981)	0.000 (1981)	I(1)
YIELDSAV	0.961	0.328	0.005	0.021	0.600 (1987)	0.754 (1987)	0.078 (1983)	0.000 (1983)	I(1)

Source: Authors' Computation
Note: The break year is indicated in the parentheses of the unit root test with breakpoint

Table 4.
Markov Switch Model

Switch Parameters	CASSAVA	COCOYAM	COWPEAS	GROUNDNUTS	MAIZE	MILLET	OKRA	RICE	SORGHUM	YAM	MeanYIELDS
μ1 (Regime1)	-0.041 (-27.24)***	0.003 (0.517)	0.001 (0.129)	0.000 (0.000)	0.031 (26.856)***	0.008 (0.461)	0.010 (2.293)*	0.018 (0.392)	0.014 (0.296)	0.015 (2.006)*	0.036 (2.892)**
μ2 (Regime2)	0.006 (0.562)	-0.013 (-0.441)	0.020 (0.310)	-0.032 (-0.092)	0.013 (0.526)	-0.002 (-0.021)	-0.078 (-0.733)	0.010 (1.048)	0.007 (0.570)	-0.021 (-0.438)	0.040 (117.914)***
σ_1^2 Regime1)	-5.794 (-17.54)***	-4.016 (-10.501)***	-3.472 (-18.053)***	-1.891 (-16.192)***	-6.364 (-15.545)***	-2.647 (-13.690)***	-3.691 (-26.586)***	-1.548 (-8.871)***	-1.494 (-9.600)***	-3.420 (-18.892)***	-2.525 (-23.124)***
σ_2^2 (Regime2)	-2.648 (-23.58)***	-1.931 (-12.629)***	-1.085 (-7.740)***	-0.365 (-0.971)	-1.859 (-16.979)***	-1.160 (-6.134)***	-1.132 (-4.907)***	-3.294 (-13.799)***	-3.161 (-17.720)***	-1.599 (-9.665)***	-7.633 (-18.282)***
Switch Regressors (Regime 1)											
D(Rainfall)	-1.405 (-111.8)***	0.224 (3.399)***	-0.003 (-0.036)	0.441 (2.112)**	0.309 (53.456)***	-0.169 (-1.209)	-0.017 (-0.387)	0.229 (0.531)	-0.174 (-0.481)	-0.349 (-0.548)	0.255 (2.249)**
D(Temp)	-2.485 (-24.27)***	1.456 (2.246)**	-0.165 (-0.226)	1.457 (0.718)	0.804 (5.714)***	0.018 (0.014)	0.202 (0.571)	-1.112 (-0.309)	-6.576 (-1.776)*	-0.765 (-1.091)	-1.231 (-1.274)
Switch Regressors (Regime 2)											
D(Rainfall)	0.193 (1.962)**	-0.160 (-0.698)	1.118 (2.171)**	1.174 (0.174)	0.615 (2.680)**	1.786 (2.696)**	2.139 (3.112)**	-0.112 (-1.021)	-0.061 (-0.566)	1.256 (2.492)**	0.212 (94.950)***
D(Temp)	0.948 (1.058)	0.064 (0.028)	-3.241 (-0.666)	-14.554 (-0.372)	-1.866 (-1.001)	-2.017 (-0.309)	-3.347 (-0.457)	1.294 (1.743)*	0.669 (0.868)	0.117 (0.034)	-0.122 (-4.343)***
Transition Probabilities											
P(low/low)	0.00	0.41	0.65	0.98	0.93	0.78	0.93	0.58	0.93	0.72	0.93
P(low/high)	1.00	0.59	0.35	0.02	0.07	0.22	0.07	0.42	0.07	0.28	0.07
P(high/low)	0.12	0.41	0.23	0.26	0.02	0.40	0.21	0.39	0.10	0.36	1.00
P(high/high)	0.88	0.59	0.77	0.74	0.98	0.60	0.79	0.61	0.90	0.64	0.00
Expected durations											
State1 (low)	1.0	1.7	2.9	41.2	14.4	4.6	14.90	2.36	14.89	3.60	14.76
State 2 (high)	8.3	2.4	4.4	3.8	60.5	2.5	4.69	2.57	10.38	2.75	1.00
Tests of Equality across states (F-statistics)											
μ1= μ2	17.23***	0.28	0.08	0.01	0.58	0.01	0.69	0.03	0.02	0.55	0.12
$\sigma_1^2 = \sigma_2^2$	81.04***	33.03***	104.53***	15.64***	113.25***	33.76***	93.79***	46.13***	53.54***	59.69***	140.16***
Statistics											
Log-likelhood	70.7	54.4	11.5	12.9	37.0	22.0	80.8	38.8	34.5	45.0	67.4
DW	2.1	2.4	2.3	2.0	2.3	2.2	2.4	2.8	2.2	2.1	1.9
Observations	55	55	55	55	55	55	55	55	55	55	55

Source: Authors' Computation

Note: z-statistics are in the parentheses. *,**,*** implies significance at 1%, 5%, and 10%, respectively.

Shocks to Nigerians Living Standards via Climate Change Effects on Food Production

There are four variables of focus under this section namely, the climate change (rainfall and temperature), consumer prices, crops' yields and real GDP per capita. The SVAR estimates of climate change effect of temperature is presented in Figure 12 and 13. Meanwhile, the optimal lag selection criteria picked lag 1 in both rainfall and temperature SVAR models (Table 4 and 5). The statistics do not agree with alternative lag selections.

Table 4.

Optimal lag length criteria (Rain)

Lag LogL	LR	FPE	AIC	SC	HQ	Lag LogL
0 205.1492	NA	6.83e-09	-7.449969	-7.302637	-7.393149	0 205.1492
1 238.2439	60.06074*	3.64e-09*	-8.083106*	-7.346445*	-7.799004*	1 238.2439

Source: Authors' Computation

Table 5.

Optimal lag length criteria (Temp)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	320.5267	NA	9.52e-11	-11.72321	-11.57588	-11.66639
1	356.6120	65.48822*	4.54e-11*	-12.46711*	-11.73045*	-12.18301*

Source: Authors' Computation

The impulse response for rainfall emanating from the SVAR model shows that the welfare of Nigerians declines when there is a shock to the average yields of the selected crops for about three periods before it neutralizes in the fourth period (bottom right panel of Figure 8). This means that a period shock to average yields of the selected crops will have about three years declining effect on the welfare of Nigerians. The shocks to average crop yields come directly from shocks to rainfall and it lasts for about two periods (see top right panel of figure 8). Also, the shocks to consumer prices comes majorly from shocks to average crop yields (bottom left panel of Figure 8) when consumer prices will increase for about two periods. This shows that shocks to consumer prices due to shocks to crop yields will be temporary within a year or two after which it dies out. These results imply that shocks to rainfall will have longer declining impact on average yields of crops than shocks to average yields will have on increasing consumer prices. It confirms seasonality characteristics of the sampled food crops which could make them scarce in a particular season with higher prices and abundance in other season with very low prices (see Olakojo 2016). However, rainfall shortage impacts on crops yields go beyond a season. This outcome is convincing given that next farm output depends significantly on the current output bearing in mind that farmers use part of the current farm yields as seedlings for the next planting season. The significance response of all the variables to shocks from others do not go beyond 7th period (Figure A4 and A5).

Unlike the impulse response estimations for rainfall, temperature impulse response shows that the welfare of Nigerians declines directly not only with innovations to crops yields but also to temperature shocks (bottom right panel of Figure 9). This implies that rising temperature has some direct effect on the welfare of Nigerians beyond its indirect impact through food production. The effect of temperature on welfare may be associated with the heat-related ailments. For instance, Akpodiogaga and Odjugo (2010) noted that excessive heat and other climate change factors may result in increasing incidence of heat exhaustion, inflammatory and respiratory diseases (cough, and asthma), depression, and cataract. Other heat-related illnesses also include heat cramps, and heat or sun stroke. These heat-related ailments increase health expenditure burdens of households leading to decline in real income per capita.

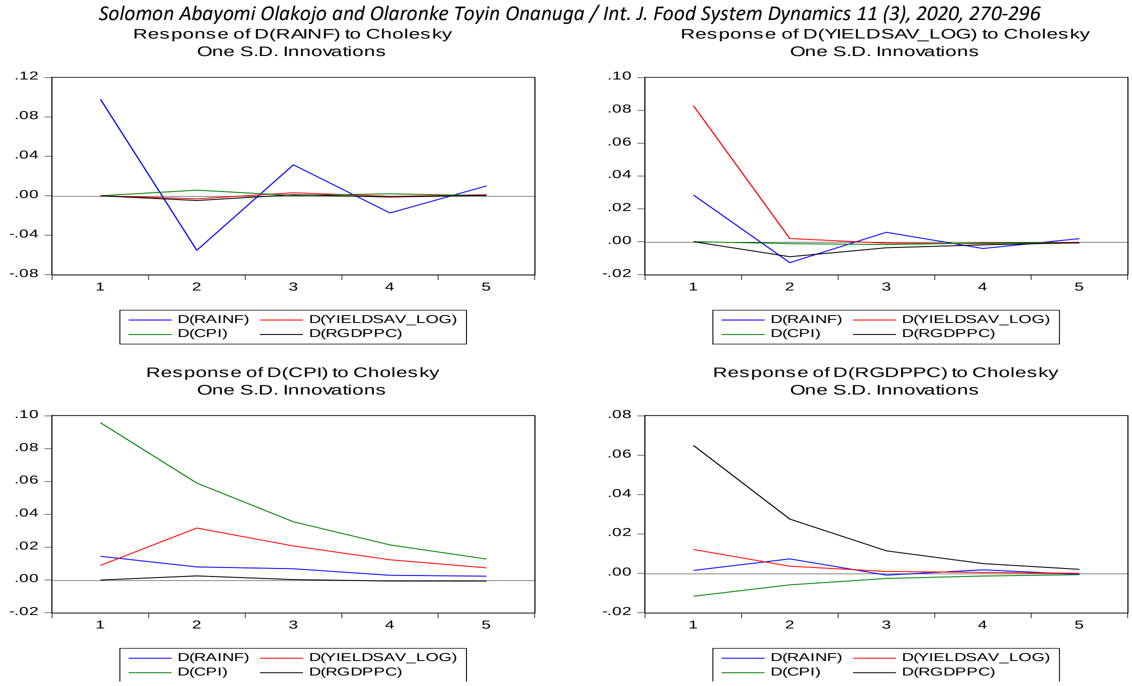

Figure 8. Impulse response of rainfall to other variables (5 periods)
Source: Authors' Computation

The response of crop yields to temperature is initially positive in the first period after which shocks to temperature reduces yields up to the fourth period. This supports the Paris Agreement of the Conference of Parties to the United Nations Framework Convention on Climate Change to keep the global temperature rise below 2^{o}C. Consumer price is equally found to increase as a result of shocks to temperature and crop yields from first to third period (bottom left panel of Figure 9). The shocks to average crop yields come from shocks to temperature but the impact is felt in the second period up to the fourth period unlike in the rainfall equation where the effect is immediate. This implies that crops yields are more sensitive to rainfall than temperature in the short but the opposite was the case in the long run, as previously estimated. Hence, this outcome corroborates Kang, Khan, and Ma (2009). It is equally noticed that the impact of temperature is longer, though not immediate. This relates to the long-run results.

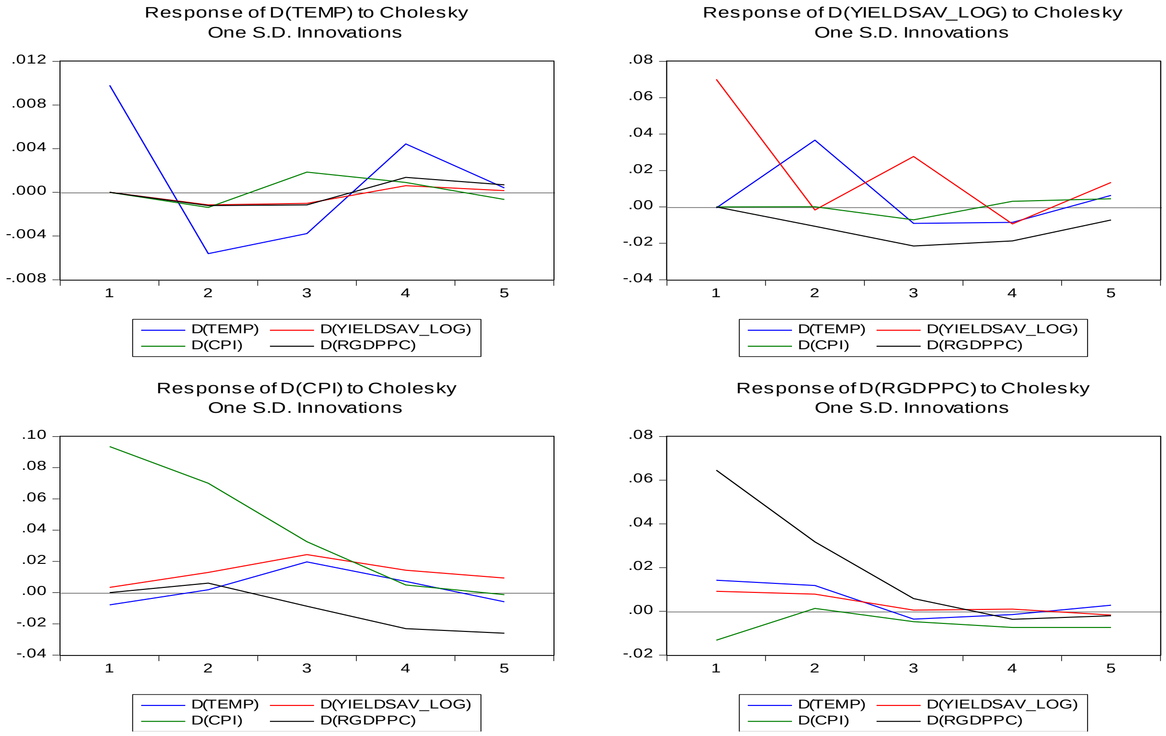

Figure 9. Impulse response of temperature to other variables (5 periods)
Source: Authors' Computation

6 Conclusion and Policy Lessons

This study investigated the impact of climate change (measured with temperature and rainfall changes) on long-run yields of 10 leading food crops in Nigeria between 1961 and 2017. The Markov switch estimates show that there have been significant shifts in the sampled crops' yields between high and low yields over time and climate change has been a significant factor in the shifts. The impact of climate change varies with crops. In the regime of low cassava yield, an increase in rainfall and temperature reduces cassava yield. However, rising rainfall increases cassava yield in the period of high yield regime. Increase in temperature and rainfall improves the yields of cowpeas during the low yields regime while increase in rainfall increases cowpeas yields in high yields regime. Overall, the expected duration of low crop yields episodes is more than high crop yields episodes which is pointing to the food shortage in the Nigeria agricultural space. The SVAR results indicated that shocks to Nigerians' welfare is traceable to shocks to average crop yields, while shocks to crop yields are traceable to shocks to climate change. Besides, shocks to consumer prices are traceable to shocks to crop yields. Hence, agricultural research in the area of developing temperature resistant crops (especially, cassava) will help to minimize the effect of global warming. Also, irrigation that reduces the effect of rainfall variability will help to improve the yields of many of the sampled crops.

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Appendix

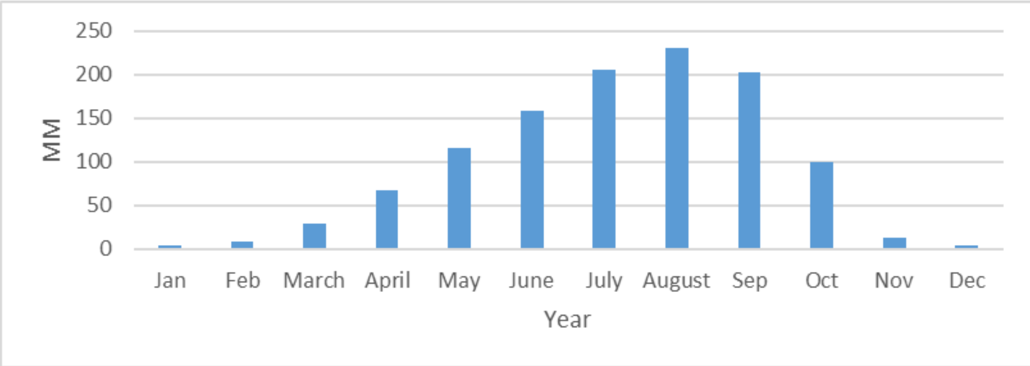

Figure A1. Average Monthly Rainfall Distribution (MM), 1960-2016.
Source: Climate Knowledge Portal (https://climateknowledgeportal.worldbank.org/download-data)

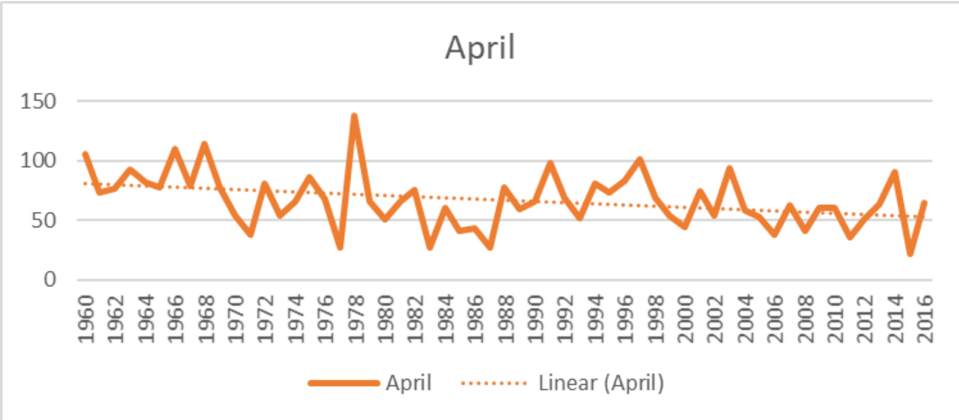

Figure A2. April Rainfall (MM), 1960-2016.
Source: Climate Knowledge Portal (https://climateknowledgeportal.worldbank.org/download-data)

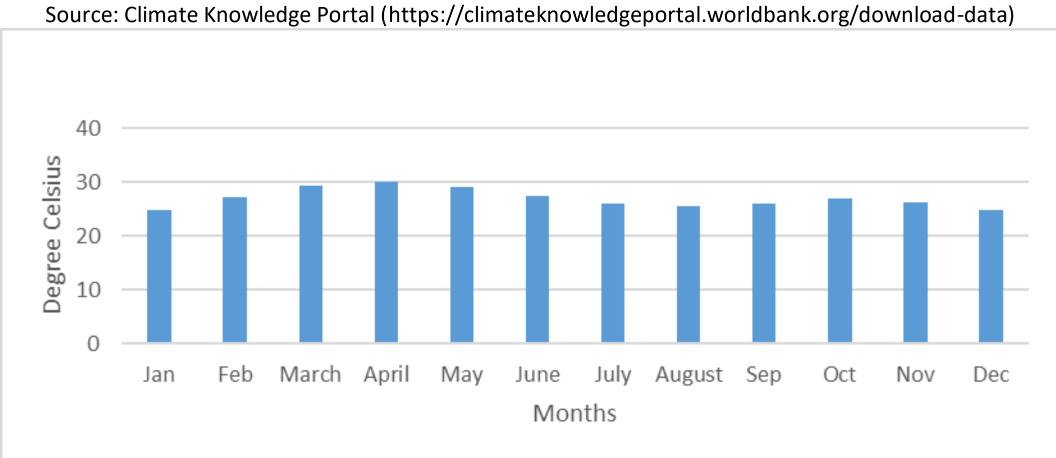

Figure A3. Monthly Temperature Distribution, 1960-2016
Source: Climate Knowledge Portal (https://climateknowledgeportal.worldbank.org/download-data)

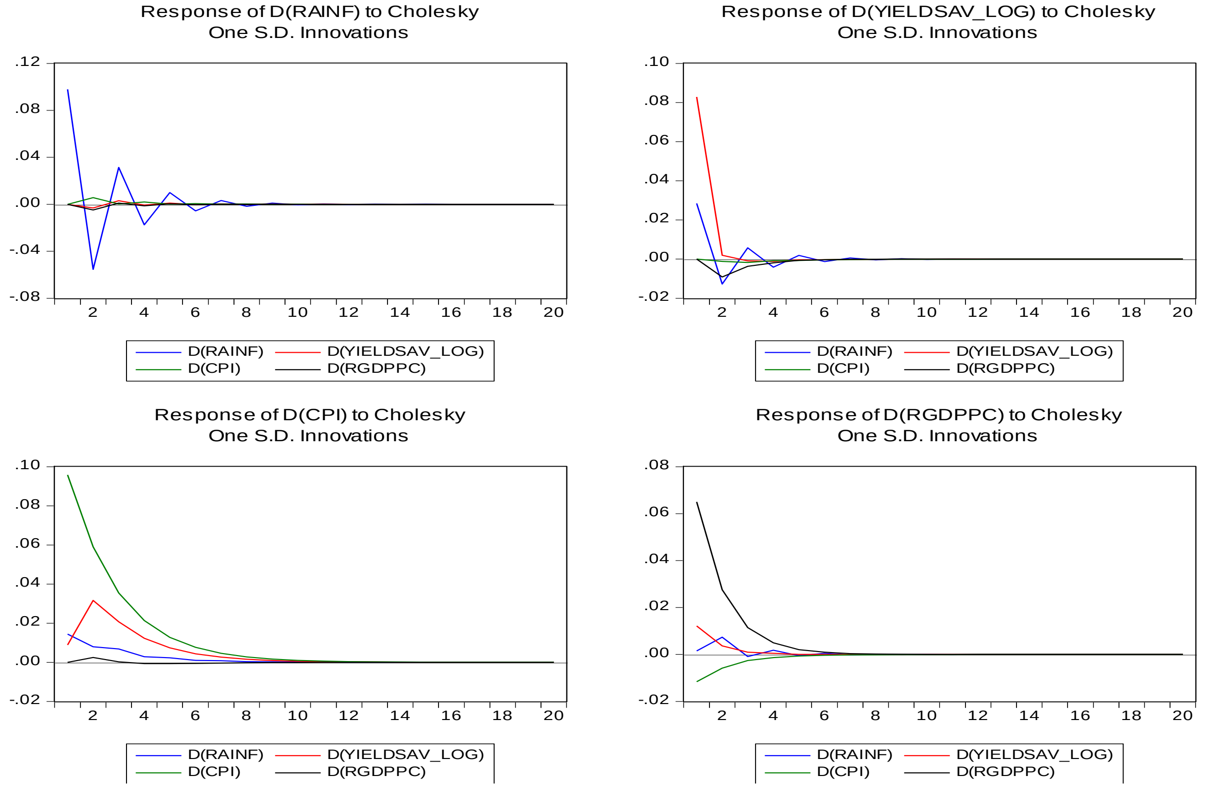

Figure A4. Impulse response of rainfall to other variables (20 periods)

Source: Authors' Computation

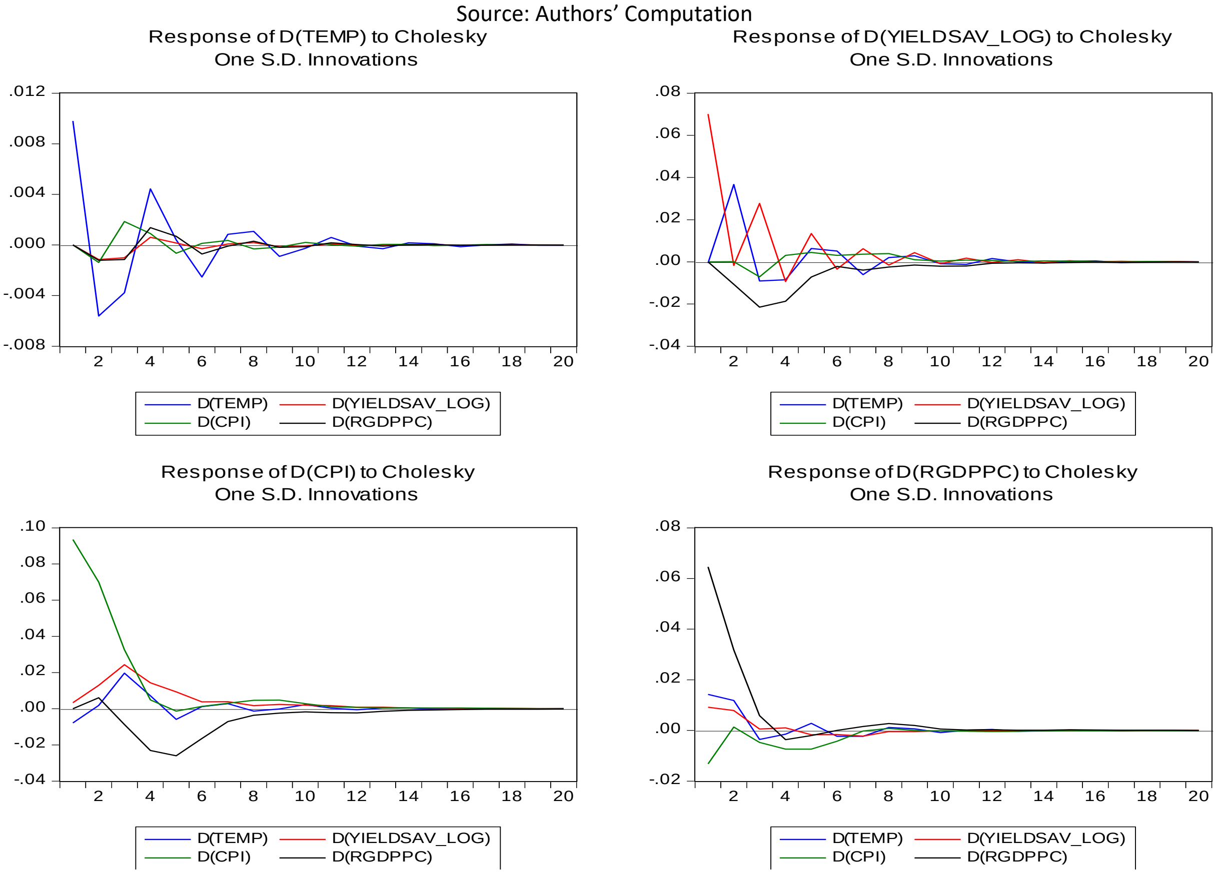

Figure A5. Impulse response of temperature to other variables (20 periods)

Source: Authors' Computation

Long-Run Causality Test

Table A1.
Cassava

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_CASSAVA(-1) does not Granger Cause D(CASSAVA)	53	5.09904	0.0098
D(CASSAVA) does not Granger Cause ECT_CASSAVA(-1)		268.368	9.E-27
D(RAINF) does not Granger Cause D(CASSAVA)	53	0.63455	0.5346
D(CASSAVA) does not Granger Cause D(RAINF)		0.47845	0.6227
D(TEMP) does not Granger Cause D(CASSAVA)	53	0.24155	0.7864
D(CASSAVA) does not Granger Cause D(TEMP)		0.37508	0.6892
D(RAINF) does not Granger Cause ECT_CASSAVA(-1)	53	1.85772	0.1671
ECT_CASSAVA(-1) does not Granger Cause D(RAINF)		0.36733	0.6945
D(TEMP) does not Granger Cause ECT_CASSAVA(-1)	53	0.17101	0.8433
ECT_CASSAVA(-1) does not Granger Cause D(TEMP)		0.62149	0.5414
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A2.
Cocoyam

Pairwise Granger Causality Tests
Sample: 1961 2016

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_COCOYAM(-1) does not Granger Cause D(COCOYAM)	53	0.67827	0.5123
D(COCOYAM) does not Granger Cause ECT_COCOYAM(-1)		16.1549	4.E-06
D(RAINF) does not Granger Cause D(COCOYAM)	53	0.80316	0.4538
D(COCOYAM) does not Granger Cause D(RAINF)		0.42139	0.6585
D(TEMP) does not Granger Cause D(COCOYAM)	53	0.03936	0.9614
D(COCOYAM) does not Granger Cause D(TEMP)		0.50973	0.6039
D(RAINF) does not Granger Cause ECT_COCOYAM(-1)	53	13.4985	2.E-05
ECT_COCOYAM(-1) does not Granger Cause D(RAINF)		0.68146	0.5107
D(TEMP) does not Granger Cause ECT_COCOYAM(-1)	53	3.05697	0.0563
ECT_COCOYAM(-1) does not Granger Cause D(TEMP)		0.93826	0.3984
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A3.
Cowpeas

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_COWPEAS(-1) does not Granger Cause D(COWPEAS)	53	1.14874	0.3256
D(COWPEAS) does not Granger Cause ECT_COWPEAS(-1)		27.6443	1.E-08
D(RAINF) does not Granger Cause D(COWPEAS)	53	0.28535	0.7530
D(COWPEAS) does not Granger Cause D(RAINF)		0.35350	0.7040
D(TEMP) does not Granger Cause D(COWPEAS)	53	0.10287	0.9024
D(COWPEAS) does not Granger Cause D(TEMP)		0.72095	0.4915
D(RAINF) does not Granger Cause ECT_COWPEAS(-1)	53	2.09393	0.1343
ECT_COWPEAS(-1) does not Granger Cause D(RAINF)		0.18626	0.8307
D(TEMP) does not Granger Cause ECT_COWPEAS(-1)	53	22.9158	1.E-07
ECT_COWPEAS(-1) does not Granger Cause D(TEMP)		1.35647	0.2673
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A4.
Groundnut

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_GROUNDNUT(-1) does not Granger Cause D(GROUNDNUTS)	53	1.57529	0.2175
D(GROUNDNUTS) does not Granger Cause ECT_GROUNDNUT(-1)		49.6958	2.E-12
D(RAINF) does not Granger Cause D(GROUNDNUTS)	53	0.79213	0.4587
D(GROUNDNUTS) does not Granger Cause D(RAINF)		1.95415	0.1528
D(TEMP) does not Granger Cause D(GROUNDNUTS)	53	1.92993	0.1563
D(GROUNDNUTS) does not Granger Cause D(TEMP)		0.96632	0.3878
D(RAINF) does not Granger Cause ECT_GROUNDNUT(-1)	53	0.34078	0.7129
ECT_GROUNDNUT(-1) does not Granger Cause D(RAINF)		1.23934	0.2987
D(TEMP) does not Granger Cause ECT_GROUNDNUT(-1)	53	6.62227	0.0029
ECT_GROUNDNUT(-1) does not Granger Cause D(TEMP)		0.29448	0.7463
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A5.
Maize

Pairwise Granger Causality Tests

Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_MAIZE(-1) does not Granger Cause D(MAIZE)	53	1.93779	0.1551
D(MAIZE) does not Granger Cause ECT_MAIZE(-1)		29.6483	4.E-09
D(TEMP) does not Granger Cause D(MAIZE)	53	0.48569	0.6183
D(MAIZE) does not Granger Cause D(TEMP)		1.03327	0.3636
D(RAINF) does not Granger Cause D(MAIZE)	53	0.95729	0.3911
D(MAIZE) does not Granger Cause D(RAINF)		6.53584	0.0031
D(TEMP) does not Granger Cause ECT_MAIZE(-1)	53	20.0285	5.E-07
ECT_MAIZE(-1) does not Granger Cause D(TEMP)		3.16031	0.0514
D(RAINF) does not Granger Cause ECT_MAIZE(-1)	53	0.95108	0.3935
ECT_MAIZE(-1) does not Granger Cause D(RAINF)		1.85973	0.1668
D(RAINF) does not Granger Cause D(TEMP)	53	0.81407	0.4491
D(TEMP) does not Granger Cause D(RAINF)		0.20875	0.8123

Table A6.
Millet

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_MILLET(-1) does not Granger Cause D(MILLET)	53	1.67018	0.1990
D(MILLET) does not Granger Cause ECT_MILLET(-1)		100.527	7.E-18
D(RAINF) does not Granger Cause D(MILLET)	53	1.43410	0.2484
D(MILLET) does not Granger Cause D(RAINF)		1.43218	0.2488
D(TEMP) does not Granger Cause D(MILLET)	53	0.02967	0.9708
D(MILLET) does not Granger Cause D(TEMP)		1.36321	0.2656
D(RAINF) does not Granger Cause ECT_MILLET(-1)	53	4.04830	0.0237
ECT_MILLET(-1) does not Granger Cause D(RAINF)		0.96805	0.3871
D(TEMP) does not Granger Cause ECT_MILLET(-1)	53	6.15209	0.0042
ECT_MILLET(-1) does not Granger Cause D(TEMP)		0.93236	0.4006
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A7.
Okra

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_OKRA(-1) does not Granger Cause D(OKRA)	53	0.95771	0.3910
D(OKRA) does not Granger Cause ECT_OKRA(-1)		294.488	1.E-27
D(TEMP) does not Granger Cause D(OKRA)	53	1.14503	0.3268
D(OKRA) does not Granger Cause D(TEMP)		0.21901	0.8041
D(RAINF) does not Granger Cause D(OKRA)	53	0.64463	0.5293
D(OKRA) does not Granger Cause D(RAINF)		3.29199	0.0457
D(TEMP) does not Granger Cause ECT_OKRA(-1)	53	0.63243	0.5357
ECT_OKRA(-1) does not Granger Cause D(TEMP)		0.09591	0.9087
D(RAINF) does not Granger Cause ECT_OKRA(-1)	53	0.26753	0.7664
ECT_OKRA(-1) does not Granger Cause D(RAINF)		1.85024	0.1682
D(RAINF) does not Granger Cause D(TEMP)	53	0.81407	0.4491
D(TEMP) does not Granger Cause D(RAINF)		0.20875	0.8123

Table A8.
Rice.

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_RICE(-1) does not Granger Cause D(RICE)	53	2.97121	0.0607
D(RICE) does not Granger Cause ECT_RICE(-1)		54.9111	4.E-13
D(RAINF) does not Granger Cause D(RICE)	53	0.04019	0.9606
D(RICE) does not Granger Cause D(RAINF)		0.59517	0.5555
D(TEMP) does not Granger Cause D(RICE)	53	1.68443	0.1963
D(RICE) does not Granger Cause D(TEMP)		0.50047	0.6094
D(RAINF) does not Granger Cause ECT_RICE(-1)	53	7.66654	0.0013
ECT_RICE(-1) does not Granger Cause D(RAINF)		0.39344	0.6769
D(TEMP) does not Granger Cause ECT_RICE(-1)	53	2.79903	0.0708
ECT_RICE(-1) does not Granger Cause D(TEMP)		0.04548	0.9556
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A9.
Sorghum

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_SORGHUM(-1) does not Granger Cause D(SORGHUM)	53	2.94495	0.0622
D(SORGHUM) does not Granger Cause ECT_SORGHUM(-1)		75.0091	2.E-15
D(RAINF) does not Granger Cause D(SORGHUM)	53	0.07760	0.9255
D(SORGHUM) does not Granger Cause D(RAINF)		0.11579	0.8909
D(TEMP) does not Granger Cause D(SORGHUM)	53	4.47017	0.0166
D(SORGHUM) does not Granger Cause D(TEMP)		0.18352	0.8329
D(RAINF) does not Granger Cause ECT_SORGHUM(-1)	53	0.59741	0.5543
ECT_SORGHUM(-1) does not Granger Cause D(RAINF)		0.14300	0.8671
D(TEMP) does not Granger Cause ECT_SORGHUM(-1)	53	13.2883	3.E-05
ECT_SORGHUM(-1) does not Granger Cause D(TEMP)		1.21990	0.3042
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491

Table A10.
Yam

Pairwise Granger Causality Tests
Sample: 1961 2016
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ECT_YAM(-1) does not Granger Cause D(YAM)	53	3.10979	0.0537
D(YAM) does not Granger Cause ECT_YAM(-1)		34.0526	6.E-10
D(RAINF) does not Granger Cause D(YAM)	53	0.27339	0.7620
D(YAM) does not Granger Cause D(RAINF)		6.56606	0.0030
D(TEMP) does not Granger Cause D(YAM)	53	2.00541	0.1457
D(YAM) does not Granger Cause D(TEMP)		0.52155	0.5969
D(RAINF) does not Granger Cause ECT_YAM(-1)	53	4.25825	0.0198
ECT_YAM(-1) does not Granger Cause D(RAINF)		6.07670	0.0044
D(TEMP) does not Granger Cause ECT_YAM(-1)	53	0.15880	0.8536
ECT_YAM(-1) does not Granger Cause D(TEMP)		1.91530	0.1584
D(TEMP) does not Granger Cause D(RAINF)	53	0.20875	0.8123
D(RAINF) does not Granger Cause D(TEMP)		0.81407	0.4491